Mitigating Human-Elephant Conflict through an Engineering Approach

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Abstract

ELEPHANTS and humans existed with a long tradition of interdependence up until contemporary times. However, today human-elephant conflict (HEC) has become one of the most significant environmental and socio-economic crises in some parts of the world. The conflict primarily is a consequence of frequent attacks from crop-raiding elephants to the rural agricultural communities. The primary objective of this research is to reduce the occurrences of human-elephant conflict by developing a solution in a way that rural agricultural communities gain the ability to identify elephant migration towards the village in advance. The proposed solution is basically to incorporate a sensor network to detect, localize and track elephants before they move into the village area.

In this thesis first, we studied the social structure and behavioural patterns of elephants and identified significant characteristics that can be utilized in the proposed solution. We have recognized the seasonal characteristics which indicate the probability of elephants migrating towards the villages and more importantly their behavioural pattern of utilizing the same travel routes. We have further investigated their communication and call patterns and identified that low-frequency elephant calls called rumbles can be utilized to detect the presence of elephants from a faraway distance.

Next, we developed a framework which was utilized to investigate the feasibility of using acoustic sensor network for elephant localization. Then we analysed the effects on the accuracy of elephant localization and detection based on the characteristics of sound propagation over the air. We investigated the effect of various meteorological parameters in elephant vocalization propagation medium and their consequential effects on elephant positioning accuracy. In addition, we evaluated the effect of signal-to-noise ratio (SNR) on the detection of vocalization signal which subsequently affects the localization ac-

curacy. Extensive simulation results revealed that the temperature variations between sensors and deviation in wind velocity have a significant effect on positioning accuracy of the system. In addition, localization accuracy decreased enormously once the SNR level fell under certain marginal level.

We then introduced a novel technique with sound generating probes to estimate the average speed of sound which is affected by environmental parameters. The technique was then integrated with the elephant localization system framework which utilizes acoustic sensor network. Performance of the system was evaluated under real-world ecological scenarios against a sensor network which is equipped with wind and temperature sensors. Analysis revealed that the sensor network with the proposed probe technique achieved the best overall accuracy of localization, despite the limited information it gathers from the environment.

Finally, we built a hardware system to test and validate our approach. Initial experiments were designed and performed by replaying recorded elephant sounds under different environmental conditions. The results overall illustrated that the system can provide significant localization accuracy under a range of wind and temperature conditions. An identical hardware set up was then used to localize wild elephants in Sri Lanka. Our approach enabled localization of wild elephants at a distance of over 500 m from the sensors to within 30 m accuracy, providing adequate time for the villages to take appropriate safety measures.

Declaration

This is to certify that

1. the thesis comprises only my original work towards the PhD,
2. due acknowledgement has been made in the text to all other material used,
3. the thesis is less than 100,000 words in length, exclusive of tables, maps, bibliographies and appendices.

Chinthaka M. Dissanayake, October 2018

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Preface

The content related to this thesis has been partially published in an international conference and in a scientific journal. The publications has beed carried out during the period of PhD candidature of the author of the thesis.

1. Chinthaka M. Dissanayake, K. Ramamohanarao, M. N. Halgamuge, B. Moran, and P. Farrell "Propagation Constraints in Elephant Localization Using an Acoustic Sensor Network" , IEEE 6th International Conference on Information and Automation for Sustainability (ICIAfS'12), pp 101-105, Beijing, China, 27-29 September 2012.
   [Chapter 5 partially contains meterial from this publication. Appendix A presents the published material in the international conference.]

2. Chinthaka M. Dissanayake, K. Ramamohanarao, M. N. Halgamuge, and B. Moran, "Improving Accuracy of Elephant Localization using Sound Probes", Applied Acoustics, Volume 129, pp 92–103, 2018.
   [Chapter 6 and Chapter 7 partially contains meterial from this publication. Appendix B presents the published material in the international journal.]

To my parents & family...!

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Chapter 1

Introduction

ELEPHANTS and humans existed with a long tradition of interdependence up until contemporary times. Elephants figured prominently in work, warfare, culture, religion and pageantry throughout history [1]. Changes in social and ecological conditions precipitated by human needs are resulting in serious depletion in certain animal populations. Human-elephant conflict (HEC) is one such significant socio-ecological problem in some parts of the world. The conflict primarily is a consequence of frequent attacks from crop-raiding elephants on the rural agricultural communities. Humans are clearing large areas of land for food production, increasing pressure on traditional elephant habitats. This results in migration of elephants to villages to fulfill their food requirements and ensuing HEC.

In Sri Lanka where the field trials for this research was primarily conducted, it is estimated that there are approximately 4,200$-$5,000 wild elephants. Typically, one elephant needs at least five square kilometres of optimum habitat to inhabit [2]. In consequence, the population require in total, minimum of $21,000$ to $25,000$ square kilometres or 32$-$38% of the overall land area of the country [2]. The national parks only cover 12.5% of the total requirement and almost 70% of the elephants live outside the national parks, sharing the land with rural people. As a result, human-elephant conflict is common in eight of the nine administrative provinces in Sri Lanka affecting over three million people.

The consequences of HEC are the loss of human lives or permanent disability, damage to properties and cultivation while creating negative attitudes towards the elephants [3]. From 2012 to 2016, in Sri Lanka alone 316 people were killed by elephants and $1,171$ elephants were killed by people. During the same period, an overall total of 6,415 residences in the country were damaged by elephants. Until 2007 the average number of elephants killed per year in Sri Lanka was around 150. Since 2012 this number has increased to 250 elephants per annum and in 2016 the elephant deaths reached its recorded highest of 279 [4]. Over 90% of the elephant fatalities were resulted from retaliatory killing by farmers for destroying their crops, homes and lives [2]. The gravity of the HEC is serious considering the fact that the Asian Elephants (*Elephas maximus*) categorized as *Endangered* in the International Union for Conservation of Nature (IUCN) Red List [5].

1.1 Motivation

Various strategies have been implemented to mitigate HEC. Traditional methods such as chasing elephants away by shouting, building fires and lighting fire crackers are still used by rural farmers and villages. Approaches such as implementing electric fencing systems and using satellite imaging and radio and Global Positioning Systems (GPS) collars to detect the presence of elephants [6] are also employed with the support of government authorities and conservation support groups. However, these strategies suffer from inherent drawbacks ranging from lack of effectiveness to inadequacy of resources [7].

Within the current context of human-elephant conflict, it is important to take every possible action to manage the problem at tolerable levels. Accurately detecting the presence of elephants plays a significant role in this process [8–10].

Recently, interest has grown in the detection of elephants through their low-frequency calls, commonly referred to as “rumbles” [7]. This technique is a safe, practical and non-intrusive methodology to detect these highly social animals that use rumbles for long distance communication. Once the elephants are detected at a sufficient distance from the village boundaries countermeasures and warnings to the local population can be deployed. The proposed solution in this thesis is basically to deploy an acoustic sensor network to detect and localize elephants before they move into the village area.

1.2 Key Challenges

In this thesis, the research question addresses a multidisciplinary real practical problem. The following key challenges are identified as the research problems.

- General and favourable elephant behaviour patterns need to be identified for effective implementation of a theoretical and practical elephant detection framework.
- Sensors should be able to detect the presence of elephants. This will, in practice, be achieved by positively identifying low-frequency elephant calls originating from a location where is a long distance away from the area of interest.
- Finding the location of elephants in the given environment is a challenging task. Mathematical modelling need to be performed to determine the effectiveness of acoustic localization algorithms.
- These infrasound calls travel through the air and the effects of changes in the medium need to be determined. For instance, the environmental factors such as temperature and wind velocity change the speed of sound in air. Quantitative analysis needs to be performed to estimate the effect on such variations in localization accuracy.
- A practical hardware system needs to be designed and implemented to gather data for analysis purposes. The designed hardware should be capable of implementation in a real-world system.
- The number of actual implemented wireless sensor network systems is extremely low compared to the theoretical publications presented in the wireless sensor network area. To fill the gap, sensor network hardware systems need to be designed and implemented to test and validate proposed theoretical framework and algorithms.

1.3 Scope and Limitations

This thesis investigates the feasibility of utilizing acoustic sensor network to detect the presence of elephant and accurately estimate the elephant location. Challenges in localization estimation are extensively discussed and naval methodology to improve the localization accuracy is proposed and implemented in this thesis.

Real-world implementation in this thesis focuses on proof of the concept, and due to time and resources constraints, data collection is limited to above aspect. Challenges in the long-term operation of the system framework proposed are out of the scope of this thesis. The thesis focuses on detecting the presence of the elephant(s). Feature extraction or similar techniques has not been utilized in this research to classify specific elephant or estimate the number of elephants in the vicinity of the network.

1.4 Contributions of the Thesis

Major contributions are listed in the order they appear in the thesis.

1. Evaluation of the key elephant social behaviours and characteristics to identify favourable behavioural patterns for an elephant detection and localization system.

2. Development of the mathematical model to estimate source (elephant) locations with a passive acoustic sensor network and analysis of the network scale on localisation accuracy.

3. Evaluation of probabilistic bounds and error validation of the elephant localization model, identifying probabilistic estimation error regions.

4. Proposal for a simulation framework to study the performance of the designed elephant localization algorithms considering real-world model inputs.

5. Investigation of the impact of environmental constraints and signal to noise ratio on an elephant localization sensor network. Identification of the variables that significantly compromise the estimation accuracy with respect to the application.

6. Introduction of a novel “probe” technique to estimate the accurate sound speed in the air which is affected by the environmental parameters of the medium.

7. Comparative study of the proposed novel probe technique under different environmental scenarios and evaluation of position estimation error.

8. Design and implementation of a hardware system framework addressing our application requirements and including the novel probe technique and deployment. Collection of data in real-world and forest environment using developed hardware system.

9. Practical validation of proposed methodologies system consists of both hardware and software in Sri Lanka.

1.5 Structure of the Thesis

After this introductory chapter, the thesis is organized as follows:

Chapter 2: Literature Review

This chapter carries out a literature survey related to the thesis. In our approach, we utilize a sensor network to detect and localize elephants. A brief review of implemented wireless sensor network applications for habitat monitoring has been discussed in the early part of the chapter. Even though there are extensive theoretical publications related to wireless sensor networks, practical implementations are limited. The later parts of the chapter present the current strategies utilized in mitigating HEC. There are wide limitations in current approaches in terms of effectiveness and resource availability and these concerns are elaborated in Chapter 2.

Chapter 3: Social Behaviour and Vocalizations of Elephants

Understanding animal characteristics and behaviour under different socio-ecological conditions is important in any conservation project. This chapter presents the behaviour patterns and the social structure of elephant society. Important behavioural characteristics of elephants utilized in this thesis are highlighted and discussed. Elephants are highly social animals and they make long distance rumble calls for their communication. The frequency and time domain responses of these elephant calls are presented in this chapter whilst evaluating the effects of noise levels.

Chapter 4: Elephant Localization System Framework

This chapter describes the underlying mathematical representation of the elephant localization system framework. Initially, we explain the passive acoustic localization approaches in terms of Time of arrival (TOA) and time difference of arrival (TDOA) techniques and then mathematically model the elephant localization problem using timing observations. Elephant location estimation is obtained using two estimation models namely the Best Linear Unbiased Estimator (BLUE) and the Maximum Likelihood Estimator (MLE). Then the performances of the estimator models are evaluated in a simulation framework and results are presented. Finally, statistical bounds on the elephant localization error estimation is derived and illustrated in this chapter.

Chapter 5: Propagation Constraints in Elephant Localization

The passive acoustic sensor network described in this thesis utilizes elephant rumble calls that travel through the air as the signal. Sound propagation in air is affected by various environmental parameters, especially the temperature. In addition, the wind carries the medium that the sound propagates and wind velocity affects the speed of sound in air. Moreover, the intensity of the signal is inversely proportional to the distance it travels and therefore, signal to noise ratio (SNR) of the received signal depends on the source-sensor distance. This chapter quantitatively analyses the effects of meteorological parameters on the speed of sound in air and evaluates the significance of the phenomenon on elephant localization accuracy. Additionally, the chapter investigates the SNR dependence of the elephant localization accuracy. Analyses are performed on a simulation testbed defined with respect to the application and results are presented.

Chapter 6: Localization Accuracy Enhancement Technique

The extensive analysis in Chapter 5 emphasises the importance of incorporating the wind and temperature information into the elephant localisation system to attain acceptable positioning accuracy with respect to the application. In this chapter, we propose a novel technique to improve the localization accuracy of the elephant localization framework. The novel mechanism basically incorporates sound generating probes into the sensor network providing a means to estimate the accurate speed of sound in the observation area. The chapter presents an extensive simulation analysis on this methodology as well as interesting findings concerning the effectiveness of using sound probes in elephant localization system framework.

Chapter 7: Sensor Hardware Implementation, Data Collection and Analysis

Human-elephant conflict is a real-world problem and countermeasure require practical implementations. This chapter provides a detailed explanation of the hardware implementation of our approach. We have conducted experiments using the sensor network that we built in an outdoor environment to understand the effectiveness of the system under different ecological conditions. Elephant calls were replicated by replaying the rumble calls from a surrogate elephant system and data was collected and analysed. An identical sensor network system was then deployed to localize wild elephants in Sri Lanka. This chapter presents the results of out-door experiments performed and experiments carried out in a forest environment using our sensor-probe framework.

Chapter 8: Conclusion

This chapter summarizes the contribution of the thesis and provides some insight for future research.

1.6 Publications by the Author Related to the Thesis

Journal Article

- Chinthaka M. Dissanayake, K. Ramamohanarao, M. N. Halgamuge, and B. Moran, "Improving Accuracy of Elephant Localization using Sound Probes", Applied Acoustics, Volume 129, pp 92–103, 2018

International Conference Article

- Chinthaka M. Dissanayake, K. Ramamohanarao, M. N. Halgamuge, B. Moran, and P. Farrell "Propagation Constraints in Elephant Localization Using an Acoustic Sensor Network", IEEE 6th International Conference on Information and Automation for Sustainability (ICIAfS'12), pp 101-105, Beijing, China, 27-29 September 2012.

Chapter 2

Literature Review

Our proposed solution to mitigate human-elephant conflict incorporates a wireless sensor network to detect and localize elephants. Therefore, the first part of this chapter we present a brief literature review related to wireless sensor networks for habitat monitoring. Despite the extensive theoretical publications in the area, there are quite limited practical implementations conducted on the wireless sensor network on monitoring animals in their natural habitats. In the latter part of the chapter, we mainly discuss the currently implemented strategies to mitigate HEC. We further explain the practical limitations and drawbacks in terms of effectiveness and resource constraints with related to these methodologies.

2.1 Sensor Networks for Habitat Monitoring

PREVIOUS wildlife monitoring employed for large mammals has almost entirely been based on reasonably low-technology VHF transceivers that regularly send out a ping signal [11]. Consequent advancements have included global positioning system (GPS) based trackers, which have been used for tracking numerous animals including birds [12] and sea turtles [13], but these depend on high-power transmitters that transmit data up to a satellite, and they function from a non-recharged battery supply.

One of the earliest researches carried out using sensor network for habitat monitoring is the monitoring of seabird nesting environment at Great Duck Island [14]. There, researchers deployed the sensors statically in a grid-like fashion across two wildlife habitats. These sensors observe the animals and report the observation back to the base station through a sensor network. ZebraNet [15] was another wireless sensor network (WSN) which was designed for monitoring and tracking zebras at the Sweetwaters reserve, Kenya. The system includes custom tracking collars (nodes) carried by animals under study and the collars operate as a peer-to-peer network to deliver logged data back to researchers. The collars include a wireless computing device which consists of Flash memory, GPS module, wireless transceivers, and a small central processing unit (CPU). The architecture had been designed for an always mobile, multi-hop wireless network.

WSNs for habitat monitoring have been studied by several other research groups as well. Multi-tiered architecture for habitat monitoring was proposed by Cerpa *et al.* [16]. A system was developed based on PC104 hardware platform and it was introduced as an experimental test bed for habitat monitoring. Wen Hu *et al.* [17] investigate a wireless, acoustic sensor network application for monitoring Cane Toads populations in the monsoonal woodlands of northern Australia. They have used a hybrid mixture of resource-rich Stargate devices and resource-poor Mica2 hardware devices. Mica2s were used to collect acoustic samples and expand the sensor coverage while Stargates were used for resource-intensive tasks such as fast Fourier transforms (FFT) and machine learning. Recently, it has been presented a vision-based monitoring system for biological phenomenon [18]. This system has enabled the automated analysis of thousands of images in a study of avian behaviour during nesting cycles.

The amount of implemented wireless sensor network systems is extremely low compared to the theoretical publications presented in the area. There is certainly little data about the extended behaviour of the sensor networks, due to much less wireless networks utilized for habitat monitoring.

2.2 Current Strategies Deployed in Mitigating HEC

Methods currently adapted in mitigating HEC can be divided into two main categories [19]; combative methods and preventive measures.

2.2.1 Combative Methods

Combative methods are mainly used in dealing with the elephants after they elephants entered to the protected area.

Use of Spotlights

Use of powerful spotlights have been tried in dealing with ccrop-raiding elephants in India and it has been found that some elephants tend to move away from the beam of light [20]. The light needs to be powerful and strong enough to be effective and if used torchlight, in fact it attracts curious elephants towards the source. The spotlight fitted in vehicles such as tractors and jeeps were also experimented, however, vehicles need to be close enough to the elephants for this method to be effective. However, once the vehicle is moved away, the elephants are very smart and tend to come back [21].

Use of Domesticated Elephants

Domesticated elephants (called koonkies) are utilized to drive away the wild elephants from the crop fields in India, mainly over the daytime [20]. In 1980, a herd of around 60 wild elephants was chased away successfully by using domesticated elephants in West Bengal in northeast India. Capturing and domesticating elephants is a time consuming, social-ecologically unfriendly and bureaucratically unrealistic approach.

Use of Firecrackers

Use of firecrackers is one of the most generally used methods to drive the wild elephants away from cultivated areas. Elephants are intelligent creatures and soon identifies such psychological bluffs. The use of rockets that ends with a bang was appeared to be more successful, especially with a group of elephants. Farmers used bamboo gun rockets effectively to chase wild elephant away from of cultivation in India [22]. In the past, wildlife department authorities used to supply thunder flashes to the farmers. These devices were successful in mitigating elephant problem in short-term, but not a sustainable solution to eradicate elephant raids [23].

Use of Loudspeakers

An experiment has been done in southern India, with playback of a tape contains a jumble of noises via loudspeakers and found effective in short-term, moving raiding bull elephants from coconut farms [21]. However, a controlled experiment carried out using recorded tiger calls for deterring elephants was inconclusive [20]. In [24], it has been suggested that high-frequency sound beep may have a possibility of repelling elephants, but would not be a standalone solution.

Use of Firearms

Shooting the guns or firearms may be effective in driving away elephants back to the forest. However, elephants being one of the endangered species, shoot to kill is not authorised in any of the elephants residing countries. Therefore, the farmers and wildlife officers must use the noise of shooting to chase away the elephant. However, some aggressive bull elephants may disregard such noises and move into farming areas [19].

2.2.2 Preventive Measures

Preventive strategies are deployed to avoid elephants from migrating into protected areas.

Use of Repellents

One of the main sensory channels of elephants is the smell. Considering this fact, chemical repellents have been used as barriers for elephants without much success [20]. This is mainly due to the difficulty of keeping chemicals in the effective conditions under wet weather. However, Dutch planters in Sumatra tried to hang rags soaked in human urine as a repellent to deter wild elephants from oil palm plantation. In the recent past, experiments were conducted on free-ranging elephants in Zimbabwe to test the effectiveness of Capsicum-based aerosol as a repellent. The results have illustrated that it has a potential of being a short-term repellent up to 100 m [25].

Use of chilli briquettes found to be effective as a short-term deterrent for crop raiding elephants. The chilli briquettes were made of ground dried chillies combined with fresh elephant or cow dung and dried the mixture to make briquettes [26, 27]. Burning these briquettes create a noxious smoke which act as the repellent for elephants. However, the effectiveness of this method significantly depends on the wind direction [26]. If the prevailing wind drifts towards the crop field, the chilli-dung fires are of no-use as the smoke do not warn the elephants in the forest area.

Trenches

Trenches to be effective, it needs to be at least 2 m deep and 2 m accords at the top and 1.8 m wide at the base [19]. In addition to the higher cost of building them, because of wet weather and erosion, the effective depth of trenches often gets affected reducing the effectiveness of the barrier [28]. The potential of the trench can be enhanced by either establishing the walls with concrete (which is expensive) or by planting thorny vegetation along the inner-trench edge. Shallow trenches 1.2 m deep and 1.2 m wide along with a cover of bamboo matting has been used as a barrier in India. The bamboo mat provides a psychological rather than a physical barrier as the elephants have an instinctive sense of what surface could withstand their weight [20]. The cost of construction and maintenance of the trenches usually outweigh the extent to which it is effective in reducing the damage that elephants do to the villages or farming areas.

Log Fences and Stone Walls

In Malaysia, it has been used log fences (15 cm to 25 cm in diameter) wrapped in barbed wire in highly affected areas with HEC [19]. Constructing these fences are highly expensive and it is difficult to extract appropriate timber from the forest. Similarly, constructing stone walls also a tedious and expensive matter and as a result not a viable option for many areas.

Electric Fence

Electric fences got a higher attraction out of the existing solutions. Many people in the affected areas tend to plea electric fences, as they see it as the permanent solution for HEC. However, the high capital cost and the lack of routine maintenance have always resulted in the effectiveness of this approach to put well below expectations [29, 30].

The electrical fences consist of two strands of steel wires which are connected to a pulse generator. The power supply often operated either by battery or solar panels. The pulse generator passes an electrical pulse of 5,000 volts in every second through strand wires, which is non-lethal as of its very short duration (3/ 10,000 th of a second). The system generally works as a mental barrier for elephants rather than a physical obstacle. However, it is difficult to outsmart the elephants and they have used several tricks to get over these fences. The ivory of the tuskers is a non-conductive and they use it to dislodge the fence or insulators. In some cases, it is observed that elephants use fresh trees which they bring from the forest to trip-off the power supply by short-circuiting the wires. In other incidents, elephants have used tree branches to break the posts and wires [31].

Demand for meticulous maintenance is another factor that causes electrical fences to fall below the anticipated success in the long run. Keeping the fence line clear from the growing vegetation, especially in the wet season is a recurrent problem that needs to address in the management of electric fences. The effort to establish Collective maintenance of an electric fence through a rural community has not often been successful due to the involvement of a long chain of responsibility, that simply fails at the weakest link. Even in countries where wildlife is authorities operate in a local level the success of electric fencing projects is quite unsatisfactory due to the maintenance deficiencies [29, 32].

Beehive Fence

It has been identified through playback experiments that elephants tend to avoid sounds of disturbed honey bees [33]. The stories from local people suggested that elephants fear bees as a result of stung behind the thinner skin of the ears, around the eyes and up the trunk. This must be a painful enough experience for elephants which creates negative memories leading them to avoid future encounters with bees. Recently, researches have been conducted to monitor the effect of the beehive fences on deterring crop-raiding elephants [34–36]. A beehive fence consists of beehives that are installed into the wires connected to the posts and usually use to surround agricultural area which need to be protected.

Effectiveness of these fences highly depend on the meticulous maintenance which is labour intensive. In addition, it could take a longer period; in some cases, months for all the beehives to be occupied with bees which minimize the effectiveness of the whole fence during the interim. Further, less aggressive honey bees may have less effect when swarming out and deterring elephants. Bees are less active in the cooler conditions and as a result the effectiveness of the fence is deteriorated during the night where most crop-raiding occurs [35].

Translocation

Identify and relocate the problematic elephants who are constantly responsible for the destruction of plantation or impairment of villagers' livelihood has been a practice followed by some wildlife authorities [19, 31]. These elephants are either captured and moved by a vehicle (capture transport) or driven to a new area (elephant drives). However, in most cases elephants have returned to its usual habitats within a brief period after the translocation. It has been reported cases where elephants returned to the area of capture from a distance as far as 100 *km* [37].

Tagging Elephants with GPS Collars

During the past few years, feasibility to use Global Positioning System (GPS) collars to track elephants in the wild has gained attraction of the conservationists' and other stakeholders who are addressing the issue with HEC [6]. Generally, the collar consists of a GPS receiver, a radio-modem for data communication, a medium for data storage typically a non-volatile memory, and an independent VHF or mobile of satellite transmitter or and a battery. Once the elephants were collared, the location data is retrieved typically in 4-6 hour intervals. Subsequently, the elephant moving speed can be estimated by dividing the linear distance between successive locations by the time interval between them.

Tagging elephants with GPS collars is an expensive, dangerous to humans and elephants and tedious task which require complex procedures to be followed. First, the elephant needs to be captured and tranquilized. In general, gun-propelled syringes containing Etorphine is used to dart the elephants and this task need to be carried out by an expert personnel. The process involves the risk of approaching the elephant up to the close proximity of the propelled-gun range. Typically, the elephants were approached on foot or ground vehicle, but there were cases reported where it used helicopters in the process of darting [6]. While the elephant is anesthetized, heart rate, vital signs, respiration rate, blood pressure and body temperature need to be monitored continuously. Once the collaring is completed a Diprenorphine need to be injected as the reversal drug and need to make sure that elephant is act natural after recovery which again involves the risk of being near the treated animal.

Elephant collars need to be built to sustain in harsh environmental conditions and need to be water resistant. Collaring being a complex process, it needs to be robust enough to last for a longer period once it is worn. Therefore, the cost of elephant collars is considerably high (USD 3000-12000) [38] and the command unit for the collar is also expensive (USD 6500). In addition, there is a data retrieval cost involve accessing the GPS satellite data. For instance, a project tracking around 10 elephants over a period of 2 years can approximately cost at around of $200,000 onwards making the solution unaffordable for wildlife managing government authorities in most elephant residing countries [38]. Because of the risk involve in collaring elephants, the need for expert technical personnel and higher capital and operational cost, GPS-telemetry is not a sustainable method for monitoring elephants. In addition, due to the infrequent data retrieval intervals, the approach is not a viable solution for HEC.

Considering the drawbacks and constraints in the current strategies deployed in mitigating HEC, it required to investigate a possible alternative to address the problem. In this thesis, we propose to use passive acoustic sensor network to detect and localize elephants which is an effective methodology in mitigating the occurrences of HEC.

Chapter 3

Social Behaviour and Vocalizations of Elephants

This chapter presents the social behaviour and structure of elephant society. The useful behavioural patterns of elephants for localization and tracking methodology used in this thesis are highlighted and discussed. In addition, general elephant vocalizations are described, and their frequency spectrum is examined. Characteristics of elephant rumbles in spectral and temporal domains are analysed and the favourable characteristics in regard to elephant localization are highlighted.

3.1 Introduction

THERE are three main elephant species in the world; African savannah elephants (*Loxodontaafricana*), African forest elephants (*Loxodonta cyclotis* or *Loxodonta africana cyclotis*) and Asian elephants (*Elephas maximus*) [39, 40]. However, less than 50,000 wild Asian elephants presently extant on earth and fragmented populations dispersed across 13 countries [40–42]. Elephants are found in Southeast Asia and the Indian sub-continent and with half of the inhabitants live in India [43]. Almost across the all residing territories, the main threat to Asian elephant survival is the habitat loss and fragmentation [42, 44]. Contrary to African elephants, ivory poaching is of minor concern for Asian elephants' survival as only about 5% of males carry tusks [45].

Understanding of social structure and behaviour patterns of elephants is a crucial element in an elephant conservation project. The social structure of Asian and African elephants is briefly described in Section 3.2. General elephant behaviour is discussed in Section 3.3. Elephant communication and call patterns are summarised and analysed in Section 3.4.

3.2 Social Structure of Elephants

Elephants play a crucial role in balancing ecosystem functions and biodiversity in forests [46, 47]. In [47] they were named as ecosystem engineers and mega gardeners of the forests considering their part in the transformation of landscapes, influence on vegetation regeneration, and effect on the dissemination and abundance of wildlife [48, 49]. Elephants being on the edge of extinction may cause to entire forest ecosystem to be at risk. For instance, in the tropical forest of Congo, some tree species entirely solely reliant on elephants for seed dispersal [50].

Asian elephants often inhabit densely vegetated areas [44]. Consequently, only three comprehensive studies based upon individual identifications have been conducted for wild Asian elephants [51–53].

Asian elephants occupy a variety of habitats such as scrub forests, grasslands, dry deciduous forests, swamps, moist evergreen forests and mangroves [54]. The span of their prior and current ranges demonstrates that Asian elephants are capable of adapting to a broad variety of ecological conditions. Perhaps their behavioural plasticity may have contributed this adaptability which subsequently evolved in moving into the human populated areas increasing HEC.

The social composition of wild Asian elephants can be categorised into a fission-fusion social structure [51,52]. Fission-fusion reflects an adaptive group behaviour which demonstrates the group size based on costs and benefits of association. If the benefits of association outweigh the costs, sub-groups will fuse into larger groups. On the other hand, the cost of getting together exceeds the benefits fission occurs; groups divide into sub-groups. In general, fission-fusion behaviour depends upon a number of factors such as availability of food and water resources, access to mates and predation pressure [55–57].

Group size in Asian elephant's fission-fusion social system can vary extensively from few animals to a herd of hundreds of individuals [51,52,54,58]. Asian elephants live in a range of habitats which represents diverse ecological conditions based on the availability of water and vegetation resources [42, 43, 59–61]. Wild elephants in Sri Lanka have no threat of natural predators [51], and therefore the group size mostly reflects adaptability into available local resources.

Elephants are giant herbivores [62] animals who need to consume a massive amount of food and water for their survival. In general adult elephant daily consumes about 250 Kg of forage and 180 L of water. Elephants eat most of the vegetation but, like any other large mammal (*ungulates*) [63], they specifically consume plant species and plant parts that contain less fibre and more digestible carbohydrates and proteins [64, 65]. Elephants prefer young grasses over the woody vegetation as their primary food source because it contains soluble carbohydrates and lower lignin and secondary compounds [65, 66]. Thus, grasses are more digestible compared to woody plants and demand little handling time [67]. Therefore, Grass patches offer uniform concentrations of high-quality food resources for elephants [68]. Despite its higher protein content, woody vegetation such as scrub or evergreen forests is not a desired food source for elephants [63,65]. The chemical composition of woody plants varies significantly between plant parts and plant growth stages and as a result, they require longer handling time in elephant's digestive system compared to grass [67].

Similar to the most mammals, elephants depend on water for their survival; not only for drinking but for bathing and social interactions. However, they commit less than two to three hours of the day for drinking and bathing [69]. This is significantly less than the time that they spend on foraging. Depending on the age and reproductive status, elephants spend 12 to 18 hours searching for food or provisions [43, 44, 69]. Water is not just an essential resource, but it additionally provides a means for social interactions by facilitating play behaviour [70].

Water and preferable food sources are often may not be close to each other. Therefore, elephants sometimes need to travel long distances to fulfil there drinking and feeding needs [43]. The swap between drinking and feeding activities need to be synchronised among all the members of the social unit to avoid the cost of separation from the main family unit [71]. Water is less likely to be a resource of competition when it compared to food and therefore, it is possible to see elephants next to each other when they harvest water. However, when water is limited to a few hot spots, substantial aggregations of animals could be anticipated near water [72] and these may correspond to short-term gatherings of multiple social units. Similar to African forest elephants gather by hundreds near clearings [73,74] in some habitats, Asian elephant can be seen in large groups near water sources in open grass areas or at the edges of forest and grasslands [53].

In general, animal group size increases with predation pressure and openness of habitat [63, 75] and human interference is perceived as predator threat [76, 77]. Hence, the presence of tourists in some habitats may have affected the elephant group size and persuaded the formation of larger groups composed of several social units. For instance, average elephant group size in Minneria national park in Sri Lanka is significantly higher than other local habitats and can be considered as a direct impact of human disturbance.

3.3 Social Behaviour of Elephants

Though Asian and African elephant species were separated by at least six million years [78, 79] it is possible to find a similar social organization in all species to some extent. For instance, both Savannah and Asian elephant family units are led by the eldest adult females (matriarchs) and they manage the extended association between other family units. Savannah elephants who has fission–fusion society with hierarchical 'tiers' [56, 80, 81] prefer to have companionships throughout their home ranges provided that resources permits. However, controversial behavioural observations have been made on Asian elephants [53].

A study carried out utilising population genetic data, radio telemetry and behavioural observations in Yala National Park, Sri Lanka [51] reports Asian elephant family units with adult and sub-adult females and juveniles. It has been observed low levels of association and no intergroup transfer of females in this study. On the other hand, research carried out in Udawalawa National Park, Sri Lanka depending upon behavioural observations in [52] described that associations of adult females not limited to unique family units but they formed larger social groups than in previous reports. In addition, these family units were observed to be stable across years and female elephants occasionally switched between family units [52].

Asian elephants have a lifespan of 60 years in wild and are long long-lived animals

[44, 82–84]. Female elephants give birth to calves after a 20 to 22-month gestation period and calves are lactational dependent for the first 3 to 4 years of their life [44, 82]. At the age of eight to nine, female elephants become sexually mature [44, 85, 86] and typically give birth to their first calf during 14 to 20 years of age [44,87]. Even though male become sexually matured at age of 17, they in usually will not succeed in mate until the age of 20 to 25 years. This is due to limited access to receptive female elephants and male elephants generally need to outcompete other males to connect with a female [88,89]. Even females are commonly found in groups [51, 52, 59, 90], adult males are frequently observed alone [44, 59, 90].

Adult females are only receptive for a few days in their prolonged 16-week estrous cycle and they have four to five-year inter-birth period [91]. Therefore, a receptive female is an unpredictable and limited resource and male elephant competition to connect with a female is highly likely. As a result, male elephants are not benefited by permanently remain with a group of females or defending a territory [53].

The home range of individual male overlaps partly or entirely with the home range of several females. In, [92] it was investigated the home range of elephants in Yala National park, Sri Lanka using VHF tracking and have estimated that home range of male elephants could be twice as of a female elephant. In [59] it was observed that male elephants reside in an area of less than 1 km^2 for several days inactively before they migrate to a different region where they follow the identical pattern.

In African elephant society, sexually inactive adult males move to a location called the bull area where they interact with other male elephants in a relaxed manner. On the other hand, sexually active males or musth elephants leave bull areas and in generally observed alone or in the presence of female elephants. Elephants in musth are more often encounters aggressively with other sexually active males [93]. In African elephants, musth bulls are desired by females in estrous and sire most offspring [88, 94]. However, wild Asian elephant males in and out of musth have been observed mating females [53, 95].

In general, male group size decreases with age [96] and Juvenile males can be observed in larger groups than adult or sub-adult males. Early studies on African elephants suggested when males become sexually mature they were forced out of their natal family units [80,82]. In contrast, more recent studies imply that male independence is a gradual process which could take up to eight years and not enforced by other members of the family unit [84]. Males with no peers in the family unit tend to complete the transition more quickly and become independent [89].

The means of knowledge transfer between animals is a fact affecting to their social structure [97]. In [98] it claims that there is a positive correlation between animal bonding strength and information transfer. Strong ties between old and young females could affect the reproductive success through knowledge sharing and supporting each other in caring offspring. In African elephants, family units led by elderly matriarch has demonstrated greater per capita reproductive success as these females are capable of distinguishing known from unknown male elephants and assessing risk accurately [99]. Thus, a strong association between elderly and younger females is proven to be beneficial in conflictive situations. Alloparenting can be observed in societies of elephants and other mammals [83,100,101]. Alloparental care denotes the care and attention given towards young by the individuals apart from their parents. Being allomother is a beneficial factor for successfully raising the first offspring of a female and it is observed short inter-birth intervals if the alloparental care is available [102]. Allomothering is a vital fact that defines the infant survival in African elephants [80,103]. After giving birth to the offspring, adult females need to spend 12-18 hours per day to search and consume food to obtain sufficient food for lactation. Therefore, strong bonds between mothers, infants and allomothers are highly beneficial for infant survival and reproductive success [44,69]. Similar allomother caring observation has been made in African and Asian elephant societies [53].

Elephants march through the same travel routes even the environmental conditions change. Elephant marching through a hotel lobby is reported from Zambia after it was built on their migration trail [104]. The traditional travel routes may be communicated from generations to generation and elephants seem dedicated on defending their traditional elephant routes. Recently Sri Lankan government have recognised the significance of this characteristic and imposed rules on freeing elephant corridors [105]. Elephant's behaviour of using the same itinerary is one of the key behavioural features that we utilised in our study.

3.4 Elephant Communication and Call Patterns

Elephants use acoustic signals in different contexts such as mate search [106], male–male competition [107], and maintenance of social bonds etc. [106]. They are able to detect low-frequency calls over a range of several kilometers [108–111]. Further, they use alternative sensory channels such as chemical signals (e.g. smell), and visual and tactile displays all involved in short-distance interactions. It is further suggested seismic energy transmission may be viable channel for elephant communication [112, 113].

The elephant calls could be grouped into four distinctive categories, namely, trumpets, chirps, roars, and rumbles [114]. Juveniles produce three of the four call types, including trumpets, roars, and rumbles, in the context of play and distress. Adults make trumpets and roars in the context of aggression, disturbance, and play. Chirps were generally produced in circumstances of confusion and alarm. Elephants produce rumbles when coordinating family and larger group behaviours, when attracting mates and announcing reproduction and, when competing for resources and/or dominance [106].

Strength of elephant calls varies extensively from very soft calls made between mothers and their nearby infants to the extremely loud calls produced by females announcing their availability. Playback experiments indicated that savannah elephants responded to each others' loud vocalizations over a range of at least two kilometers. For the reason that playbacks were only broadcasted at half the amplitude of the strongest elephant calls in their sample, the researchers concluded that actual range should be at least four kilometres [108]. The advantage that elephant calls can travel several kilometres enables elephant societies to coordinate migrations over large areas.

Females vocalize more often than males; the frequency of vocalization in both males and females is extremely variable and dependent on social circumstances. Researches carried out in Namibia and in the Central African Republic have shown that rate of calling increases predictably with the number of elephants present [111].

3.4.1 Elephant Rumbles

Typically, elephant rumbles are rich in infrasound; however, most of these consist of frequencies high enough to be audible to humans. Infrasound is sound below the level of human hearing. Basically, the infrasonic frequency range is considered to be between 1 Hz to 20 Hz. The lower the frequency, longer the sound wave is and therefore they can travel farther without being absorbed or reflected by the environment. The structure of elephant rumbles is quite varied, but readily recognizable. The elephant calls have roughly eyebrow-shaped time-frequency response as shown in Fig. 3.1. Typically, the rumbles are in the frequencies between 10−250 Hz and last between 2−10 seconds. The other infrasonic noises present in the environment such as the broadband wind or thunder often could obscure the elephant's rumble calls. Figures 3.2, 3.3 depict spectrograms of same elephant rumble call while signal is corrupted by the noise. Additive white Gaussian noise (AWGN) is used for the illustration. Time domain representation of elephant calls are shown in Figs. 3.4−3.6.

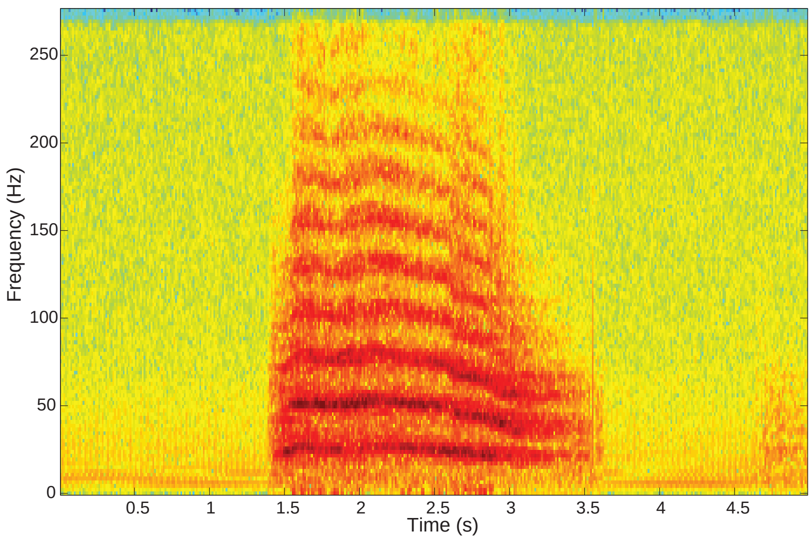


Figure 3.1: A spectrogram of a recorded elephant rumble call. Eyebrow-shape structure indicates the harmonics present in the elephant in the signal.

From the above analysis, it is evident that the pattern of elephant rumbles can be used as a tool to recognize the presence of an elephant.

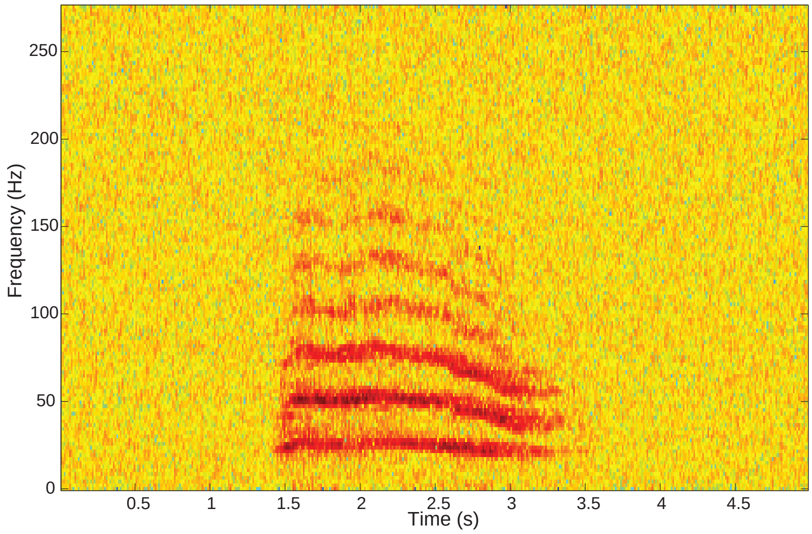


Figure 3.2: A spectrogram of an elephant rumble call while signal is corrupted by noise (AWGN with SNR = 10 dB).

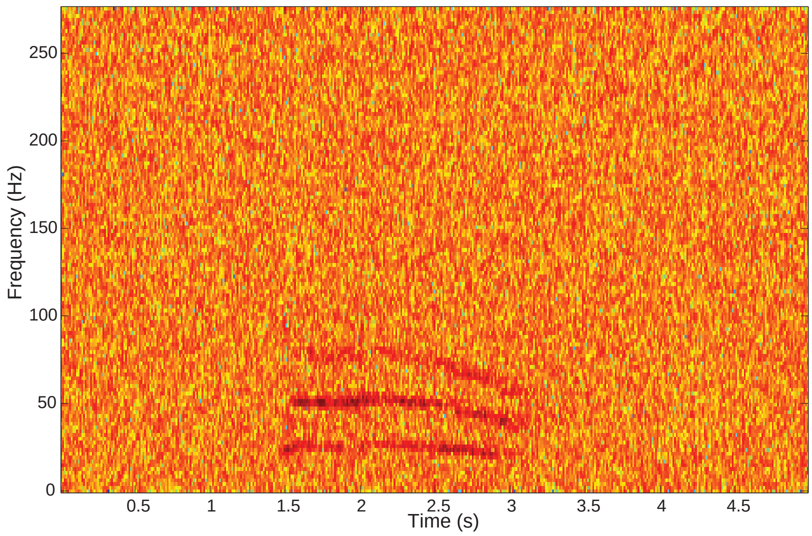


Figure 3.3: A spectrogram of an elephant rumble call while signal is corrupted by noise (AWGN with SNR = -8 dB).

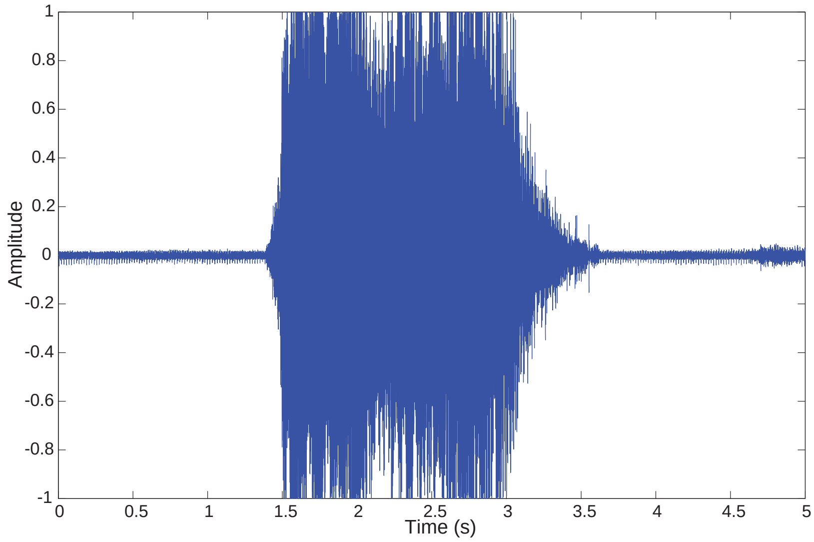


Figure 3.4: Time domain representation of a recorded elephant rumble call. Note that the recorded signal contains minimal background noise. However, detection will be much more challenging in the presence of environmental noise

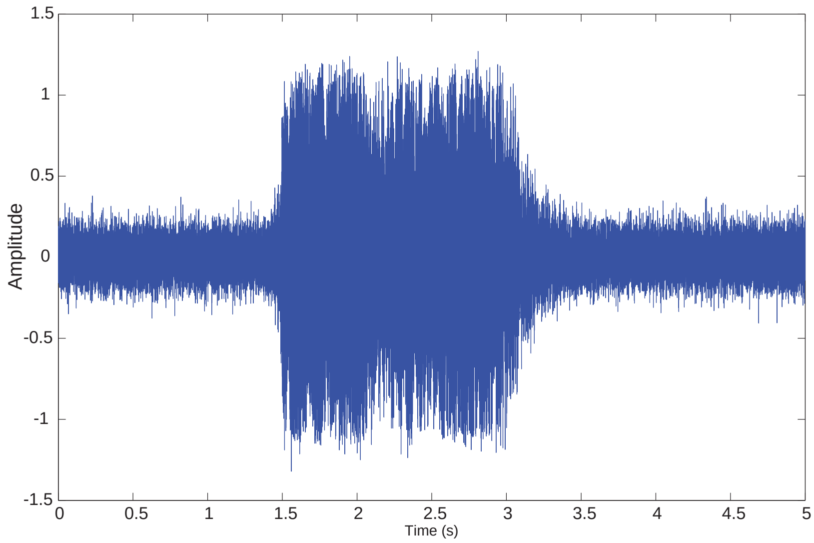


Figure 3.5: Time domain representation of elephant rumble call while the signal is corrupted by noise (AWGN with SNR = 10 dB).

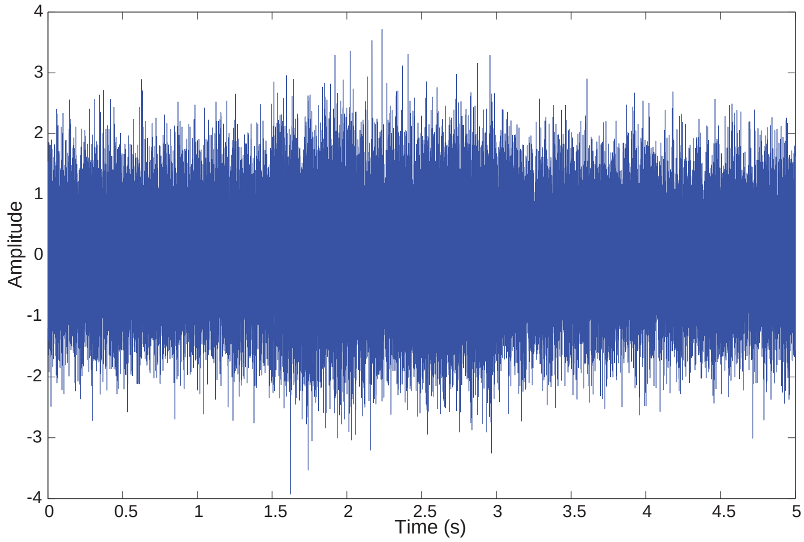


Figure 3.6: Time domain representation of elephant rumble call while signal is corrupted by noise (AWGN with SNR = −8 dB).

3.4.2 Frequency Comparison with Other Animal Calls

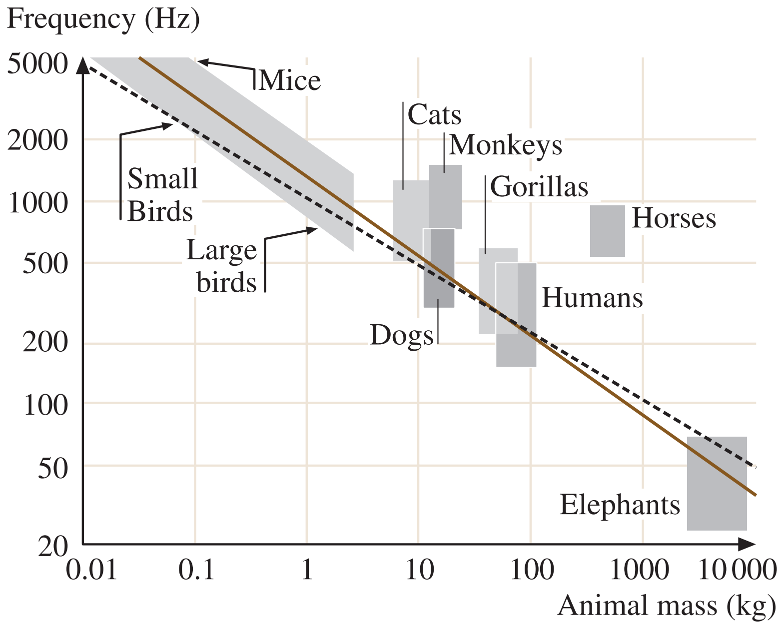


Figure 3.7: The frequency ranges of the emphasized frequencies of vocalization in a large range of land−dwelling animals, plotted as a function of the mass of the animal [115].

The frequency of an animal call is determined simply by the physical properties of the sound-producing mechanism. In [115] it is proposed a model for this phenomenon and suggested that vocalization frequency f should be inversely proportional to the linear size of the animal or, equivalently, that $f \propto M^{-1/3}$, where M is the mass of the animal. This hypothesis is quite agreed with the observations as depicted in Fig. 3.7. As shown in the figure, elephant infrasonic vocalizations are less susceptible to interfere with other animal calls.

Being the largest animal on the land, elephants are having significantly higher mass than the other animals, hence having a natural ability to make low-frequency calls. Combine the above fact with their distinctive frequency structure, elephant rumbles can be uniquely detected in a forest environment even under the presence of other animal calls.

3.5 Chapter Summary

Ascertaining the animal behaviour is important in any conservation project. In this chapter we described the social behaviour and structure of the elephant society. We highlighted the factors effecting to elephant group size, there marching patterns and other behaviours which are favourable in mitigating HEC thorough our approach. Then we summarised the call patterns of these highly social animals and analysed the low frequency elephant call named “rumbles” in time and frequency domain. Finally, the chapter provides frequency comparison of elephant calls with other animal calls and discuss the interference on rumble signals from other animal sounds.

Chapter 4

Elephant Localization System Framework

The approach we propose to mitigate HEC require localization of elephants through a passive acoustic sensor network. In this chapter we brief the underlying mathematical representation of the elephant localization system framework. First, we summarise the passive acoustic localization approaches in terms of Time of arrival (TOA) and time difference of arrival (TDOA) techniques and mathematically model elephant localization problem. Finally, statistical bounds on elephant localization error estimate are derived and presented.

4.1 Introduction

IN cases where a known or easily distinguishable signature is embedded in the signal, the sensor can correlate the signal with the signature to accurately estimate time of arrival. The timing estimation accuracy relies on the signature as well as the sensor capability. This is meaningful only if the sensor is synchronized either with the emitting node or another receiving node. In the former case, which computes time of arrival (TOA) measurements, an absolute distance can be computed. In the latter case where it measures the time difference of arrival (TDOA) a relative distance follows. Geometrically, these two cases constrain the position to be on a circle or on a hyperbolic function, respectively [116]. In both the cases, it is assumed that the sensor nodes are stationary with known positions.

The approach proposed in this thesis to mitigate HEC is by locating the elephants incorporating a sensor network. In ideal conditions, if the synchronized sensors identify the rumbles signals with a timing stamp, trilateration or triangulation methodology can be utilizing to estimate the location of the elephant. Section 4.2 explains the different timing observations utilize in localization strategies and comparable measurement model for our application is introduced. In Section 4.3 two different estimation models for Localisation System are derived and presented.

4.2 Timing Observations and Localization

4.2.1 TOA Measurements

Each receiver measures the arrival time of a transmitted signal from an unknown position, using accurate and synchronized clocks. If the transmitter is also synchronized, the signal propagation time can be computed, which leads to a TOA measurement. Propagation time corresponds to a distance, which leads to the distance circles around each receiver and the intersection point gives the target position.

4.2.2 TDOA Measurements

If the transmitter is unsynchronized, each pair of receivers can compute a time-difference of arrival TDOA. Each receiver pair computes separate hyperbolic function for the distance in terms of TDOA and again the intersection point results the target position.

Elephant localization is exactly identical to the hypothesis described here Section 4.2.2. The vocalization made by the elephant can be considered as distinguishable signature and the elephant call can be treated as unsynchronized transmitter. Therefore, by using TDOA measurements it is possible to localize the elephants.

4.3 Mathematical Models for Elephant Localisation System

The approach of elephant localisation by TDOA measurements can be represented mathematically utilizing estimation models [117, 118]. Here we present two different estimation models to represent elephant localisation problem.

4.3.1 Best Linear Unbiased Estimator (BLUE) Model

Let the localization sensor network has N sensors that each receives the signal of interest. It is assumed that the sensors are deployed at known locations and each has identical capabilities. Each sensor is Omni-directional and can detect and receive the interested signals. Further, it is assumed that all the sensors are synchronized perfectly and have accurate timing.

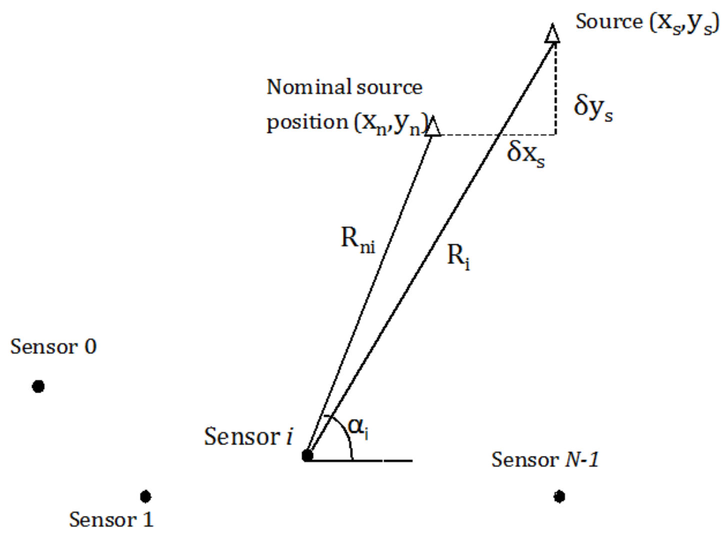


Figure 4.1: Source localization using N number of sensors. The nominal source position (x_n, y_n) assumed to be known. It is necessary to determine actual source position (x_s, y_s).

Let the time of arrival measurements for each sensor to be t_i for $i = 0, 1, ..., N - 1$. It is necessary to locate the source position (x_s, y_s). The arrival time measurements can be modelled by

$$t_i = T_0 + \frac{R_i}{c} + e_i \qquad i = 0, 1, ..., N - 1 \tag{4.1}$$

where T_0 is the signal emitted time by the source, c is the sound propagation speed, e_i is the uncorrelated measurement noise with zero mean and σ^2 variance. Let the known position of ith sensors to be (x_i, y_i). The range difference between the source and the ith sensor is given by

$$R_i = \sqrt{(x_s - x_i)^2 + (y_s - y_i)^2} \tag{4.2}$$

Substituting (5.3) in (5.2), the model will become nonlinear with respect to the unknown parameters x_s and y_s, and the problem will then become difficult to solve. Therefore, following the standard approach, it is assumed that nominal source position (x_n, y_n) is available where nominal range is denoted by R_{n_i}. In fact, this nominal position which is close to the actual source position could have been obtained from previous measurement, especially in a case of target is being tracked. Now, if it is estimated $\boldsymbol{\theta} = [(x_s - x_n)(y_s - y_n)]^T = [\delta x_s \delta y_s]^T$, then the new source position can be determined. By using a first-order Taylor series expansion of R_i in (5.2) about the nominal position $x_s = x_n$, $y_s = y_n$, the range can be written as

$$R_i \approx R_{n_i} + \frac{x_n - x_i}{R_{n_i}} \delta x_s + \frac{y_n - y_i}{R_{n_i}} \delta y_s \tag{4.3}$$

By substituting (4.3) in (5.2)

$$t_i = T_0 + \frac{R_{n_i}}{c} + \frac{x_n - x_i}{R_{n_i} c} \delta x_s + \frac{y_n - y_i}{R_{n_i} c} \delta y_s + e_i$$

we obtain linear model for the unknown parameters δx_s and δy_s. For convenience, as in the the Fig. 4.1 we represent,

$$\frac{x_n - x_i}{R_{n_i}} = cos\alpha_i, \tag{4.4}$$

$$\frac{y_n - y_i}{R_{n_i}} = sin\alpha_i, \tag{4.5}$$

and the model simplifies to

$$t_i = T_0 + \frac{R_{n_i}}{c} + \frac{cos\alpha_i}{c}\delta x_s + \frac{sin\alpha_i}{c}\delta y_s + e_i$$

By incorporating the term R_{n_i}/c into the measurement by letting

$$\tau_i = t_i - \frac{R_{n_i}}{c}$$

the linear model finally becomes to

$$\tau_i = T_0 + \frac{cos\alpha_i}{c}\delta x_s + \frac{sin\alpha_i}{c}\delta y_s + e_i \tag{4.6}$$

However, the signal emitted time T_0 is not known in the case of our application. Therefore, it is incorporating TDOA measurements for the model. The TDOAs are generated as

$$\begin{aligned} \xi_1 &= \tau_1 - \tau_0 \\ \xi_2 &= \tau_2 - \tau_1 \\ &\vdots \\ \xi_{N-1} &= \tau_{N-1} - \tau_{N-2} \end{aligned}$$

Then from (4.6) the final linear model can be denoted by

$$\xi_i = \frac{1}{c}(cos\alpha_i - cos\alpha_{i-1})\delta x_s + \frac{1}{c}(sin\alpha_i - sin\alpha_{i-1})\delta y_s + e_i - e_{i-1}$$

for $i = 0, 1, ..., N-1$. Therefore our model now is in the form of

$$\boldsymbol{x} = \boldsymbol{H\theta} + \boldsymbol{w} \tag{4.7}$$

where

$$\begin{aligned}
\boldsymbol{\theta} &= \begin{bmatrix} \delta x_s & \delta y_s \end{bmatrix}^T \\
\mathbf{H} &= \frac{1}{c}\begin{bmatrix} cos\alpha_1 - cos\alpha_0 & sin\alpha_1 - sin\alpha_0 \\ cos\alpha_2 - cos\alpha_1 & sin\alpha_2 - sin\alpha_1 \\ \vdots & \vdots \\ cos\alpha_{N-1} - cos\alpha_{N-2} & sin\alpha_{N-1} - sin\alpha_{N-2} \end{bmatrix} \\
\mathbf{w} &= \begin{bmatrix} e_1 - e_0 \\ e_2 - e_1 \\ \vdots \\ e_{N-1} - e_{N-2} \end{bmatrix}
\end{aligned}$$

Further, the noise vector $\mathbf{w}$ can be represented as

$$\mathbf{w} = \mathbf{Ae}$$

where

$$\mathbf{A} = \begin{bmatrix} -1 & 1 & 0 & 0 & \cdots & 0 \\ 0 & -1 & 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & 0 & -1 & 1 \end{bmatrix},$$

and

$$\mathbf{e} = \begin{bmatrix} e_0 \\ e_1 \\ \vdots \\ e_{N-1} \end{bmatrix}.$$

Since the covariance matrix of $\mathbf{e}$ is given by $\sigma^2\mathbf{I}$ the covariance matrix $\mathbf{C}$ of the noise vector $\mathbf{w}$ is given by

$$\mathbf{C} = E[\mathbf{A}\mathbf{e}\mathbf{e}^T\mathbf{A}^T] = \sigma^2\mathbf{A}\mathbf{A}^T$$

Now by applying Gauss-Makov theorem for the above linear model the best linear unbiased estimator (BLUE) for the source position can be given by

$$\hat{\boldsymbol{\theta}} = (\mathbf{H}^T\mathbf{C}^{-1}\mathbf{H})^{-1}\mathbf{H}^T\mathbf{C}^{-1}\xi \tag{4.8}$$

$$= \left[\mathbf{H}^T(\mathbf{A}\mathbf{A}^T)^{-1}\mathbf{H}\right]^{-1}\mathbf{H}^T(\mathbf{A}\mathbf{A}^T)^{-1}\xi \tag{4.9}$$

The minimum variance is given by

$$var(\hat{\boldsymbol{\theta}}_i) = \sigma^2\left[\left\{\mathbf{H}^T(\mathbf{A}\mathbf{A}^T)^{-1}\mathbf{H}\right\}^{-1}\right]_{ii} \tag{4.10}$$

In addition, the covariance matrix of above estimator $\hat{\boldsymbol{\theta}}$ is given by

$$C_{\hat{\boldsymbol{\theta}}} = \sigma^2\left[\mathbf{H}^T(\mathbf{A}\mathbf{A}^T)^{-1}\mathbf{H}\right]^{-1}$$

4.3.2 Performance Evaluation on Loclaization using BLUE Model

The localization methodology discussed in Section 4.3.1 is simulated using Matlab 7.9.0 (R2009b). Figure 4.2 shows an example sensor and source configuration and the true and estimated positions of the source. Initially, sensors are deployed randomly in an area of $5000 \times 5000\ m^2$ and the actual source also located inside the same area. It is assumed that each sensor has line of sight propagation path between the source and the sensors. The algorithm needs an initial source position guess to estimate the true source position from TDOA measurements. However, the system discussed above use passive localization and therefore the initial position of the source is unknown. Therefore, the arithmetic mean $(\bar{x}, \bar{y})$ between sensors is used as the initial position guess $[x_{es_0}\ y_{es_0}]^T$. Then, the distance from ith sensor to derived source location is calculated by

$$R_{n_{ik}} = \sqrt{(x_{es_k} - x_i)^2 + (y_{es_k} - y_i)^2}$$

where $[x_{es_k}\, y_{es_k}]^T$ is the estimated source location at kth iteration. This value is utilized in calculating $cos\alpha_i$ and $sin\alpha_i$ terms in (4.4) and (4.5) to construct the matrix H in (4.7). Variance of the uncorrelated measurement noise (σ^2) is chosen as 0.1, assuming significant noise is present at the receiver measurements. The δx_s and δy_s are calculated as per (4.9) and the new source position for next iteration is then determined as

$$[x_{es_{k+1}}\, y_{es_{k+1}}]^T = [(x_{es_k} + \delta x_s) \;\; (y_{es_k} + \delta y_s)]^T.$$

This estimated location is utilized as the source location for the next iteration. Likewise, the algorithm iteratively converges into the actual source location. By comparing minimum variance given by (4.10), it can be determined whether the algorithm has converged to a solution or more iterations of the estimator are needed. Figure 4.2 depicts how the location estimator derived above converged into a solution within three iterations.

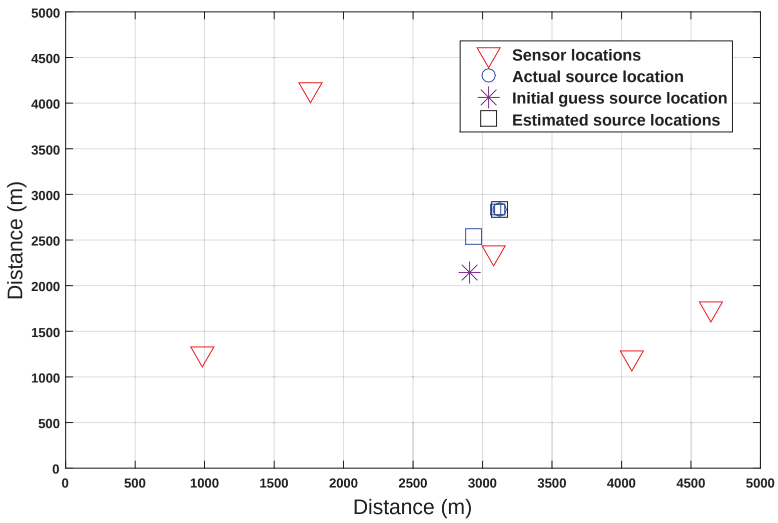
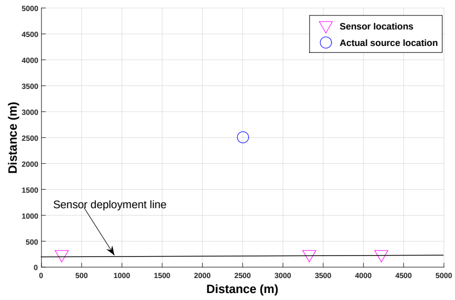
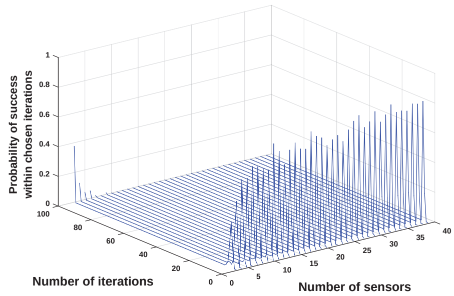


Figure 4.2: Source position estimation using algorithm described in Section 4.3.1. TDOA measurements from five sensors are utilized. The estimated source position in each iteration is depicted.

The effect of sensor positioning for the overall performance is further analyzed through simulations. Figures 4.3– 4.5 depicts the performance of the algorithm for different sen-

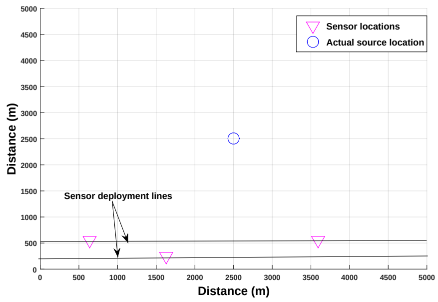


(a) Sensor deployment in a single line (250 m line in the Y axis)

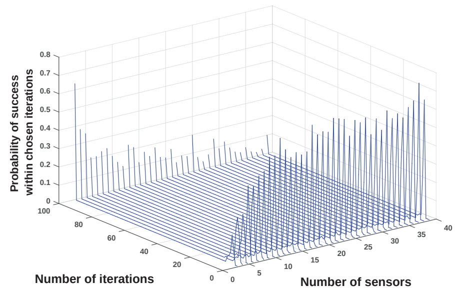


(b) Performance profile

Figure 4.3: Sensors were deployed in a single line. Number of sensors were changed from 3 to 40. For each trial locations of the sensors were changed 100 times randomly. Note that the successive estimations of source always converge before 10 iterations.



(a) Sensor deployment in two lines separated by 300 m below the source

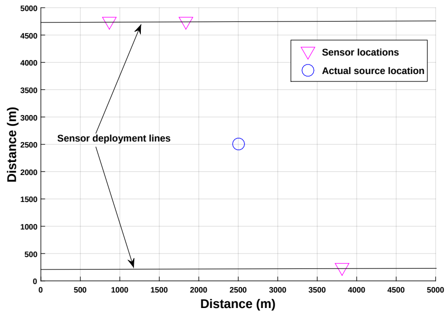


(b) Performance profile

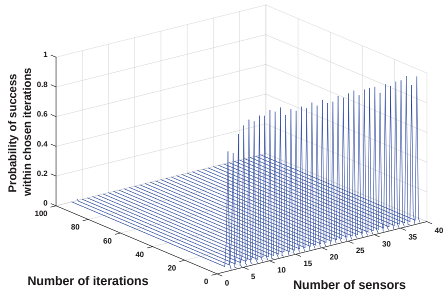
Figure 4.4: Sensors were deployed in two lines below the source. Number of sensors were changed from 3 to 40. For each trial locations of the sensors were changed 100 times randomly. Note that the successive estimations of source always converge before 10 iterations.

sor configurations. Note that if the number of iterations exceed 100, the algorithm exits from estimating source position, deciding that it could not locate the source position for that particular sensor configuration. In typical WSN TDOA localization system if the sensors are very close to each other, then one of the sensors is virtually redundant and it provides little additional information. The result could be significant positioning error. The effect of the redundant sensors is significant while the number of sensors is low. This fact is represented in the algorithm by unsuccessful localizations.

However, it should be noted that the positioning of the sensors play a major role on the performance of the localization algorithm. For instance, the success rate is much



(a) Sensor deployment in two lines above and below the source



(b) Performance profile

Figure 4.5: Sensors were deployed in two lines above and below the source. Number of sensors were changed from 3 to 40. For each trial locations of the sensors were changed 100 times randomly

significant when the sensors are deployed around the source position rather than positioning them in a single side from the source. This phenomenon can be identified by examining the success rates of Fig. 4.5b with respect to Fig. 4.3b and 4.4b.

The Fig. 4.6 depicts the effect of increasing the number of sensors with respect to the successive convergence of the algorithm. Note that after the number of sensors increased to a certain value, there is no significant improvement in the probability of success in estimating the source position in lower iterations. In this particular case, this number of sensors can roughly be identified as seven. In some situations, having a higher number of sensors could be a disadvantage in the presence of noise, because each sensor can contribute for some amount of positioning error. Therefore, the optimal number of sensors needed to cover a particular area has to be estimated while maximizing the range of detection and minimizing the localization error.

4.3.3 Maximum Likelihood Estimator (MLE) Model

As mentioned in Section 4.3.1 Arrival time measurements can be modelled as

$$\tau_i = T_0 + \frac{\| Z_S - Z_i \|}{c} + w_i \qquad i = 0, 1, ..., N-1$$

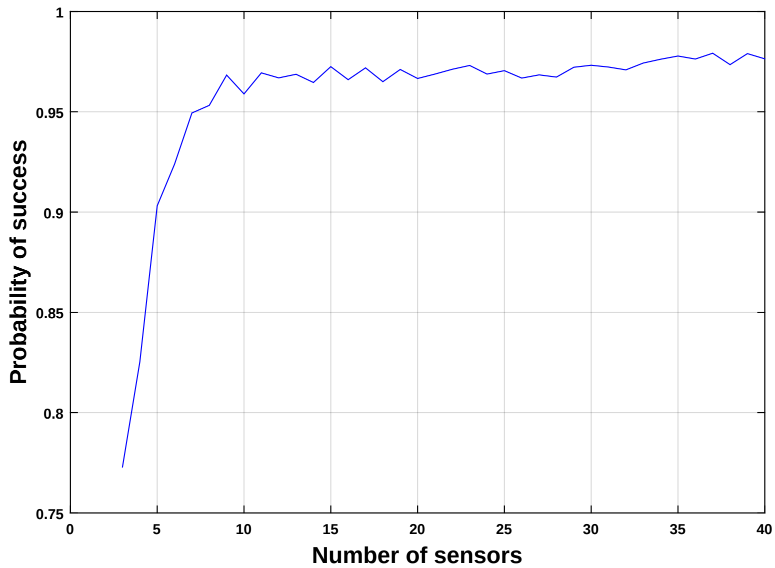


Figure 4.6: The effect of number of sensors over the probability of success within three iterations. (The result was obtained from 10000 executions)

where $w_i \sim N(0, \sigma^2)$.

The TDOA meausrement between i^{th} and j^{th} sensor is given by

$$\tau_{ij} = \tau_i - \tau_j = \frac{1}{c}\left[\| Z_S - Z_i \|\right] - \frac{1}{c}\left[\| Z_S - Z_j \|\right] + w_i - w_j$$

where $\| Z_S - Z_i \|$ is range difference between source and the i^{th} sensor. Therefore, with N number of sensors we get $N-1$ independent TDOA measurements.

We consider $N-1$ independent measurements with respect to 1^{st} sensor. Then the system of measurements can be written as

$$\underbrace{\begin{bmatrix} \tau_{12} \\ \tau_{13} \\ \vdots \\ \tau_{1N} \end{bmatrix}}_{\triangle\tau} = \underbrace{\begin{bmatrix} 1 & -1 & 0 & \cdots & 0 \\ 1 & 0 & -1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \cdots & \vdots \\ 1 & 0 & \cdots & \cdots & -1 \end{bmatrix}}_{\mathbf{A}} \underbrace{\begin{bmatrix} \| Z_S - Z_1 \| \\ \| Z_S - Z_2 \| \\ \vdots \\ \| Z_S - Z_N \| \end{bmatrix}}_{\zeta_{Zs}} + \underbrace{\begin{bmatrix} 1 & -1 & 0 & \cdots & 0 \\ 1 & 0 & -1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \cdots & \vdots \\ 1 & 0 & \cdots & \cdots & -1 \end{bmatrix}}_{\mathbf{A}} \underbrace{\begin{bmatrix} w_{12} \\ w_{13} \\ \vdots \\ w_{1N} \end{bmatrix}}_{\mathbf{W}}$$

where $Z_S = (x_{S,}y_S)$ is the source location and the $Z_i = (x_{i,}y_i)$; $i = 1, 2, ..., N$ are the sensor locations.

Therefore the probability distribution of MLE can be written as

$$\triangle\tau \sim N(\mathbf{A}\zeta_{Zs}, \sigma^2\mathbf{A}\mathbf{A}^T)$$

where explicitly given by

$$p\left(\frac{\triangle\tau}{Z_S}\right) = \frac{1}{\sqrt{2\pi} \mid \sigma^2\mathbf{A}\mathbf{A}^T \mid^{\frac{1}{2}}} e^{-\frac{1}{2}(\triangle\boldsymbol{\o} - \boldsymbol{A\zeta_{Zs}})^T\left(\sigma^2\mathbf{A}\mathbf{A}^T\right)^{-1}(\triangle\boldsymbol{\tau} - \boldsymbol{A\zeta_{Zs}})}$$

From [118], for any unbiased estimator $\hat{\theta}$ of the parameter θ the FIM elements are given by

$$[J(\theta)]_{k,l} = E\left\{\frac{\partial logf(y)}{\partial\theta_k}\frac{\partial logf(y)}{\partial\theta_l}\right\}$$

where $1 \leq k, l \leq M$.

For a Gaussian time series, the FIM is given by

$$[J(\theta)]_{k,l} = \frac{1}{2}tr\left\{R^{-1}(\theta)\frac{\partial\mathbf{R}(\theta)}{\partial\theta_k}R^{-1}(\theta)\frac{\partial\mathbf{R}(\theta)}{\partial\theta_l}\right\} + \left[\frac{\partial\mathbf{m}(\theta)}{\partial\theta_k}\right]^T R^{-1}(\theta)\left[\frac{\partial\mathbf{m}(\theta)}{\partial\theta_l}\right]$$

.

In the localization problem that we are considering, the covariance matrix does not depend on Z_s. Therefore,

$$[J(Z_S)]_{k,l} = \left[\frac{\partial A\zeta_{Zs}}{\partial Z_S}\right]^T\left(\sigma^2 AA^T\right)^{-1}\left[\frac{\partial A\zeta_{Zs}}{\partial Z_S}\right]$$

Note that Z_s is bivariate with $x_{S,}y_S$. Therefore, let us compute the elements of FIM separately. Consider partial derivative of single element of $\boldsymbol{\zeta_{Zs}}$ with respect to x_S

$$\frac{\partial \parallel Z_S - Z_i \parallel}{\partial x_S} = \frac{\partial\sqrt{(x_s - x_i)^2 + (y_s - y)^2}}{\partial x_S} = \frac{(x_s - x_i)}{\parallel Z_S - Z_i \parallel}.$$

Similarly

$$\frac{\partial \parallel Z_S - Z_i \parallel}{\partial y_S} = \frac{\partial \sqrt{(x_s - x_i)^2 + (y_s - y)^2}}{\partial y_S} = \frac{(y_s - y_i)}{\parallel Z_S - Z_i \parallel}$$

.

Therefore, elements of FIM can be derived as

$$[J(Z_S)]_{x,x} = \begin{bmatrix} \frac{(x_s - x_1)}{\|Z_S - Z_1\|} \\ \frac{(x_s - x_2)}{\|Z_S - Z_2\|} \\ \vdots \\ \frac{(x_s - x_N)}{\|Z_S - Z_N\|} \end{bmatrix}^T \mathbf{A}^T \left(\sigma^2 \mathbf{A}\mathbf{A}^T\right)^{-1} \mathbf{A} \begin{bmatrix} \frac{(x_s - x_1)}{\|Z_S - Z_1\|} \\ \frac{(x_s - x_2)}{\|Z_S - Z_2\|} \\ \vdots \\ \frac{(x_s - x_N)}{\|Z_S - Z_N\|} \end{bmatrix}$$

$$[J(Z_S)]_{y,y} = \begin{bmatrix} \frac{(y_s - y_1)}{\|Z_S - Z_1\|} \\ \frac{(y_s - y_2)}{\|Z_S - Z_2\|} \\ \vdots \\ \frac{(y_s - y_N)}{\|Z_S - Z_N\|} \end{bmatrix}^T \mathbf{A}^T \left(\sigma^2 \mathbf{A}\mathbf{A}^T\right)^{-1} \mathbf{A} \begin{bmatrix} \frac{(y_s - y_1)}{\|Z_S - Z_1\|} \\ \frac{(y_s - y_2)}{\|Z_S - Z_2\|} \\ \vdots \\ \frac{(y_s - y_N)}{\|Z_S - Z_N\|} \end{bmatrix}$$

$$[J(Z_S)]_{x,y} = [J(Z_S)]_{y,x} = \begin{bmatrix} \frac{(x_s - x_1)}{\|Z_S - Z_1\|} \\ \frac{(x_s - x_2)}{\|Z_S - Z_2\|} \\ \vdots \\ \frac{(x_s - x_N)}{\|Z_S - Z_N\|} \end{bmatrix}^T \mathbf{A}^T \left(\sigma^2 \mathbf{A}\mathbf{A}^T\right)^{-1} \mathbf{A} \begin{bmatrix} \frac{(y_s - y_1)}{\|Z_S - Z_1\|} \\ \frac{(y_s - y_2)}{\|Z_S - Z_2\|} \\ \vdots \\ \frac{(y_s - y_N)}{\|Z_S - Z_N\|} \end{bmatrix}$$

Further, it can be derived that

$$A^T \left(\sigma^2 A A^T\right)^{-1} A = \frac{1}{N\sigma^2} \begin{bmatrix} N-1 & -1 & -1 & \cdots & -1 \\ -1 & N-1 & -1 & \cdots & -1 \\ \vdots & \vdots & \ddots & \cdots & \vdots \\ -1 & -1 & \cdots & \cdots & N-1 \end{bmatrix}_{N \times N} = \frac{1}{N\sigma^2} \left(N\mathbf{I} - \mathbf{1}\right)$$

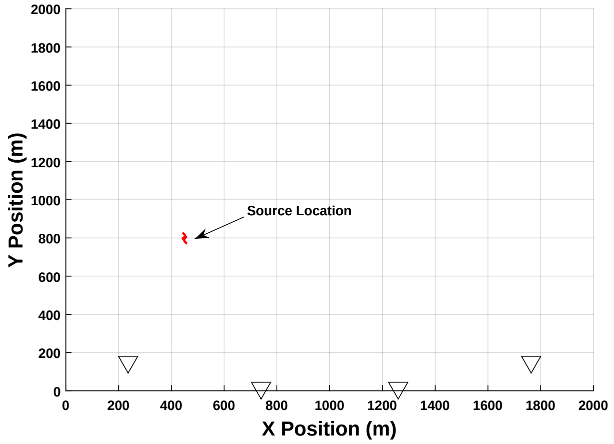
Finally, with the derivation of the above elements FIM for our problem can be represented by

$$[\mathbf{J}(Z_S)] = \begin{bmatrix} [J(Z_S)]_{x,x} & [J(Z_S)]_{x,y} \\ [J(Z_S)]_{y,x} & [J(Z_S)]_{y,y} \end{bmatrix}$$

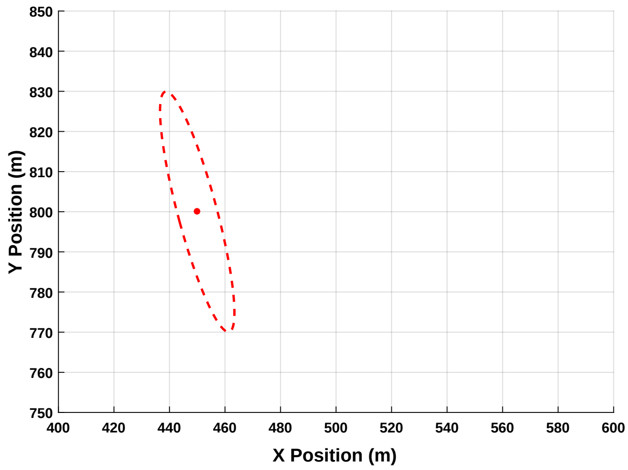
.

Therefore, the CRLB can be found by

$$var(\hat{Z})_i \geq [\mathbf{J}(Z_S)]_{ii}$$



(a) Source is placed at arbitrary source location $(450, 800)$



(b) Uncertainties in measurement is illustrated by the Covariance Ellipse (zoomed in)

Figure 4.7: Confidence assessment on localisation estimation. Uncertainty in estimation for arbitrary source location $(450, 800)$ when $\sigma = 0.2$ is illustrated by the Covariance error Ellipse.

4.4 Chapter Summary

In this chapter, we described the approach on elephant localization using timing observation measurements in a sensor network. In addition, we derived and presented mathematical models for the elephant localization system framework with two different estimation models. We evaluated the performance of the presented mathematical model implementing a simulation framework. Finally, we illustrated the statistical bounds for the localization error estimate.

Chapter 5

Propagation Constraints in Elephant Localization

In this chapter, we expand elephant localization system framework to introduce real-world input model constraints. We analyze the effect of various meteorological parameters in elephant vocalization propagation and their consequential effects on elephant positioning accuracy. In addition, we present the effect of signal-to-noise ratio (SNR) on detection of vocalization signal which consequently affects the localization accuracy.

5.1 Introduction

PASSIVE acoustic localization systems depend on the signal transmission through the propagation medium. Therefore, changes in the properties of the medium could significantly affect the detection and the localization accuracy. Positioning estimation in these systems is computed based on speed and sound in the medium and the timing measurements. If the received signals are processed in a centralized location or if the sensors are synchronized, the timing measurement error can always be controlled within acceptable margins. However, the speed of sound in the medium is an external factor and could vary extensively with the properties of the medium. In our application of elephant localization utilizing acoustic sensor network, the signal for the sensors is elephant rumbles and propagation medium for the signal is air. It is important to examine the sound signal variation through the air and its effect on localization error. Therefore, in this chapter of the thesis, we quantitatively analyse the effects of various environmental parameters on the positioning accuracy of the system. In Section 5.2 we discuss about the sound propagation in air as the basis for understanding the environmental effects.

Section 5.3 we revisit the localization algorithm that utilized in this framework. In Section 5.4 we explain the simulation setup and Section 5.5 outlines results of the analysis and discuss it, further.

5.2 Sound Propagation in Air

The accuracy of elephant localization and detection significantly depends on the characteristics of sound propagation in the air. The sound propagates through the air as longitudinal waves and the propagation is affected by the properties of the medium. For instance, the variations in the metrological parameters such as temperature, wind, relative humidity ect. results in the sound propagation variations in terms of intensity and speed. In this chapter we basically focus on temperature and wind effects on the speed of sound.

5.2.1 Sound Propagation Model

Elephant vocalization generation can be assumed as a point acoustic source and if the medium of air is assumed to be homogeneous, the sound propagation is considered to be spherical. Therefore, the sound intensity in a certain direction is inversely proportional to the expanding surface area of the sphere. The sound pressure level (SPL) at distance r is given by $SPL = SWL_{point} - 10log(4\pi r^2)$ dB where SWL_{point} represent the sound pressure level measured at one meter from the source. The model can be simplified to $SPL = SWL_{point} - 20log(r) - 11$ dB which is often referred to as the standard inverse square law for point source sound propagation [119]. In summary, the relative sound intensity is reduced by 6 dB per doubling of distance. Depletion in sound intensity reduces the SNR levels at the sensors. Consequently, signals of interest which concealed in the background noise become difficult to detect.

5.2.2 Temperature Effect

The speed of sound in air changes with respect to variations in several phenomena such as temperature, water vapour mole fraction, pressure and CO_2 content in the air. Cramer [120] has proposed a following closed form equation for the relationship between speed of sound and the above environmental factors.

$$\begin{aligned} v_0(t, p, x_w, x_c) = a_0 + a_1 t + a_2 t^2 + (a_3 + a_4 t + a_5 t^2) x_w \\ +(a_6 + a_7 t + a_8 t^2) p + (a_9 + a_{10} t + a_{11} t^2) x_c \\ +a_{12} x_w^2 + a_{13} p^2 + a_{14} x_c^2 + a_{15} x_w p x_c, \end{aligned} \tag{5.1}$$

where v_0 is zero−frequency speed of sound, t is the temperature of air in Celcius, x_w is the water vapor mole fraction, x_c is the $\mathrm{CO_2}$ mole fraction, and p is the air pressure. The coefficients a_0 to a_{15} are given in Table 5.1.

However, the speed of sound mainly depends on temperature and effects of other variables are insignificant. Therefore, the speed of sound in air can be expressed in terms of temperature as $C_{Sound_T} = C_{Sound_0}\sqrt{(1 + \frac{T}{273.15})}$ where $C_{Sound_0} = 331.45\ \mathrm{ms^{-1}}$ is sound speed at $0\,^0C$ [121]. In general, per degree Celsius rise in temperature, the speed of sound increases by $0.61\ \mathrm{ms^{-1}}$.

Table 5.1: Coefficients of Eq. (5.1) (Carmer [120] equation for speed of sound dependencies in air.)

Coefficient	Modified Cramer Values
a_0	330.8860 m/s
a_1	0.6324 m/s °C
a_2	-0.000528 m/s °C^2
a_3	51.471935 m/s
a_4	0.1495874 m/s °C
a_5	-0.000782 m/s °C^2
a_6	-1.82x10-7 m/s Pa
a_7	3.73x10-8 m/s °CPa
a_8	-2.93x10-10 m/s °C^2 Pa
a_9	-85.20931 m/s
a_{10}	-0.228525 m/s °C
a_{11}	5.91x10-5 m/s °C^2
a_{12}	-2.835149 m/s
a_{13}	-2.15x10-13 m/s Pa^2
a_{14}	29.179762 m/s
a_{15}	0.000486 m/s Pa

5.2.3 Wind Effect

Sound propagation medium of air itself is in a motion due to the wind. The sound propagating through the air will be transported by the moving air mass. Therefore, when the sound propagates towards the direction of the wind, the sound speed will decrease. On the otherhand, if the sound propagates along wind direction, the speed of sound will increase. In a situation, wind makes an angle with the sound path it is necessary to take the vector component along the sound path. In our application, sound path is the elephant−sensor path and Fig. 5.1 depicts a situation where wind flows in an angle of $\beta(= |\theta_2 - \theta_1|)$ with respect to sound path. Let V_1 be the speed of sound without wind effect, and V_2 be the wind speed. Then, the resultant sound speed V in the direction of

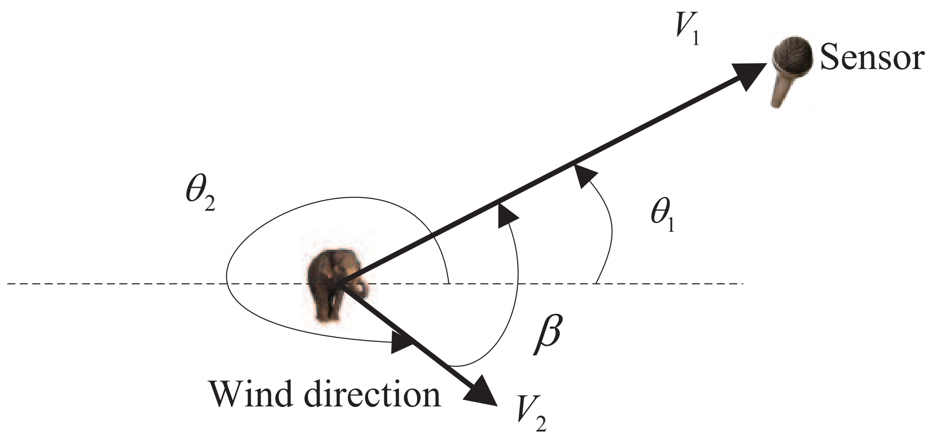


Figure 5.1: Wind effect on sound speed in the direction of propagation. Effective component of V_2 along the elephant−sensor direction should be incorporated.

source−sensor is given by

$$V = V_1 + V_2 cos(\beta).$$

In the follwoing section we present the localization algorithm utilized in our framework.

5.3 Localization Algorithm

Once an elephant (source) generates a vocalization, the sound signal propagates through the air following the model discussed in Section 5.2. The sensors at the vicinity of the source receive the attenuated and noise corrupted signal. In our analysis, we assume that all the sensors in our deployment receive the elephant vocalization generated at our interested observation area. Then, we obtain the time difference of arrival (TDOA) information by performing pair−wise cross-correlations between observation signals at each sensor pair.

Let the time of arrival measurements at sensor i to be t_i where $i = 0, 1, \cdots, N-1$. The infrasonic acoustic sensors are deployed at pre−determined coordinates (x_i, y_i). It is necessary to locate the source position (x_s, y_s). The arrival time measurements can be

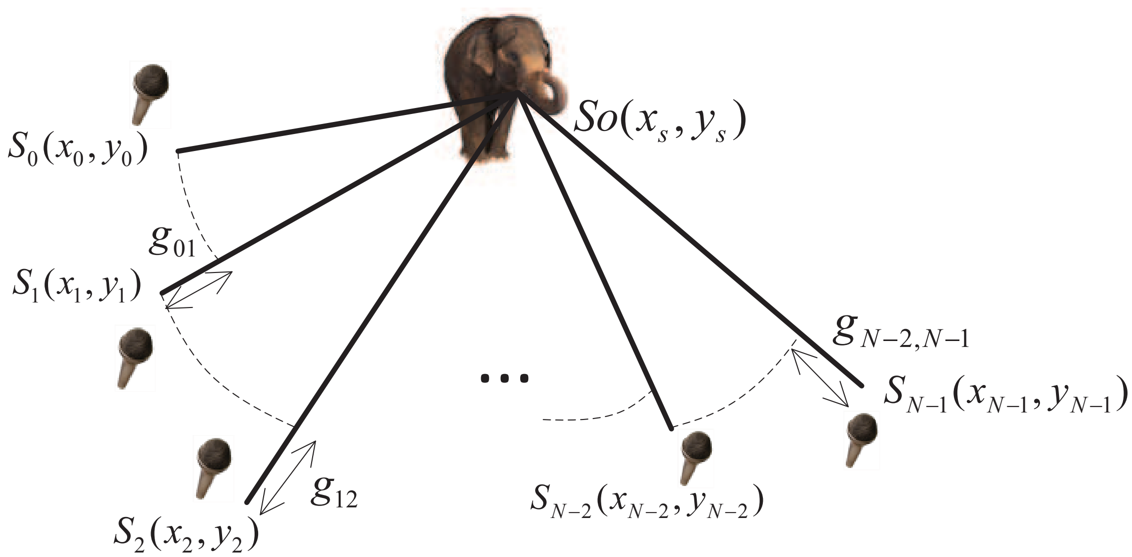


Figure 5.2: N number of sensors are deployed at the vicinity of the expected elephant location. Here, the distance difference between source and the p^{th} and q^{th} sensor is defined as g_{pq}.

modelled by

$$t_i = T_0 + \frac{R_i}{c_i} + w_i \qquad i = 0, 1, \cdots, N-1 \tag{5.2}$$

where T_0 is the signal emitted time by the source, R_i is the range difference between source and the i^{th} sensor, c_i is the sound propagation speed and w_i is the uncorrelated measurement noise with zero mean and σ^2 variance. It should be noted that the speed of sound between source and each sensor could vary due to the ecological effects discussed in Section 5.2. The distance from source to i^{th} sensor R_i is given by

$$R_i = \sqrt{(x_s - x_i)^2 + (y_s - y_i)^2}. \tag{5.3}$$

The signal emitted time T_0 in (5.2) is unknown. Therefore, now we incorporate TDOA measurements to the model. Let the TDOA measurement between p^{th} and q^{th} sensor denoted by Δt_{pq} which is given by

$$\Delta t_{pq} = t_p - t_q + w_{pq} \tag{5.4}$$

where $p = 0, 1, \cdots, N-2$ and $q = p+1, p+2, \cdots, N-1$. The equation (5.4) can be written in terms of (5.3) by

$$\Delta t_{pq} = \frac{R_p}{c_p} - \frac{R_q}{c_q} + w_{pq} \tag{5.5}$$

which can be explicitly characterized by the non linear model

$$\mathbf{Y} = \mathbf{h}(\mathbf{x}) + \mathbf{w} \tag{5.6}$$

where

$$\mathbf{Y} = \begin{bmatrix} \Delta t_{01} \\ \Delta t_{02} \\ \vdots \\ \Delta t_{N-2,N-1} \end{bmatrix}$$

$$\mathbf{h}(\mathbf{x}) = \begin{bmatrix} \frac{R_0}{c_0} - \frac{R_1}{c_1} \\ \frac{R_0}{c_0} - \frac{R_2}{c_2} \\ \vdots \\ \frac{R_{N-2}}{c_{N-2}} - \frac{R_{N-1}}{c_{N-1}} \end{bmatrix}$$

$$\mathbf{w} = \begin{bmatrix} w_{01} \\ w_{02} \\ \vdots \\ w_{N-2,N-1} \end{bmatrix}.$$

Solving non linear equation in (5.6) can be approached with diverse techniques [118] [122]. We appreciate the problem in a geometrical approach as depicted in Fig. 6.1. Lets assume that the $w_{pq} = 0$ and the $c_p = c_q = c$ for $\forall(p, q) = 0, 1, \cdots, N-1$. Here, Δt_{pq} corresponds to the distance difference between source and the pair of sensors p and q. Let

$$h_{pq} = c \times \Delta t_{pq} \tag{5.7}$$

and

$$g_{pq} = R_p - R_q \tag{5.8}$$

where both (5.7), (5.8) represent the distance differences. However, g_{pq} consists of the unknown source location. Therefore, the source location can be determined by solving the function defined by

$$f(x_s, y_s) = \underset{x_s, y_s}{argmin} \sum_{p,q} \left(h_{pq} - g_{pq}\right)^2 . \tag{5.9}$$

However, the location estimation found by (6.1) does not consider the measurement errors and the sound propagation velocity variances discussed previously. Therefore, by introducing those constraints externally to the localization routine, we can attain the effect of those parameters. The next section of the chapter presents the simulaions of the estimation accuracy that affected by different constraints.

5.4 Simulation Framework

The simulation is involved in two major steps. Former part of the simulation is carried out to implement elephant vocalization signal detection at the sensors. This routine also provides the time delay information between each pair of sensors. In this section, the SNR effects on signal detection and acquiring time delay information are also considered. The latter part of the simulation estimate the source position utilizing the time delay information provided by the previos section. The wind and temperature effect on source position estimation is considered in this section.

5.4.1 Vocalization Detection

In real world scenario, once an elephant made a rumble signal, each sensor in the vicinity of the source location hear time delayed and noise corrupted versions of the original signal. This is simulated by shifting and zero padding the original rumble vocalization data file by relevent time delays for each sensor. Then, the noise corruption is incorporated by adding white Gaussian noise to time shifted signal. Now at the receiver, if the signal is cross−correlated with signature rumble vocalization signal, it is possible to find the peak cross−correlation coefficient at number of samples which represent the original time delay information. We perform multiple cross−correlations between each pair of sensors' observation signals to find the time delay information represented by Δt_{pq} in (5.7).

5.4.2 Sensor Placement and Source Localization

In this part of the simulation several real world aspects are taken into the consideration. We chose 2000 m $\times$ 2000 m square as our analysis area which represent the woodland. We assume that coordinate axis $y = 0$ as our village boundary. Countermeasure can be taken only if the elephants are localized at least before they enter into the 500 m margin from the village boundary. Therefore, we choose interested source observation area as the rectangle bounded by coordinates $\{(0, 500), (0, 2000), (2000, 500), (2000, 2000)\}$.

Sensors might need occasional maintenance, for instance, to replace the batteries, to sensor health checks etc. Practically people could not frequently move into deep forest area which is not pleasing in terms of risk and the cost of the visits. Therefore, the sensors need to be placed close to the village boundary. We decide that the sensors should be placed within 200 m distance from the village boundary. Consequently, the sensor deployment area is a rectangle bounded by coordinates $\{(0, 0), (0, 200), (2000, 0), (2000, 200)\}$. However, sensors need to be placed optimally so that they avoid the redundancy and provide maximum accuracy. We, considered several options, such as placing sensors randomly, homogeneously, in a line and in a curvature. In the line deployment, we selected centre line of the chosen sensor deployment strip ($y = 100$ m) and we deployed sensors in equidistance separations. In curvature deployment, the proper arc is found as follows. First, we drew a circle centred at $(1000, 2000)$ and radius 2000 m. Then we select the arc which is laid inside the sensor placement strip. Then the sensors are placed such that they are separated from each other by equal arc distances. In our simulations, we used four sensors which have identical capabilities. It is identified, by means of several simulation experiments that the curvature sensor placement outperforms other methods in source localization. Therefore, it is chosen as the sensor placement criteria for the results presented in this work.

The effect of each constraint discussed in Section 5.2 is attained by placing the source at different positions in the interested observation area and calculating the estimation error. Initially, the rectangular observation area is divided into 100 m $\times$ 100 m small girds. Then, the source is placed 100 times randomly inside the small grid and the source position is estimated according to the algorithm discussed in Section 5.3. However, each of position estimation obtained here is affected by different parameters such as wind, temperature and SNR and thus they are erroneous. We compute the error for each random source position by calculating the Euclidean distance between actual and the estimated source locations. Then the mean estimation error is calculated for the above 100 source placements. The computed mean error is considered as the average inaccuracy in positioning when the source is located at the area represented by that particular grid. The above process is repeated for each grid in the observation area. The effects of different meteorological parameters and SNR are presented in the subsequent section.

5.5 Results and Discussions

The simulation setup discussed in the Section 5.4 is obtained using Matlab 7.9.0 (R2009b) development environment for the analysis. The effect of individual parameter is analyzed via simulations while keeping the other parameters constant. Figures 5.3$-$5.5 show the temperature effects on the source positioning. Initially, it is assumed that the temperature is uniform throughout the area. Results for the instances of temperature 22^0C and 30^0C are depicted in Figs. 5.3, 5.4, respectively. The maximum mean estimation errors in these incidents are less than one meter throughout the observation grid. Therefore, the increase in the temperature equally, does not affect the source positioning accuracy significantly. Then, we varied the temperatures at each node such that $T_{S1} = 25^0$C, $T_{S2} = 23^0$C, $T_{S3} = 22^0$C, $T_{S4} = 24^0$C, and execute the simulation again. Figure 5.5 shows that in this scenario the positioning error increases, drastically.

The wind has a very significant effect on localization accuracy as depicted in Fig.

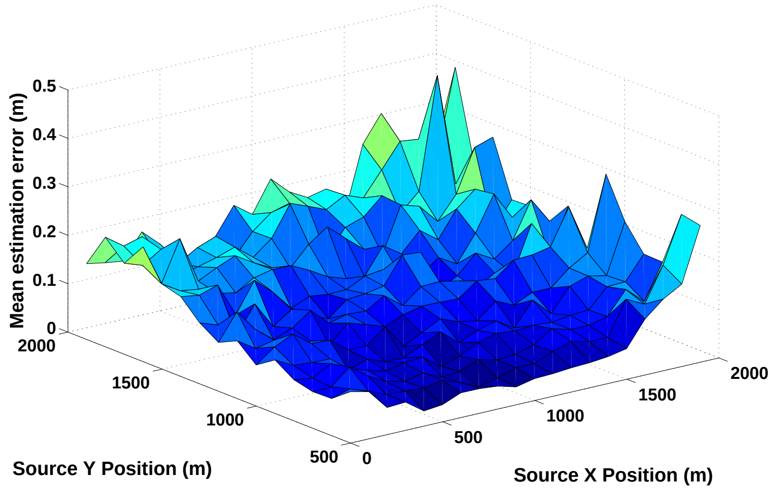


Figure 5.3: The source localization error variation at different source positions within the observation area. Four sensors are deployed in curvature with equal arc length separations as discussed in Section 6.4. The $\mathbf{T} = \mathbf{22}\ ^{\mathbf{0}}\mathbf{C}$ uniform throughout the area. $V_2 = 0$ ms^{-1}, $\theta_2 = 270^0$, SNR = 10 dB

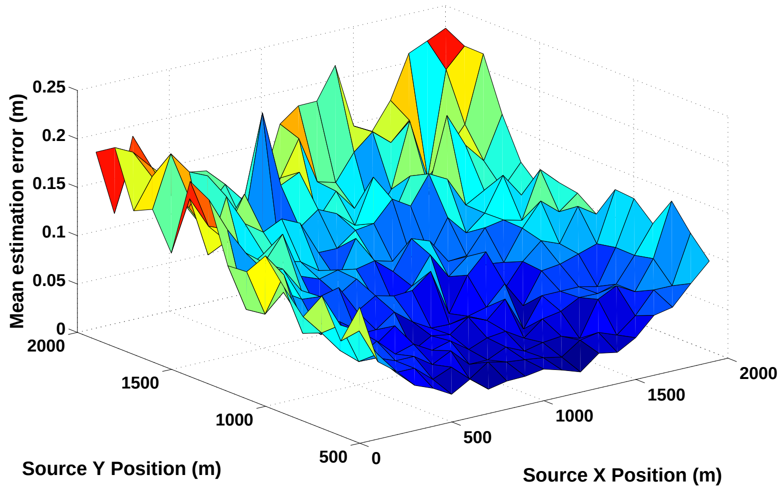


Figure 5.4: The source localization error variation at different source positions within the observation area. Four sensors are deployed in curvature with equal arc length separations as discussed in Section 6.4. The $\mathbf{T} = \mathbf{30}\ ^{\mathbf{0}}\mathbf{C}$ uniform throughout the area. $V_2 = 0$ ms^{-1}, $\theta_2 = 270^0$, SNR = 10 dB

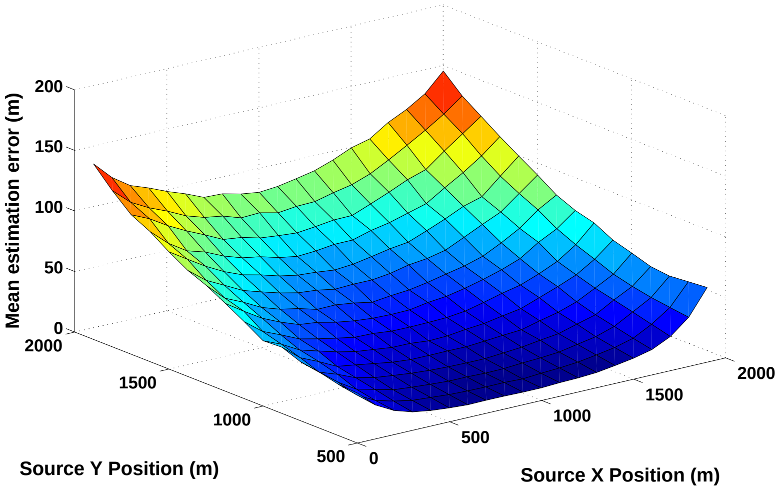


Figure 5.5: The source localization error variation at different source positions within the observation area. The sensors are deployed in curvature with equal arc length separations as discussed in Section 6.4. The Temperature varies between each sensor path. $\mathbf{T_{S1} = 25\ ^0C}$, $\mathbf{T_{S2} = 23\ ^0C}$, $\mathbf{T_{S3} = 22\ T_{S4} = 24\ ^0C}$. $V_2 = 0\ \mathrm{ms}^{-1}$, $\theta_2 = 270^0$, SNR $= 10$ dB

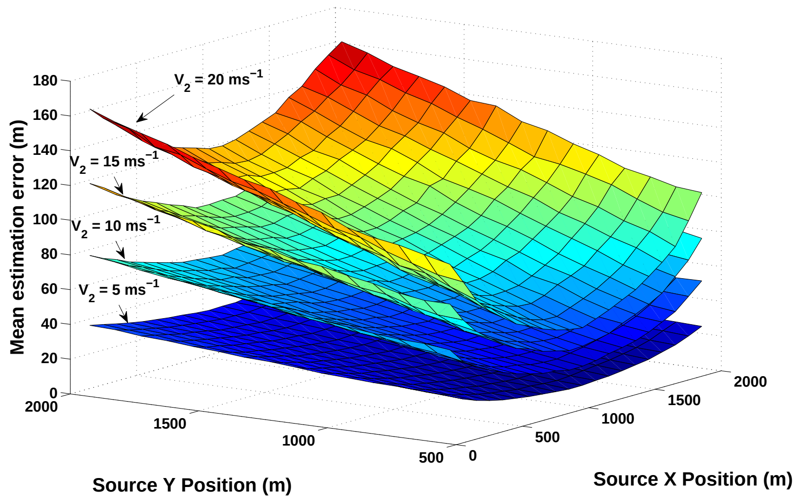


Figure 5.6: The source localization error variation at different source positions within the observation area for wind velocities $\mathbf{V_2 = 5}\ \mathrm{ms}^{-1}$, $\mathbf{V_2 = 10}\ \mathrm{ms}^{-1}$, $\mathbf{V_2 = 15}\ \mathrm{ms}^{-1}$, $\mathbf{V_2 = 20}$ ms^{-1}. Four sensors are deployed in curvature with equal arc length separations as discussed in Section 6.4. The $T = 22\ ^0C$ uniform throughout the area. $\theta_2 = 270^0$, SNR $= 10$ dB.

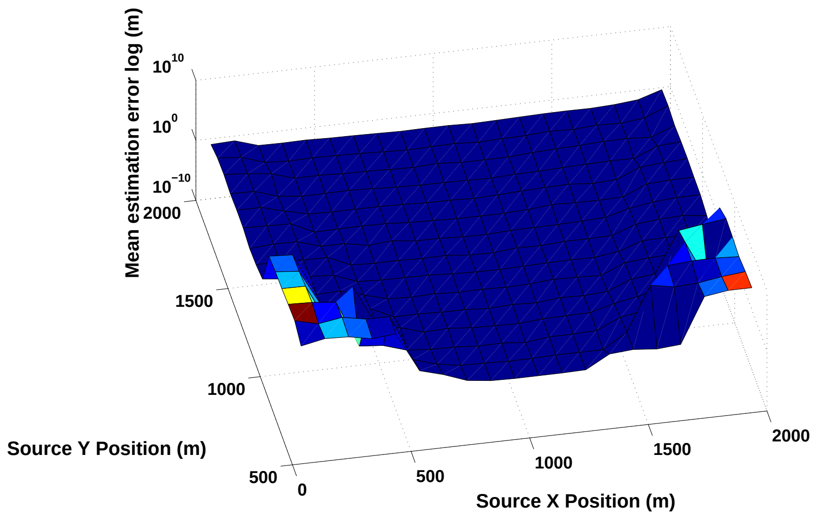


Figure 5.7: The source localization error variation at different source positions within the observation area. Four sensors are deployed in curvature with equal arc length separations as discussed in Section 6.4. The T $= 22\ ^0$C uniform throughout the area. $V_2 = 0$ ms^{-1}, $\theta_2 = 270^0$, **SNR = -15 dB.**

5.6. The rise in the wind velocity increases error in positioning especially towards the boundaries of x axis. In lower wind velocities, perhaps the error margin of $\pm$ 20 m at 500 m might not exceed; however, inaccuracy at higher velocities cannot be tolerated. Faster wind velocities toward the sensors will increase the sound velocity while decreasing the time-of-flight (TOF) of the signal from the source to the sensor. The TOF is higher when the source is far away from the sensors. Therefore, the errors in time delay increase with the distance resulting in higher positioning errors at far away source locations from the sensors.

The SNR has a much more considerable effect on the source localization accuracy in our algorithm. Figure 5.7 depicts the distribution of mean estimation error throughout our observation grid, while the SNR is set to -15 dB. Note that in our analysis we add the noise from a uniform distribution, assuming the noise is equivalent even for far away distances from the sensors. However, this assumption does not follow the actual scenario. According to the discussion in Section 5.2.1 the sound intensity depletes with the distance, resulting in lower SNR levels at the sensors when the source is far away. Therefore, it can be expected higher SNR levels while the elephants are closer to the sensors. The SNR level has substantial effect when the source is placed in the XY corners of the observation area. This results from inaccurate time delay information provided by correlation routine, at lower SNR levels. The inaccuracy is significant once sensors are spatially in closer to the source. These erroneous time delays subsequently cause the minimization algorithm to estimate enormously inaccurate source positions as depicted in Fig. 5.7. The effect was further analyzed by increasing the SNR level in steps. The inaccuracy disappeared at the SNR level of -12 dB. We identified this as the marginal SNR level that is necessary for the system to provide proper localization estimation in this simulation setup.

5.6 Chapter Summary

In this chapter we have analysed major propagation constraints that could affect the elephant localization framework. Our results show that the impact of the temperature for the accuracy of source localization is insignificant if the temperature is uniform over the considered area. In contrast, the temperature variation between each source$-$sensor path significantly affects the source positioning error. Therefore, in real implementation integrating mechanism to compensate temperature variations will vastly improve the localization accuracy. In addition, it is identified that wind velocity has a very significant effect on positioning error. Therefore, incorporating real-time wind velocity information is also important in this localization system. The SNR levels at the sensors also play major role in localization error. The system provides enormously inaccurate position estimations once the SNR level drops under certain marginal level. More precisely, this level is -12 dB with respect to our simulation framework discussed in this chapter. Therefore, in an actual implementation, incorporating signal processing techniques for noise reduction will increase the overall performance of the system.

Chapter 6

Localization Accuracy Enhancement Technique

In this chapter, we propose a novel "probe" technique to estimate the average speed of sound which is affected by the environmental parameters. The novel technique is incorporated to enhance the accuracy of elephant localization system which utilizes an acoustic sensor network. We explain the localization system framework and then we introduce the probe technique for wind and temperature affected sound speed correction. Incorporation of probes in our sensor network eliminates the requirement to explicitly measure temperature and wind velocity for accurate determination of sound velocity. Performance of the system is evaluated against a conventional sensor network equipped with wind and temperature sensors. The performance of the technique is evaluated under different real-world ecological scenarios and results are presented.

6.1 Introduction

ESTIMATED position accuracy dependency on accurate signal propagation speed used in the computation algorithm in a passive acoustic sensor network is significant in some applications [123, 124]. In Chapter 5 the possibility of using an acoustic sensor network to detect and localize elephants has been extensively analysed. However, the speed of sound propagation in air, depends on ecological parameters such as temperature and wind velocity. Therefore, wind and temperature variations are identified as the main cause of performance deterioration of such system.

In this chapter, we propose a novel technique to correct the errors arising from variations in sound speeds due to environmental effects. We propose a system framework to implement the algorithms that have been developed and describe the results of experiments, under different environmental profiles.

In Section 6.2 we revisit the localization algorithm that will be utilized in the proposed system. In Section 6.3 the technique used to correct the speed of sound to mitigate temperature and wind velocity effects is described in detail. In Section 6.4 we explain the simulation framework and Section 6.5 outlines performance of the novel technique.

6.2 Localization Algorithm

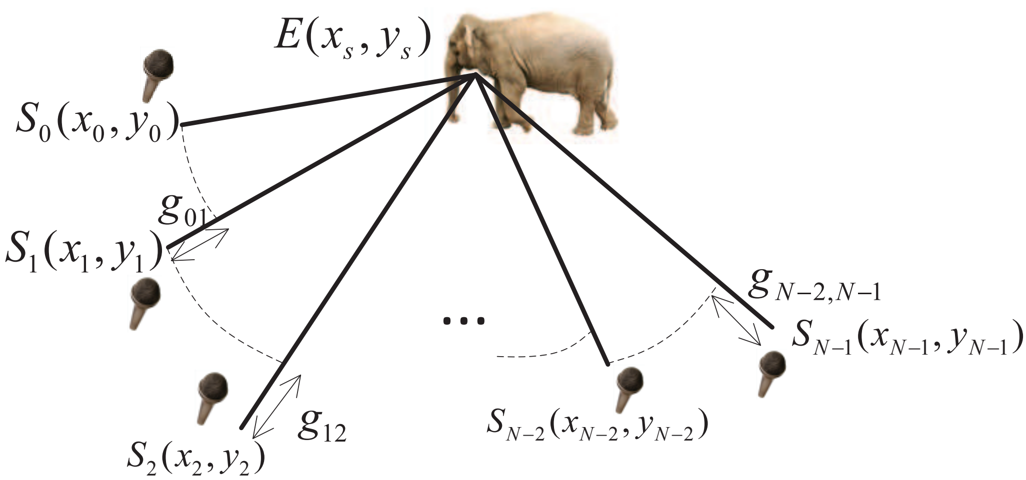


Figure 6.1: N number of sensors are deployed at the vicinity of the expected elephant location. The distance difference between source and the p^{th} and q^{th} sensor is defined as g_{pq}.

We consider an acoustic sensor network with N sensors that listen to elephant vocalizations. In consideration of the long propagation range of infrasonic rumble signals [108], it is assumed that all sensors receive an attenuated and noise corrupted replica of a call generated by an elephant (source). Let the time of arrival measurements at sensor S_i be t_i where $i = 0, 1, \cdots, N-1$. The infrasonic acoustic sensors are deployed at predetermined coordinates (x_i, y_i). It is necessary to locate the source position (x_s, y_s). The arrival time measurements at sensor S_i can be modeled by $t_i = T_0 + R_i/c_i + \epsilon_i$ where T_0 is the signal emitted time by the source, R_i is the distance between source and the i^{th} sensor, c_i is the sound propagation speed and ϵ_i is the normally distributed measurement noise with zero mean and σ^2 variance. It should be noted that the c_i

between the source and each sensor could vary because of environmental effects such as wind and the temperature. The distance from source to i^{th} sensor R_i is given by $R_i = \sqrt{(x_s - x_i)^2 + (y_s - y_i)^2}$. The time T_0 of signal emission is unknown, and so it is appropriate to perform a time-difference-of-arrival (TDOA) estimation. TDOA information is obtained by performing pair-wise cross-correlations between the observation sound signals at each sensor pair. TDOA measurement between the p^{th} and q^{th} sensors denoted by Δt_{pq} is given by $\Delta t_{pq} = t_p - t_q + \epsilon_{pq} = R_p/c_p - R_q/c_q + \epsilon_{pq}$, where $p = 0, 1, \cdots, N-2$ and $q = p+1, p+2, \cdots, N-1$, $\epsilon_{pq} = \epsilon_p - \epsilon_q$.

Let the measured TDOA ranges be

$$\mathbf{m} = [m_{2,1} \quad m_{3,1} \quad \cdots \quad m_{n,1}]^T = \mathbf{d} + \boldsymbol{\epsilon}$$

where

$$\boldsymbol{d(\theta)} = [r_{2,1} \quad r_{3,1} \quad \cdots \quad r_{n,1}]$$

and $r_{p,q} = R_p - R_q$. The probability density function [125] of $\mathbf{m}$ given θ is

$$f(\boldsymbol{m/\theta}) = 2\pi^{-n/2}(\det \mathbf{Q})^{-1/2} \exp\{-J/2\}$$

where

$$J = [\boldsymbol{m} - \boldsymbol{r(\theta)}]^T \mathbf{Q}^{-1} [\boldsymbol{m} - \boldsymbol{r(\theta)}].$$

The Maximum Likelihood Estimate (MLE) is the $\theta(x_s, y_s)$ that minimizes J. This can be reduced to minimizing the non-linear least square problem [126] of

$$f(x_s, y_s) = \arg\underset{x_s, y_s}{min} \sum_{p,q} \left(h_{pq} - g_{pq}\right)^2 . \tag{6.1}$$

where $h_{pq} = c \times \Delta t_{pq}$ and $g_{pq} = R_p - R_q$.

The solution to (6.1) gives the unknown source location. However, to locate the source accurately the above system needs the correct sound propagation speeds between the source and each sensor, which is affected by wind and temperature variations. Our approach to estimate sound speed with mitigated temperature and wind velocity effects is presented in the next section.

6.3 Average Sound Speed Estimation Methodology

Our goal is to estimate the approximate speed of sound that signals propagate with respect to each sensor. In order to build a solution that attains the above sound speeds in a real world environmental scenario we first develop a model assuming uniform environmental conditions. Then the model is extended to real world comparable, non uniform and totally unknown environmental conditions.

To locate the elephants accurately, acoustic sensors and some specific sound (chirp) signal generators are deployed at predetermined location coordinates. These sound generators are referred to as "probes" in the remainder of the chapter. The chirp signal generation time schedule is predefined and known to both devices. Therefore, by listening to the signal, each sensor can determine the time of flight (TOF) from probes to the sensor. Then, the approximate speed of sound between the source and the sensors is estimated in two different models as presented below.

Model A: The temperature over the area is assumed to be uniform but unknown. The wind speed and the direction over the area are assumed to be uniform but unknown.

We estimate the wind information and the uniform temperature over the area completely depending on the probe technique without incorporating additional sensors. Consider that the i^{th} sensor (S_i) receives the signal from the probes P_l, P_m, P_n as depicted in Model A in the Figure 6.2. The temperature affected speed of sound between S_i and P_z is $V_{P_zS_i}(T)$ where $z = l, m, n$, and, so the measured speed of sound $V_{P_zS_i}$ between S_i and P_z is given by $V_{P_zS_i} = V(T) + V_w \cos(\theta_w - \theta_{P_zS_i})$. Thus, by resolving the system of equations for each probe z and sensor S_i, it is possible to estimate the approximate speed of sound in the

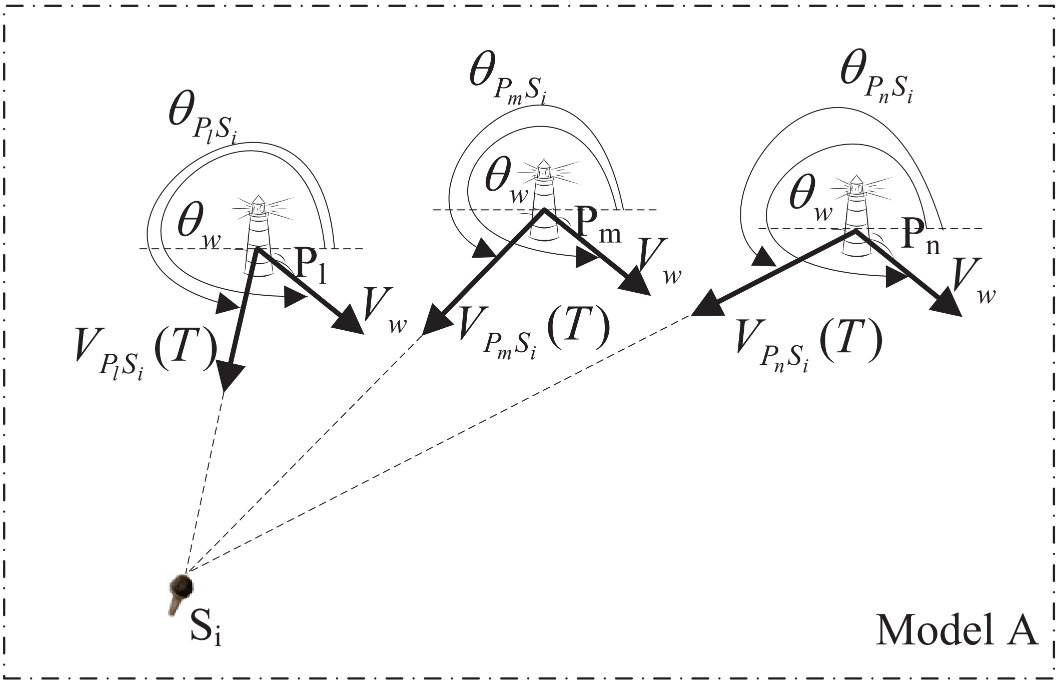


Figure 6.2: The i^{th} sensor (S_i) receiving the signal from the probes P_l, P_m, P_n. The wind flows with speed of V_w with an angle of θ_w with respect to the horizontal axis. The temperature affected speed of sound between P_z is $V_{P_z S_i}(T)$ where $z = l, m, n$.

area by evaluating three unknowns (wind speed V_w, wind direction θ_w, and temperature affected speed of sound $V(T)$). Now the wind direction can be derived as

$$\theta_w = \tan^{-1}\left[\frac{A\sin(\beta) - B\sin(\alpha)}{A\cos(\beta) - B\cos(\alpha)}\right] \tag{6.2}$$

where

$$A = \left(V_{P_lS_i} - V_{P_mS_i}\right)\sin\left(\left(\theta_{P_nS_i} - \theta_{P_lS_i}\right)/2\right),$$

$$B = \left(V_{P_lS_i} - V_{P_nS_i}\right)\sin\left(\left(\theta_{P_mS_i} - \theta_{P_lS_i}\right)/2\right),$$

$\alpha = \left(\theta_{P_mS_i} + \theta_{P_lS_i}\right)/2$, and $\beta = \left(\theta_{P_nS_i} + \theta_{P_lS_i}\right)/2$. The wind speed V_w is now

$$V_w = \frac{V_{P_lS_i} - V_{P_mS_i}}{\cos(\theta_w - \theta_{P_lS_i}) - \cos(\theta_w - \theta_{P_mS_i})}. \tag{6.3}$$

Bu using (6.2) and (6.3) we obtain the temperature affected speed of sound $V(T)$ from

$$V(T) = V_{P_lS_i} - V_w\cos(\theta_w - \theta_{P_lS_i}). \tag{6.4}$$

The temperature and the wind effects compensated sound velocity can then be determined.

Model B: The temperature over the area is non−uniform and unknown. The wind speed and the direction over the area are also non−uniform and unknown.

Under the condition where wind and temperature are non-uniform and information is unavailable, it is difficult to produce closed form equations to correct the actual sound propagation speed, because not enough information is available. In this case real world spatial properties of the temperature and wind variations were incorporated. The assumption of slow spatial variation of temperature permits temperatures in adjacent regions to be considered as correlated random variables. We model this variation, therefore, as a two-dimensional Gaussian function in the phase of data generation. The temperature at particular location coordinates (x, y) is given by

$$f(x,y) = T_{min} + \Delta T_{Vmax} \exp\left(-\left(\frac{(x-x_o)^2}{2\sigma_x^2} + \frac{(y-y_o)^2}{2\sigma_y^2}\right)\right),$$

where T_{min} is the minimum temperature, ΔT_{Vmax} is the maximum temperature variation, (x_o, y_o) is the centre coordinates of the interested area, σ_x, σ_y are the x and y spreads of the temperature blob over the area. A representation of this temperature variation is depicted Fig. S7 in Section 6.7.1 of the supplemental information. In addition, the wind flow is assumed to be a Markov Random Field (MRF). The wind vector at a particular position is determined by values drawn from a normal distribution $\mathcal{N}(\mathbf{V_{wAdj}}, \sigma_w^2)$ where $\mathbf{V_{wAdj}}$ is the wind vector in adjacent locations. Representations for wind speed and direction maps under this scenario are depicted Figures S8-S9 in Section 6.7.1 of the supplemental information. Further, the probe technique is incorporated to evaluate the approximated actual sound propagation by dividing the interested area into effective isothermal spatial regions. The validity of the above approximation depends upon the selection of the spatial region. The smallest region to uniquely estimate the environmental parameters is chosen as the isothermal region. This region is the area depicted as Model A in Fig. 6.2. The set of equations derived in the Model A can be used to estimate the average sound speed correction within the effective isothermal areas. Sound signals to distinct sensors will experience different speeds of propagation as affected by wind and temperature variations. By efficiently averaging them considering the spatial proximity, approximation to the effective sound speed can be obtained.

Comparison Model 1: The temperature over the area is non$-$uniform and unknown. The wind speed and the direction over the area are also non$-$uniform and unknown. Wind and temperature sensors are incorporated at various locations for the environmental affect modelling. To compensate the environmental effects, area partitioning and sound speed averaging technique was utilized.

Comparison Model 1 comprises a conventional acoustic sensor network. In this model we incorporate temperature and wind sensors in the system and place them in the locations where probes and sensors were placed in the previous models. These wind and temperature sensors provide point measurements. To obtain a better representation of the environmental profile over the area, we partition it into small regions which include at leaset one sound sensor location and three probe locations. Then we average the measurements from temperature and wind sensors incorporated with those partitioned region. Consequently, the speed of sound with respect to each acoustic sensor is determined taken into account the measurements.

Comparison Model 2: The temperature over the area is non−uniform and unknown. The wind speed and the direction over the area are also non−uniform and unknown. Wind and temperature sensors are incorporated at various locations for the environmental affect modelling. Two-dimensional Gaussian function and MRF are used to model the environmental effect.

In Comparison Model 2 we utilize temperature and wind sensors as in Comparison Model 1. In this model instead of averaging the measurements in the regions effectively, we utilize Gaussian temperature model to determine the temperature variation over the area. This Gaussian model is similar to the one that introduced in synthetic data generation above described in Model B. Model parameters for temperature variation can be produced through the measurements at sensor and probe coordinates and subsequently, temperature values at every coordinate can be determined. In addition, the wind velocity vector over the region is also represented as a MRF. The wind speed and direction measurements from the sensors are used to determine the initial mean and the variance of the field. Consequently, this information is incorporated to estimate the wind velocity field values over the area.

6.4 Simulation Framework

To test the proposed methodology in a real elephant localization scenario, a software simulation framework was first developed; and subsequently, a hardware system was implemented. Previously recorded elephant rumble signals were used to replicate the elephants in testing the hardware system along with a sensor network to capture these elephant calls. In the software framework, signal processing and localization mechanisms were implemented. Further, a separate simulation analysis was carried out taking into account real forest environmental scenario for localization error evaluation. Three major steps in the above software simulation are summarized below.

Step 1: Sensors and Probes Placement and Sound Speed Estimation

In this part of the simulation, several real world constraints are taken into consideration. We chose a 2000 m $\times$ 2000 m square as our analysis area which represents the woodlands. The coordinate axis $y = 0$ is assumed as the village boundary. Once the elephants are detected at a sufficient distance (safety distance) from the village boundaries safety measures can be taken. As the average walking speed of elephant is around 3-6 kmh^{-1}, distance of 500 m was selected as the safety distance. Now the interested elephant observation area became the rectangle bounded by coordinates $\{(0, 500), (0, 2000), (2000, 500), (2000, 2000)\}$. Sensors need to be placed close to the village boundary for practical reasons, so that the rectangle bounded by coordinates $\{(0, 0), (0, 200), (2000, 0), (2000, 200)\}$ was chosen as the sensor deployment area. In a similar way to [123] sensors are placed at equidistance locations on a segment of circle centered at $(1000, 2000)$ with a radius 2000 m. In the simulations 12 sensors which assumed to have identical capabilities were used.

The operation of the probes are limited to generate chirp signals at a predefined time schedule. These probes are assumed more robust than sensors and need less maintenance. Further, to acquire general environmental information in the observation area, probes need to be deployed in or close to the interested observation region. We chose to place them around the lower boundary ($y = 500$ m) of the observation area. Ten equally separated probes were deployed in a strip, such that every sensor had access to at least three probes at essentially the same range.

Sound signal experiences different sound speeds across the region it travels. For instance, if it is considered an area depicted in Figure 6.3, divided into nine squares, each square can be considered as a microclimate region with a particular wind velocity W_l and temperature T_l where $l = 1, 2, \cdots, 9$. In each square, sound speed is affected by the local environmental parameters. For instance, the signal from source E to Sensor S_1 will expe-

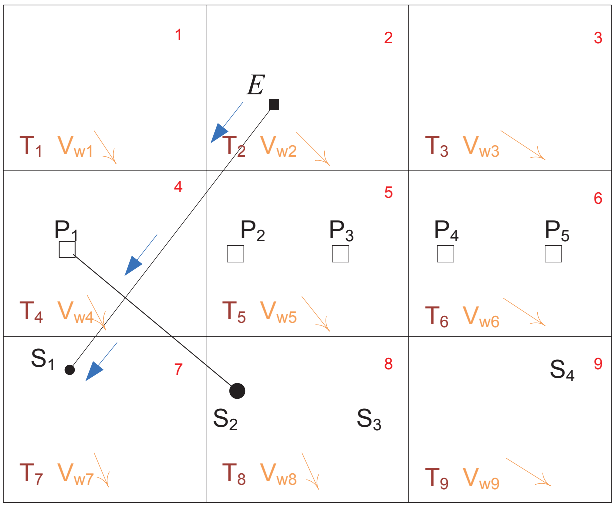


Figure 6.3: Example observation area with variable sound speeds. Each grid can be considered as a microclimate region with a particular wind velocity W_l and temperature T_l where $l = 1, 2, \cdots, 9$. The effective sound speed varies according to the environmental parameters at each grid.

rience the effects of temperatures T_2, T_4, T_5, T_7 and wind velocities V_{W2}, V_{W4}, V_{W5}, V_{W7} along the propagation path. Apparently, the most complex sound speed variation can be observed in the analysis of Model B where temperatures as well as wind velocities vary between each square. A detailed discussion on effects of sound speed variations on the propagation time delays is presented in Section 6.7.2 of the supplemental information.

Step 2: Vocalization Detection and TDOA Estimation

Once an elephant makes a rumble call, every sensor in the vicinity of the source location receives time delayed and noise corrupted versions of the original signal. This scenario is simulated by shifting and zero padding the original rumble vocalization data files by relevant time delays. Then, the noise corruption is incorporated by adding white Gaussian noise to the time shifted signals. Now the signals are cross-correlated with each other at the centralized processing unit to obtain the time delay difference information. These time delays correspond to Δt_{pq} in Section 6.2.

Step 3: Source Localization and Error Validation

The performance of the probe technique is obtained by placing the source at different positions in the observation area and calculating the estimation error. Initially, the rectangular observation area is divided into 100 m $\times$ 100 m small square. Then, the source is placed 100 times randomly inside the small grid and the source position is estimated according to the algorithm discussed in Section 6.2. We compute the error for each random source position by calculating the Euclidean distance between the actual and the estimated source locations. The mean estimation error is calculated for the above 100 source placements. The normalized mean estimation error is calculated as the ratio between the mean estimation error of the grid with respect to the distance to the grid from the village boundary ($y = 0$). The above process is repeated for each grid in the observation area. The performance of the probe technique under above simulation setup is presented in Section 6.5.

6.5 Performance Evaluation on Probe Technique

The performance of the proposed methodology discussed as in Model B was tested against comparison models described in Section 6.3. In all models identical and real world comparable environmental condition was maintained with synthetically generated temperature and wind data. The wind velocity was non-uniform and the relationship was given by the Markov-Random Field properties whilst the temperature distribution was attained through Gaussian distribution as described in Model B.

Figure 6.4 depicts the performance of Comparison Model 1. In this scenario it was assumed that all sensors and probes consist of additional temperature and wind sensors. Exact temperature and wind information is known to the centralized processor at those particular positions. Thus, the sound speed can be attained through effectively averaging these measurements. However, this averaging methodology does not represent exact environmental condition. As a result, actual effect on sound speed cannot be attained through this process and model shows higher normalized error distribution.

Analysis results for normalized error distribution over the area, for Comparison Model

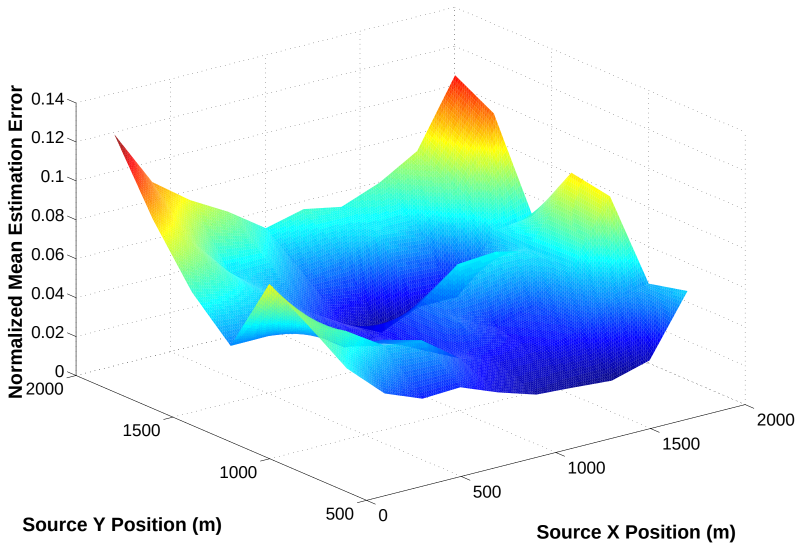


Figure 6.4: Normalized source localization error variation at different source positions within the observation area. At every sensor and probe position, a **wind** and **temperature** sensors were incorporated as in Comparison Model 1 in Section 6.3. The sound speed estimation was done through partitioning the area and effectively averaging the point measurements with respect to each sensor. (i.e. Not through probe technique). Ten probes and 12 sensors are deployed as discussed in Section 6.4. The temperature and wind velocities are non-uniform over the area. (Simulation parameters were chosen as follows: $T \in \{22-32\}°C$. Initial mean values for wind are $V_w = 20\ ms^{-1}$, $\theta_w = 120^0$. SNR $= 10$ dB.)

2 is shown in Figure 6.5. In this model, wind and temperature sensors were utilized and the measurements from these sensors were incorporated to determine the environmental model parameters as in synthetic data generation explained in Section 6.3. In the above condition, it is possible to find exact temperature values over the area as we incorporate identical Gaussian function that we utilized in data generation to represent the temperature variation attain through the measurements. However for the wind velocity variation, the measurements only provide initial mean V_{wInit} and variation σ_w^2 of the field and the exact wind velocity at each grid could be different from the values attained through the model. Therefore, even this model represents the environmental data over the area with more reasonable manner, it does not provide superior performance over the previous comparison model.

Figure 6.6 shows the performance of positioning estimation whilst sound speed eval-

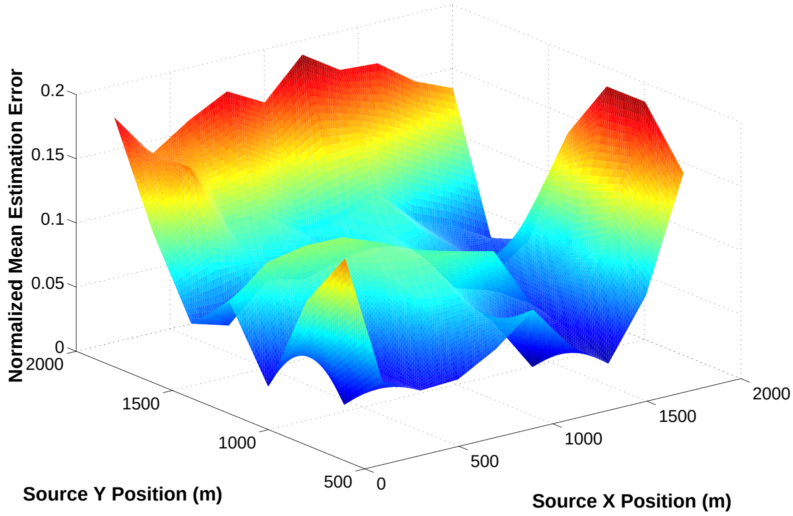


Figure 6.5: Normalized source localization error variation at different source positions within the observation area. At every sensor and probe position, a **wind** and **temperature** sensors were incorporated as in Comparison Model 2 in Section 6.3. Gaussian function was utilized to model the temperature and MRF was used to model the wind velocities over the observation field. The sound speed is then determined considering the above environmental model values. (i.e. Not through probe technique). Ten probes and 12 sensors are deployed as discussed in Section 6.4. The temperature and wind velocities are non-uniform over the area. (Simulation parameters were chosen as follows: T $\in \{22 - 32\}$°C. Initial mean values for wind are $V_w = 20$ ms^{-1}, $\theta_w = 120^0$. SNR = 10 dB.)

uation was solely done utilizing probe technique as described in Model B. Utilization of the technique has surpassed the positioning accuracy than in above scenarios despite the sound speed estimation is performed with limitations of the ecological data. The normalized mean error estimation is always below the 0.06 margin while the estimation error is just above 20 m in average around $y = 500$ m border. In an elephant localizing system, the positioning accuracy is highly important only when the elephants are close to the village. Therefore, the above accuracy attained through our inexpensive probe technique is well over the acceptable margin. In addition, this accuracy is achieved without explicitly measuring the wind and temperature over the area. A performance analysis of probe technique with respect to above sensor network scenarios under several different environmental conditions is presented in Section 6.7.4 of supplemental material.

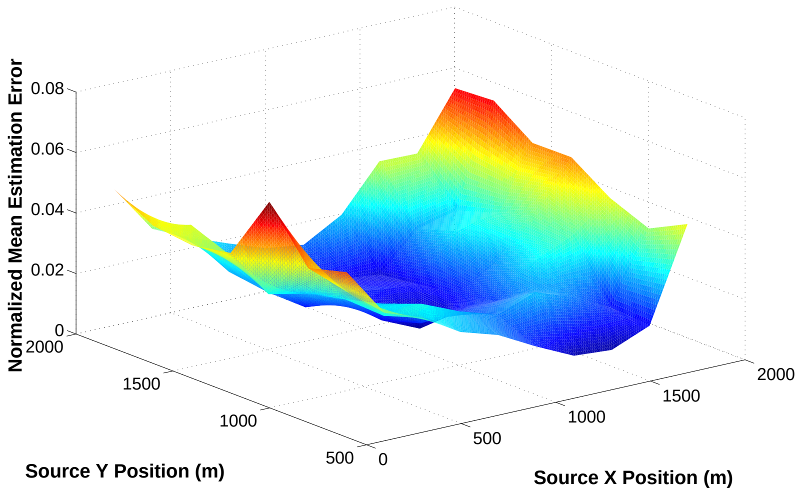


Figure 6.6: Normalized source localization error variation at different source positions within the observation area. No temperature or wind sensors utilized in the system. The sound speed estimation was done solely depending on probe technique as described in Model B in Section 6.3. Ten probes and 12 sensors are deployed as in Section 6.4. Temperature and wind velocities are non-uniform and unknown over the area. (Simulation parameters were chosen as follows: T $\in \{22 - 32\}$°C. Initial mean values for wind are $V_w = 20$ ms^{-1}, $\theta_w = 120^0$. SNR $= 10$ dB.)

6.6 Chapter Summary

In this chapter, we have investigated the feasibility of enhancing the accuracy in elephant localization system by utilizing a sound generating probe technique. The performance of the technique is analysed under different ecological scenarios in a simulation framework. Comparison models have been introduced to evaluate the performance of the technique under different environmental conditions. The results are presented to illustrate the effectiveness in utilizing the probe technique under comparable real-world wind and temperature variations. The technique preserves the normalized mean error estimation always below the 0.06 margin throughout the interested observation area. The positioning accuracy of elephant localization system is more important when the elephants are closer to the village boundaries. The analysis confirms that probe technique can limit the positioning error just above 20 m in average around $y = 500$ m from the village border.

6.7 Supplementary Material

6.7.1 Environmental Parameter Variation Maps

In the simulation analysis for the data generation purposes temperature variation over the area was represented by two dimensional Gaussian function. The temperature at particular location coordinates (x, y) is given by

$$f(x,y) = T_{min} + \Delta T_{Vmax} \exp\left(-\left(\frac{(x-x_o)^2}{2\sigma_x^2} + \frac{(y-y_o)^2}{2\sigma_y^2}\right)\right),$$

where T_{min} is the minimum temperature, ΔT_{Vmax} is the maximum temperature variation, (x_o, y_o) is the centre coordinates of the interested area, σ_x, σ_y are the x and y spreads of the temperature blob over the area. Figure S7 depicts the temperature variation map utilized in the simulation analysis.

The wind direction and the speed variation over the area are represented assuming Markov random field property. Subsequently, wind vector at a particular position was determined by values drawn from a normal distribution $\mathcal{N}(\mathbf{V_{wAdj}}, \sigma_w^2)$ where $\mathbf{V_{wAdj}}$ is the wind vector at the adjacent location. Figures S8- S9 represent the wind velocity and the direction variation maps utilised in the simulation analysis.

6.7.2 Source Localization under Sound Speed Variation

The speed of sound in air depends on several environmental variables such as temperature, water vapour mole fraction, pressure and CO_2 content in the air. Cramer [120] has proposed a closed form equation for sound speed in air as a s function of above environmental factors. However, the sound speed mainly depends on temperature variations and effects of other variables are relatively insignificant. The speed of sound in air can be expressed in terms of temperature as

$$C(T) = C(T_0)\sqrt{\left(1 + \frac{T}{273.15}\right)},$$

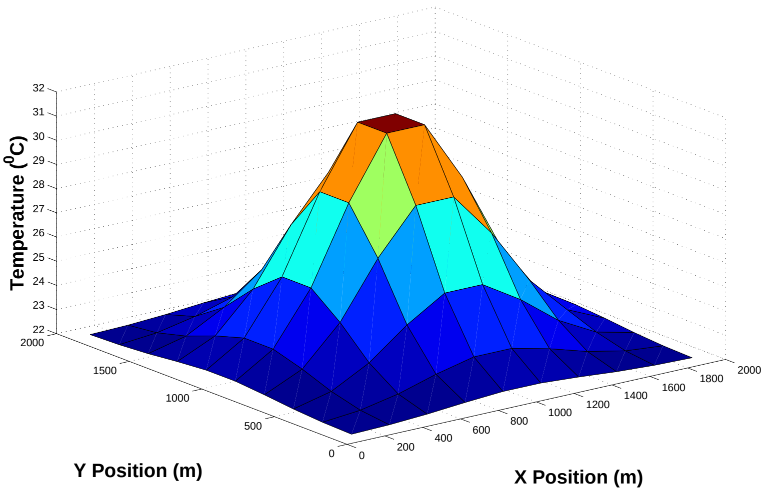


Figure S7: Temperature variation map over the simulation area. Temperature variation over the area was represented by a two dimensional Gaussian function. Simulation parameters were chosen as follows: $T_{min} = 22°\text{C}$, $\Delta T_{Vmax} = 10°\text{C}$, $(x_o, y_o) = (1000, 1000)$, and $\sigma_x = 500$, $\sigma_y = 500$.

where $C_{Sound_0} = 331.45$ ms^{-1} is sound speed at $0\,^0C$ [121]. In general, the speed of sound increases by 0.61 ms^{-1} per degree Celsius rise in temperature. When the sound propagates under wind the propagation medium itself is in a motion. The sound propagating through the air will be transported by the moving air mass. Therefore, resultant sound speed under wind condition V in the direction propagation is given by

$$C(T, V_w) = C(T) + C(W)cos(\psi)$$

where $C(W)$ is the wind speed and ψ is the angle between sound path and the wind direction.

We consider an area which is divided into grids similar to the example region depicted in Fig. S10. The temperature and the wind velocities are constant in each grid; however, these two variables vary between grids. Therefore, the sound speeds between each grid vary due to temperature and wind effects. Probes and sensors are deployed in predefined coordinates and source elephant location is unknown. Let us consider that we have M number of probes and N number of sensors. The area is divided into Q number of grids.

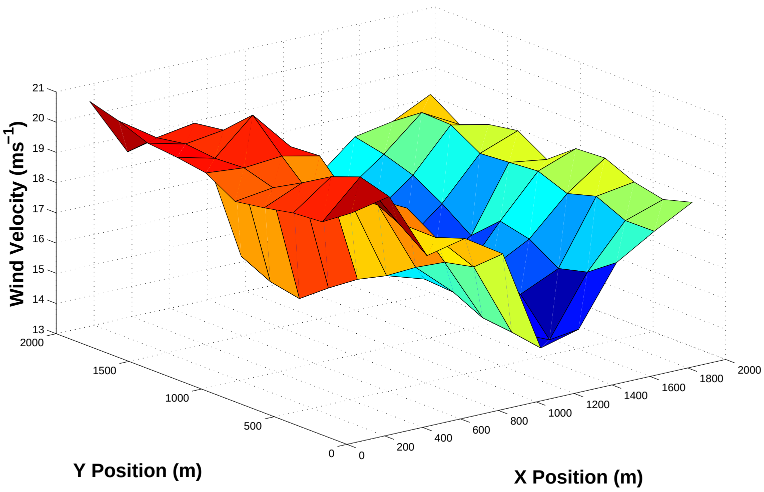


Figure S8: Wind speed variation map over the simulation area. The wind direction and the speed variation over the area are represented assuming Markov random field property. Simulation parameters were chosen as follows: Initial mean values for wind speed is $V_w = 20$ ms^{-1} and $\sigma_{wSpeed} = 0.5$.

Time of arrival measurement from i^{th} sensor to j^{th} probe is given by

$$t_{S_iP_j} = \sum_{k=1}^{Q} \frac{d_{S_iP_jk}}{C_{S_iP_jk}} + \xi_{S_iP_j} \tag{6.5}$$

where, $d_{S_iP_jk}$ is the distance that sound signal travelled from probe P_j towards sensor S_i in the k^{th} grid which is given by

$$d_{S_iP_jk} = \sqrt{(x_{S_iP_jk_1} - x_{S_iP_jk_2})^2 + (y_{S_iP_jk_1} - y_{S_iP_jk_2})^2}$$

and $C_{S_iP_jk}$ is the sound speed in the k^{th} grid at source sensor path which is given by

$$C_{S_iP_jk}(T, W) = C_{S_iP_jk}(T) + C(W)_{S_iP_jk} cos(\psi_{S_iP_j})$$

and $\xi_{S_iP_j}$ is measurement noise which was assumed to be Gaussian. In the simulation frameworks we have implemented piecewise summation of time in (6.5) to calculate the actual TDOA measurements between probes and sensor pairs. The algorithm to calculate the total propagation time from k^{th} probe to i^{th} sensor is given in Algorithm 1.

Algorithm 1 Calculating total sound propagation time from k^{th} probe to i^{th} sensor

```
Step 1: get wind velocity, temperature matrix over all grids
Step 2: calculate sound speeds at each grids
Step 3: find all grid cross points in probe sensor path
Step 4: calculate probe-sensor path angle WRT x axis (θ_{P_k S_i})
if θ_{P_k S_i} ≤ π/2 then
    for thisPiece ∈ (piece1,..., piece(totalCrossPoints-1)) do
        if piece1 then
            thisPieceVelocity = probe belong grid sound speed
        else if piece crosses only Horizontal grid line then
            thisPieceVelocity = sound speed at the grid below previous grid
        else if piece crosses only Vertical grid line then
            thisPieceVelocity = sound speed at the grid left to previous grid
        else if piece crosses Horizontal grid line and Vertical grid line then
            thisPieceVelocity = sound speed at the grid south west to the previous grid
            thisPieceTime= pieceLength/thisPieceVelocity
        end if
        totalTime=∑ thisPieceTime
    end for
else if θ_{P_k S_i} > π/2 then
    for thisPiece ∈ (piece1,..., piece(totalCrossPoints-1)) do
        if piece1 then
            thisPieceVelocity = probe belong grid sound speed
        else if piece crosses only Horizontal grid line then
            thisPieceVelocity = sound speed at the grid below previous grid
        else if piece crosses only Vertical grid line then
            thisPieceVelocity = sound speed at the grid right to previous grid
        else if piece crosses Horizontal grid line and Vertical grid line then
            thisPieceVelocity = sound speed at the grid south east to the previous grid
            thisPieceTime= pieceLength/thisPieceVelocity
        end if
        totalTime=∑ thisPieceTime
    end for
end if
```

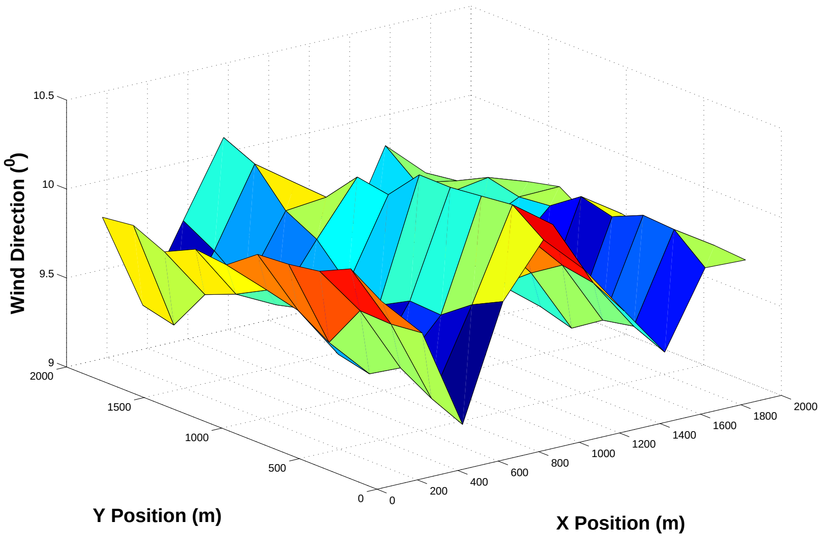


Figure S9: Wind direction variation map over the simulation area. The wind direction and the speed variation over the area are represented assuming Markov random field property. Simulation parameters were chosen as follows: Initial mean values for wind direction is $\theta_w = 120^0$ and $\sigma_{wDirection} = 0.1$.

6.7.3 Algorithm for Source Localization with Probes

Overview of the algorithm used in simulations for source localization with probe technique is summarized in Fig. S11.

6.7.4 Performance of the Probe Technique under Different Environmental Conditions

In this section we present further performance comparison between our probe technique and the conventional sensor networks. The performance is presented under three different Sensor/ Probe models as in Section 6.5 of this chapter.

Sensor/ Probe setup 1: At every sensor and probe position, a **wind** and **temperature** sensors were incorporated. The sound speed estimation was done through effectively averaging the point measurements with respect to each sensor as explained in Comparison Model 1 of this chapter. (i.e. Not through probe technique).

Sensor/ Probe setup 2: At every sensor and probe position, a **wind** and **temperature** sensors were incorporated. Gaussion function and Markov random field properties

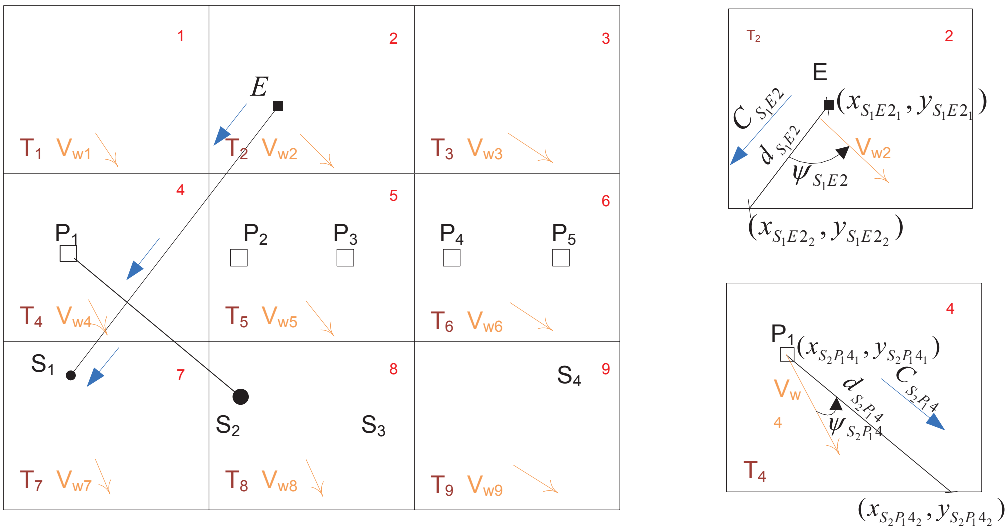


Figure S10: Sound source localization under variable sound speeds in observation area. Each grid consists of constant wind velocity and temperature. However, temperature and wind velocity varies between each grid. Therefore, sound signal experiences different sound speeds in diverse regions it is travelling in. For instance, the effective sound speed in the path of E and S_1 at grid 2 is given by $C_{S_1E2} = C(T_2) + V_{w2} \cos \xi_{S_1E2}$. Similarly, the sound propagation speed between E to Sensor S_1 will be affected by temperatures T_2, T_4, T_5, T_7 and wind velocities V_{W2}, V_{W4}, V_{W5}, V_{W7} in between the propagation path.

utilized to model the environmental effect as explained in Comparison Model 2 of this chapter. (i.e. Not through probe technique).

Sensor/ Probe setup 3: No temperature or wind sensors utilized in the system. The sound speed estimation was done solely depending on probe technique as described in Model B of this chapter.

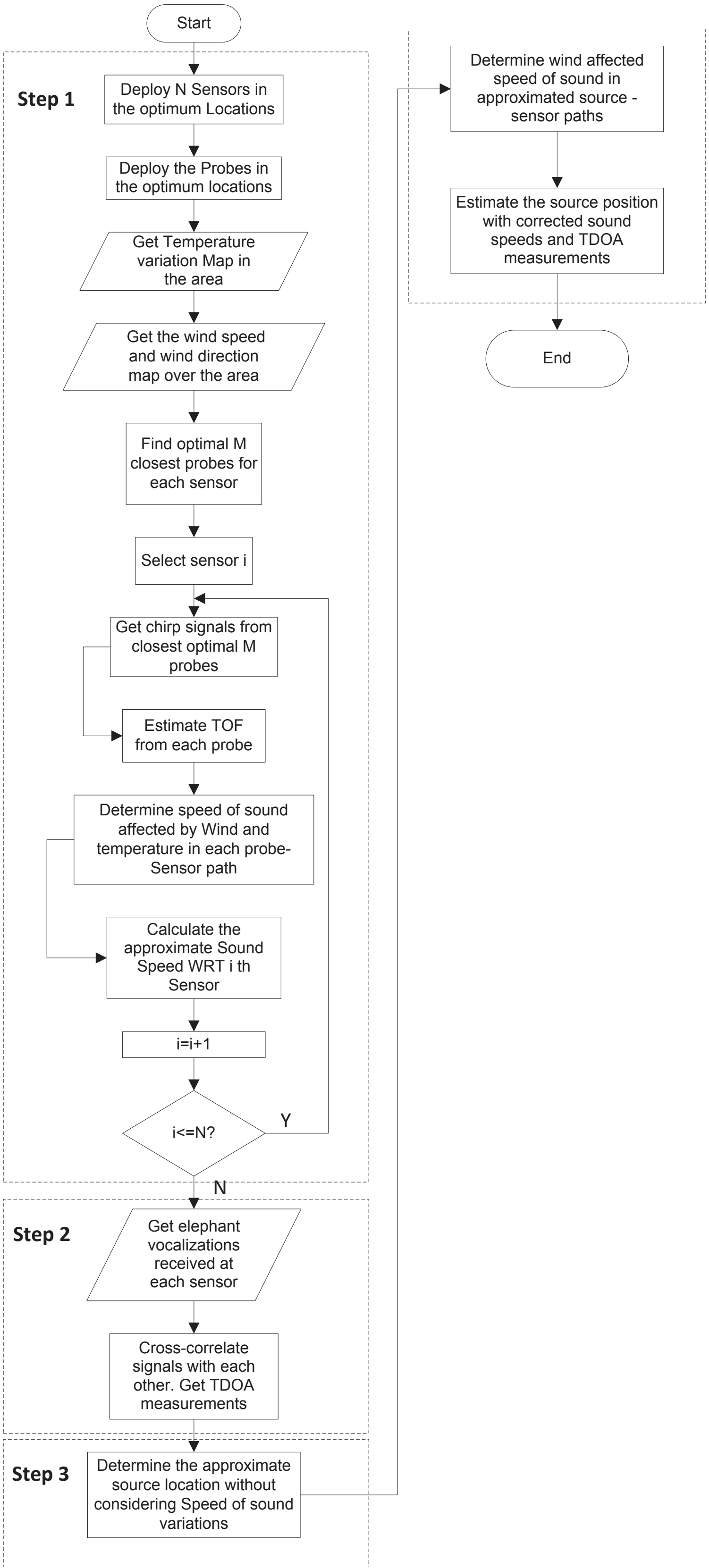
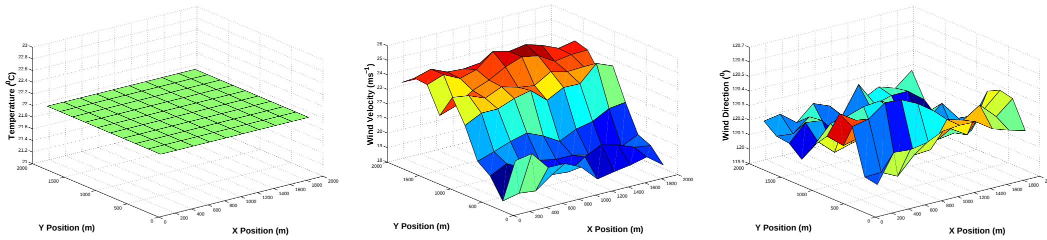


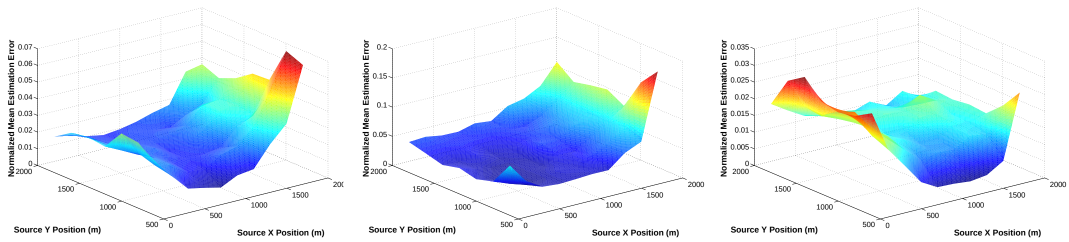
Figure S11: Summarized algorithm used in simulations explained in Section 6.4 of this chapter. The above algorithm is used to estimate unknown source (Elephant) location incorporating probe technique.



(a) Temperature variation map $T_{min} = 22°C$, $\Delta T_{Vmax} = 0°C$

(b) Wind speed variation map. $V_w = 20$ ms^{-1} and $\sigma_{wSpeed} = 0.5$

(c) Wind direction variation map. $\theta_w = 120^0$ and $\sigma_{wDirection} = 0.1$

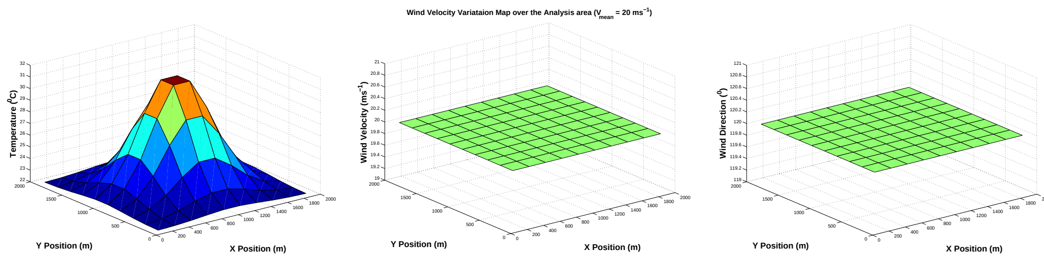


(d) Performance under Sensor set up as in Comparison Model 1

(e) Performance under Sensor set up as in Comparison Model 2

(f) Performance under Sensor/ Probe set up as in Model B

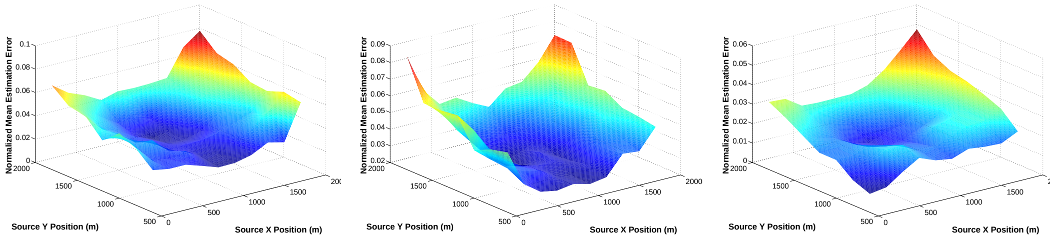
Figure S12: Performance analysis of three different sensor/ probe models under the given temperature and wind velocity variation. Sensor/ probe setup models are described in Section 6.3. In this scenario temperature is kept constant over the area. Ten probes and 12 sensors are deployed as explained in Section 6.3-Model B of this chapter.



(a) Temperature variation map $T_{min} = 22°C$, $\Delta T_{Vmax} = 10°C$

(b) Wind speed variation map. $V_w = 20$ ms^{-1} and $\sigma_{wSpeed} = 0$

(c) Wind direction variation map. $\theta_w = 120^0$ and $\sigma_{wDirection} = 0$

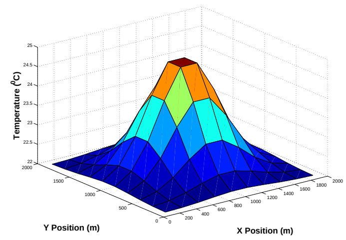


(d) Performance under Sensor set up as in Comparison Model 1

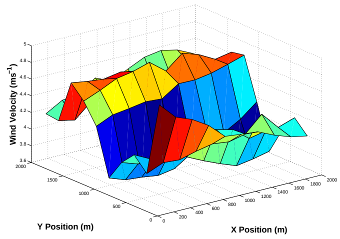
(e) Performance under Sensor set up as in Comparison Model 2

(f) Performance under Sensor/ Probe set up as in Model B

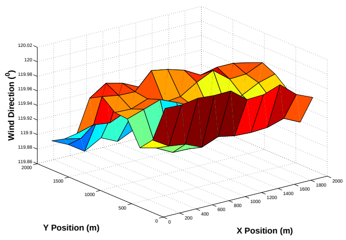
Figure S13: Performance analysis of three different sensor/ probe models under the given temperature and wind velocity variation. Sensor/ probe setup models are described in Section 6.3. In this scenario wind velocity is kept constant over the area. Ten probes and 12 sensors are deployed as explained in Section 6.3-Model B of this chapter.



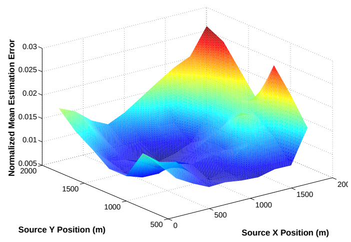
(a) Temperature variation map $T_{min} = 22°C$, $\Delta T_{Vmax} = 3°C$



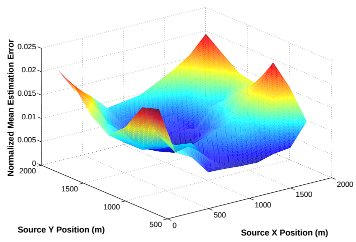
(b) Wind speed variation map. $V_w = 5\ ms^{-1}$ and $\sigma_{wSpeed} = 0.1$



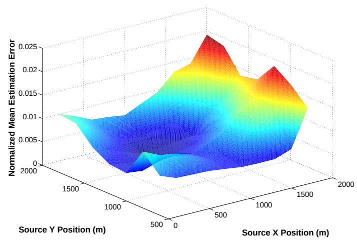
(c) Wind direction variation map. $\theta_w = 120^0$ and $\sigma_{wDirection} = 0.01$



(d) Performance under Sensor set up as in Comparison Model 1

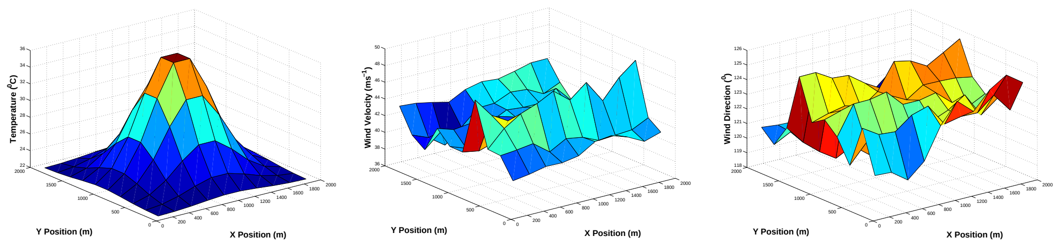


(e) Performance under Sensor set up as in Comparison Model 2



(f) Performance under Sensor/ Probe set up as in Model B

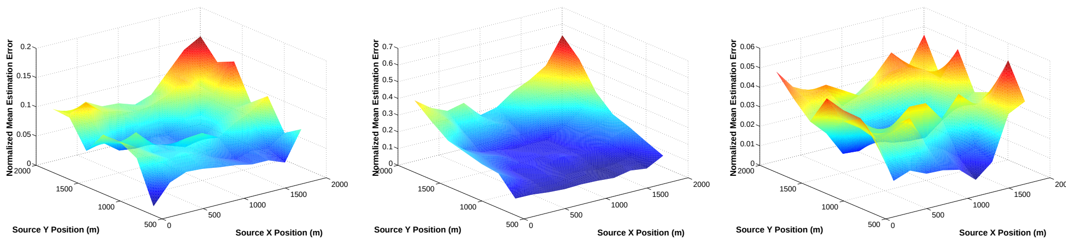
Figure S14: Performance analysis of three different sensor/ probe models under the given temperature and wind velocity variation. Sensor/ probe setup models are described in Section 6.3. In this scenario performance under low variability of temperature and wind velocity is depicted. Ten probes and 12 sensors are deployed as explained in Section 6.3-Model B of the this chapter.



(a) Temperature variation map $T_{min} = 22°C$, $\Delta T_{Vmax} = 15°C$

(b) Wind speed variation map. $V_w = 40\ ms^{-1}$ and $\sigma_{wSpeed} = 1$

(c) Wind direction variation map. $\theta_w = 120^0$ and $\sigma_{wDirection} = 2$



(d) Performance under Sensor set up as in Comparison Model 1

(e) Performance under Sensor set up as in Comparison Model 2

(f) Performance under Sensor/ Probe set up as in Model B

Figure S15: Performance analysis of three different sensor/ probe models under the given temperature and wind velocity variation. Sensor/ probe setup models are described in Section 6.3. In this scenario performance under highly varying of temperature and wind velocities is depicted. Ten probes and 12 sensors are deployed as explained in Section 6.3-Model B of the this chapter.

Chapter 7

Sensor Hardware Implementation, Data Collection and Analysis

Mitigating human-elephant conflict is a real-world challenge and it requires practical implementations. This chapter presents the implementation of hardware systems related to our approach. A sensor network that employs a sound probe technique has been built for data collection. Initially, we performed practical experiments by replaying recorded elephant sounds under different environmental conditions. Finally, the ideal system set up is tested in a real-forest environment to localize wild elephants in Sri Lanka and results. The results overall show that the system is capable of providing remarkable accuracy under distinct wind and temperature conditions.

7.1 Introduction

THE amount of implemented wireless sensor network systems is extremely low compared to the theoretical publications presented in the area [14]. The problem discussed in this thesis requires actions in the ground to mitigate human-elephant conflict. This chapter explains system hardware that we have built related to the application and real experiments conducted in the field.

Implementing hardware system to confirm theoretical and simulation analysis is a challenging task. First, it is necessary to identify the requirements related to the application and limitations. Once the hardware is built, the testing needs to be performed in a controlled environment to identify the possible constraints. Therefore, our system hardware development and experiments were carried out keeping the above concepts in mind.

During the initial stage of the project, we have made attempts to implement a standalone hardware system to record and elephant calls. The Section 7.2 briefly explains the system hardware on this attempt. In Section 7.3 we explain the sensor network hardware system implemented employing the sound probe technique. Section 7.4 describes the practical experiential set up for the tests we conducted in the open field and forest environment. Section 7.5 outlines the experimental results and discusses them further.

7.2 Standalone Signal Recording System

During the initial stage of the project, attempts were made to implement a cheap solution for digital elephant sound recorder system. The hardware system was primarily comprised of a microphone, pre-amplifier, microcontroller, power supply unit and a memory device.

The microcontroller is the interface between input signal processing and the signal recording memory device. It was chosen PIC16F877A as the microcontroller for this implementation which was a mid-range PIC at the time of implementation. MultiMediaCard (MMC) was chosen as the recording memory device. The implementation challenge was to access the MMC card using limited random-access memory (RAM) (256 bytes) of PIC16F877A. It was used in-built serial peripheral interface (SPI) of the PIC to read and write signal data. The microcontroller was programmed using PICkit 2 Development Programmer.

MMC works at max voltage of 3.6 V and PIC16F877A operates at 5.0V. Therefore, it was required a voltage level convert to interface PIC with the memory device. A simple resistor-based voltage divider is introduced to the interfacing pins of MMC (CS, SCK and CLK) [127]. As a result, 4.3 V maximum output of the PIC pins appears as 2.8 V to above three pins at the memory device. The chosen PIC also contains an inbuilt 10-bit analogue-to-digital converter (ADC) module where we used to convert amplified analogue sound signals to digital format before writing into the SD card. Pin RA0 of the PIC is configured as ADC input channel where microphone pre-amplifier output was connected. 16 x 2 LCD was interfaced to the microcontroller to recognise the status of the system. Circuit diagram for the microcontroller interfaces is shown in 7.1

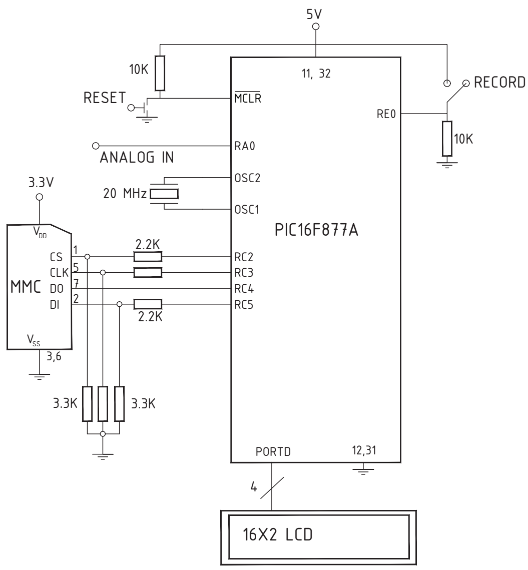


Figure 7.1: Microcontroller interface overview. RA0 PIN of the PIC is configured as ADC input channel. RC2 – RC5 PINs are interfaced with MMC with simple resister-based voltage converter. PortD is interfaced to 16 x 2 LCD.

It was chosen condenser microphone as the input device, and it was tested for frequency response using a signal generator and oscilloscope. Through experiments, it was confirmed that the microphone provides a linear response over the low frequencies required for the application. The pre-amplifier also needed to be performed in the low frequencies as the elephant rumbles were having signal components in sub-sonic range. The amplifiers were then designed and simulated using Proteus 7.7 to match the above requirement. Circuit diagram of the amplifier is shown in 7.2.

The power supply was designed to be dual supply with mains AC powered for the testing purposes and battery powered for the recording in the field. Battery charger unit was also implemented such that the system could charge the battery unit while the device is connected to the mains power. Completed system set-up is depicted in 7.3.

The above hardware system was only used in the initial elephant sound recording and was abandoned from further development due to project duration time constrains.

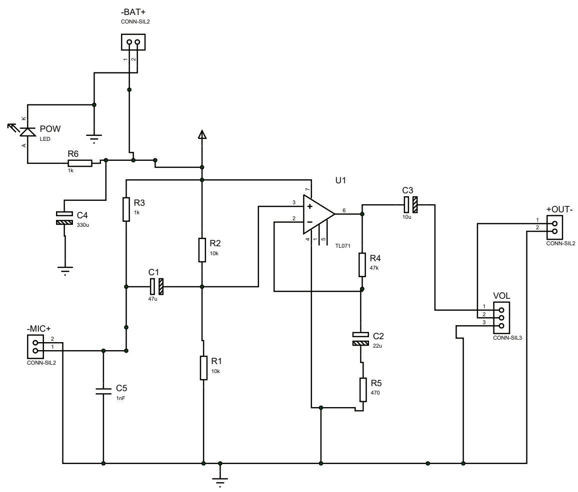


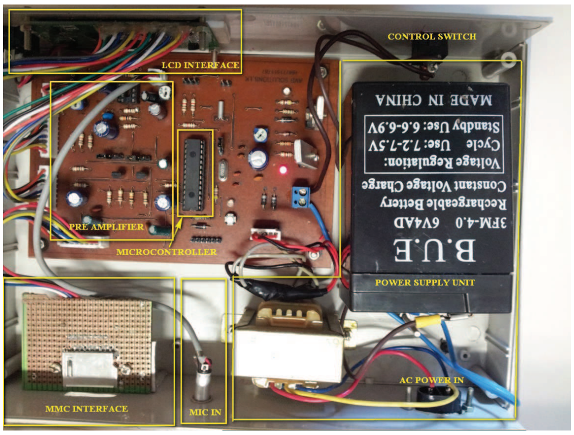
Figure 7.2: Circuit diagram of the signal pre-amplifier. The amplifier was designed with Proteus 7.7 and simulated before implementation. The amplifier performs well in the frequency range of $10 - 4000$ Hz range.

7.3 Central Processing Wireless Sensor Network

Following the extensive simulation analysis discussed in Chapter 6, analogous hardware system is designed to test the performance of the proposed probe technique and system framework.

The hardware system consisted of sensor units which contain microphones (Audio-Technica AT897) and FM transmitters (Fmuser SDA-01A) and sound probes which include chirping devices (see Figs. 7.4 and 7.5). A separate laboratory experiment was conducted to investigate the frequency response of the signal sensor microphones detection system. It was confirmed that the system performs well in the range of approximately $10-400$ Hz and can capture main signal energy components of low frequency elephant calls as shown in [7].

The sensors listen to the sound signals and transmit them in a dedicated FM channel to the centralized receiver in real time. Each sensor was assigned a distinctive FM channel to prevent the interference at the receiver. These channels were carefully selected to avoid interference with the other FM transmissions such as local radio stations and communication within police forces and emergency services. The centralized receiver consisted of a set of FM receivers (Sony CRSW08) which are synchronized to each sensor



(a) Inside of the standalone recorder hardware unit

(b) Integrated 16 x 2 LCD unit displaying initialization of the recorder system.

(c) Packaged hardware system unit

Figure 7.3: Completed standalone recorder hardware system. The system consists of mic interface, power supply unit, integrated display interface and memory (MMC) interface.

unit FM frequency. The outputs of these receivers were then streamed into a laptop computer via a USB sound card hub which enabled simultaneous signal recording. Sound signal acquisition is attained through a commercial software program named Cool Edit Pro Version 2.0. The signals from each sensor channel was recorded into separate tracks in the software program and subsequently saved and exported into wave files for further analysis. The main feature of the software program that facilitated in our experiment is that it enables synchronized data recording from separate channels. Table 7.1 provides a cost analysis of the hardware system that utilized in this implementation. The overall cost of the system including a cheap processor is less than $2750.

Figure 7.4: Snap of complete sensor unit deployed in the field. The microphone and the transmitter units are mounted on a tripod and units are protected with weather shields. Four sets of similar sensor units are deployed for the experiment. The transmitter units were powered by 12 V DC battery.

Our ultimate goal is to utilize the system to localize and track the forest elephants through their rumble signals. In our experiment, we decided to utilize a moving sound source which produces elephant rumble signals such that we can maintain the analogy up to some extent. First, we included rumble signals into a sound player (Sansa®

Figure 7.5: Snap of Probe unit deployed in the field. The unit consists of sound chirp generator and a controller unit which determines the timing of chirp generation. The unit was powered by a 12 V DC battery.

Express^{TM}) which consisted of a storage device and connected it to a large speaker through an amplifier (TOA^{TM} A-50M). The speakers had frequency response of $\pm 3\,dB$ over the range $16-250$ Hz and nearly all the elephant calls used for the simulation had acoustic energy within the above range. Then the system is mounted on a wheel cart so that it can easily be moved in the field. We called this system setup as "Surrogate Elephant" (SE).

7.4 Experimental Setup

Experiments were conducted in open field and forest area using the hardware system discussed in 7.3 to analyze and validate the elephant localization system framework.

Table 7.1: Cost analysis of the Hardware System Utilized in the Real World Implementation

Item	Brand	Model	Unit Price ($)	No. Units	Cost ($)
Acoustic Sensor	Audio-Technica	AT897	212.00	4	848.00
Long range FM Transmitter	Fmuser	SDA-01A	112.00	4	448.00
Receiver	Sony	CRSW08	48.00	4	192.00
Probe	Custom Design	Custom Design	40.00	4	160.00
Battery	B.U.E	3FM-4.0	25.00	8	200.00
Recorder Software	Cool Edit	Pro V2.0	300.00	1	300.00
Processor Unit (Laptop)	Toshiba	SATELLITE C50D	499.00	1	900.00
Interfacing units and Connectors	N/A	N/A	100.00	1	100.00
Total					2,747.00

7.4.1 Open Field Experiment

The experiment site was a playground named Weeguluwathte at the city of Gampola which is located in the Central Province of Sri Lanka. The experiment was performed in three sets during different time periods of the day such that natural variation of temperature and wind velocities can be taken into account. The experiment was carried out in a sunny day and humidity was 64%. The average temperature and wind speed with respect to north was obtained using an anemometer (Bentech GM816) during each set and is summarized in Table 7.2.

Table 7.2: Average Wind and Temperature Measurements during the Experiment Trials

Experiment Set	Average Temperature (^{o}C)	Average Wind Speed (ms^{-1})
Data Set 1	27.4	6.9
Data Set 2	29.3	8.7
Data Set 3	28.1	10.1

The sensors and the probes were deployed in the field as per the reasoning explained in the simulations in Chapter 6. The exact locations of the probes and sensors were acquired using eTrex^{TM} GPS device and recorded. In addition, the distance between each sensor and probe was accurately measured via Leica DISTO^{TM} A8 Laser distance meter. Once the probe sensor system was deployed and activated, the centralized data recorder system was positioned in a convenient location to start the recording. Then a GPS data recorder was attached to our Surrogate Elephant (SE) to obtain the actual path where it was travelling. Subsequently, SE is moved at a constant speed towards the deployed probe sensor direction whilst recording sound signals into the centralized data recording system.

7.4.2 Real Forest Experiment

Following the open field implementation and identifying the possible challenges, such as battery power limitations, general environmental parameter measurement constraints and hardware mounting requirements, we proceeded to test our methodology in real forest environment. The experimental site was a village called Swaranapaligama which was situated in North central province, Sri Lanka. The village is located adjacent to the border of the Wasgamuwa National Park and a branch of Amban river flows close to the village. The primary occupation of the villages is farming and they mainly cultivate rice and vegetables. As a result of close proximity to the forest and the continual production of crops, wild elephants frequently enter into the village especially during the dry season. Considering the above facts, we conducted our experiment in the end of September 2013 which is the latter period of the dry season.

A similar experimental setup as in the open field experiment described in Section 7.4.1 was employed in this implementation as well.

A set of sensors and probes were deployed at predetermined locations. The probes were kept in the forest area to obtain a better representation of the sound characteristics through the woodland (See Fig. 7.7). The sensors are kept close to the village boundary depending on practical considerations (See Fig. 7.8). A simplified block diagram of the hardware setup is depicted in Fig. 7.6. The probe and the sensor coordinates were

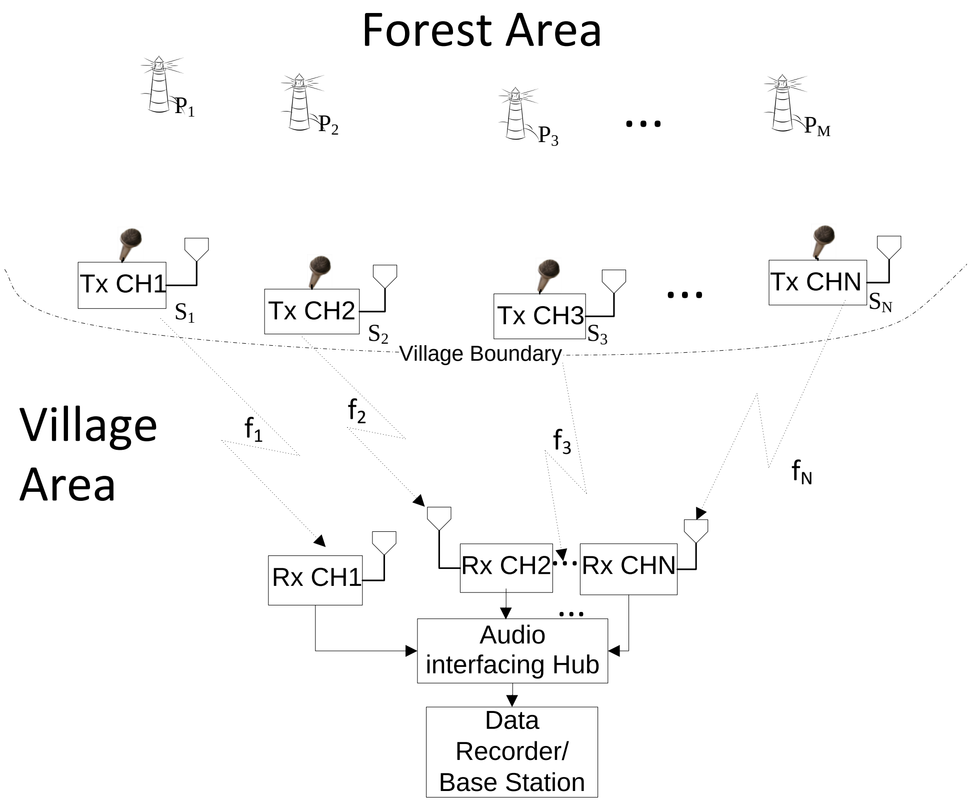


Figure 7.6: Simplified block diagram of the system hardware implementation. Each sensor consists of microphone and a FM transmitter. Vocalization data and the probe signals acquired through each microphone is transmitted through a dedicated FM channels to the centralized receiver. Probes are placed in the forest area to get a better representation of the real sound speeds of the observation area.

Figure 7.7: Snap of a Probe unit deployed in the forest implementation. The unit was deployed in a predetermined location in the forest area to obtain a better representation of the sound characteristics through the woodland.

recorded using eTrex^{TM} GPS devise as in the previous experiment and those coordinates are summarized in Table 7.3.

Table 7.3: Sensor and Probes Location Coordinates at the Real Forest Experiment

	GPS coordinates	
	Longitude	Latitude
Sensor 1	80.954352	7.863963
Sensor 2	80.953244	7.864375
Sensor 3	80.952465	7.864156
Sensor 4	80.951085	7.864182
Probe 1	80.953736	7.863446
Probe 2	80.952939	7.863341
Probe 3	80.952146	7.863349
Probe 4	80.951457	7.863455

During the background information gathering the villagers informed us that in many occasions, elephants come closer to the village shortly after the nightfall. Therefore, we set up equipment targeting to start the data collection during the above period. Owing to constrains in battery life and available resources, successful data collection was done in three consecutive days and typical weather information during the experiments is summarized in Table 7.4.

Figure 7.8: Snap of a Sensor unit deployed in the forest implementation. The unit was deployed in a predetermined location close to the village boundary.

Table 7.4: Weather Details during the Real Forest Experiment

Experiment Trial	Weather	Average Temperature (°C)	Average Wind Speed (ms^{-1})	Humidity (%)
Day 1	Sunny	29.5	4.2	64
Day 2	Sunny	29.3	8.4	72
Day 3	Sunny	28.1	7.1	68

Once the experiment was conducted, in the following day we walked through the elephant tracks to verify the presence of elephants during the previous day. The verification process was practically impossible to conduct in real time during the experiment due to safety issues. However, through the evidence such as fresh piles of elephant dung, broken tree branches, signs of browsing grass and footprints embossed in the ground, we were able to determine the presence of the elephants during the days we conducted the experiment (see Figures. 7.9-7.10). We obtained the assistance of few villages who were

Figure 7.9: A snap shot of recording information on a location where elephants were present in a day that we conducted the experiment. GPS coordinates and information on the observation were recorded manually for further reference.

experts in identifying elephant tracks and familiar with the forest area closer to the village to accomplish the above task. We recorded the coordinates of the elephant tracks using eTrex$^{\text{TM}}$ GPS device. In addition, GPS coordinates and the description of the signs were manually recorded at the specific locations where we identified as elephants were present. Through these field visits we identified that, out of three days we conducted the experiment, in two days elephants have travelled through the tracks we observed.

7.5 Results and Discussions

7.5.1 Open Field Experiment Results

The results of the practical implementation of our proposed methodology in an outdoor environment are depicted in the Figures 7.14−7.16 for three different data collection sets. It can be identified that our proposed technique clearly improves the localization accuracy of the sound source under different environmental conditions. The accuracy improves whilst the source is close to the probes. The reason for this is that, when probes

Figure 7.10: Picture of footprint embossed on the ground of an elephant that visited the area on Day 1 when we conducted the experiment. Observation locations was recorded for further reference.

and SE are in close proximity, the probes technique represents the actual sound speeds between source−sensor paths. Due to limited space and narrow variation of temperature and wind velocities in the experimental area, the localizations without probe technique correction also follow the path to a certain extent. However, this fact is invalid in a real forest application where environmental condition variation would be much more complicated.

The elephants have a behavioral characteristic of walking in the same particular paths which they have followed throughout the generations. Therefore, it is possible to incorporate these path data as a prior information whilst implementing tracking algorithms. We have implemented a particle filter considering prior information of the path data of the surrogate elephant whilst incorporating probe correction in our posterior analysis. As shown in Figures 7.14−7.16 the outcome of the implementation clearly indicates an accuracy improvement.

Figure 7.11: Snap of fresh pile of elephant dung on the ground in the elephant track. This observation was made on Day 1 of the forest experiment. Observation location was recorded for further reference.

Figure 7.12: Snap of earth marks made due to elephat bashings on the ground by an elephant on Day 3 of the foreset experiment. Observation location was recorded for further reference.

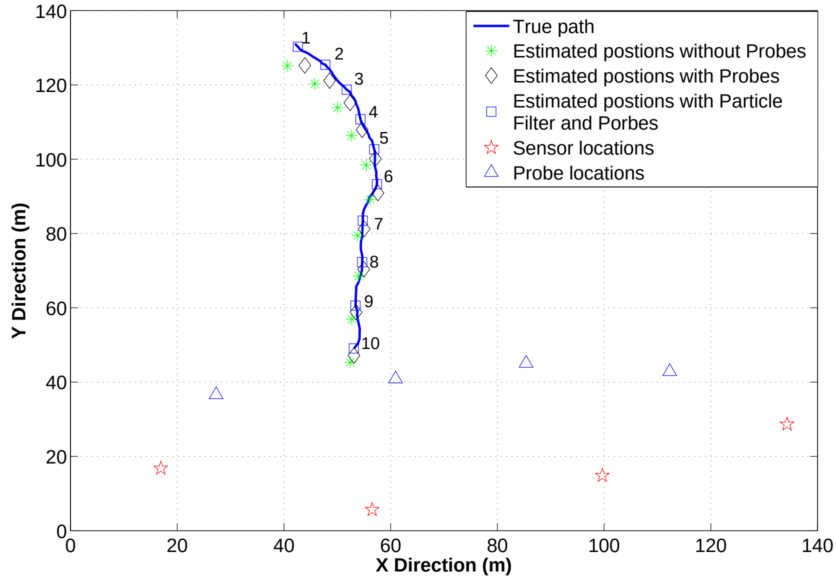
7.5.2 Real Forest Experiment Results

Figure 7.17 depicts the localization results from gathered data during the real forest experiment. The analysis revealed that elephant calls were recorded during only two days of the experiment. This is in fact verified through the observations made during the post experimental visits through elephant tracks. The probe technique has performed efficiently in this heterogeneous environment as well. Evidently, it surpasses the observation made without considering the wind and temperature variations. Due to large observation area and variations in the environmental facts, the remarkable performance of the

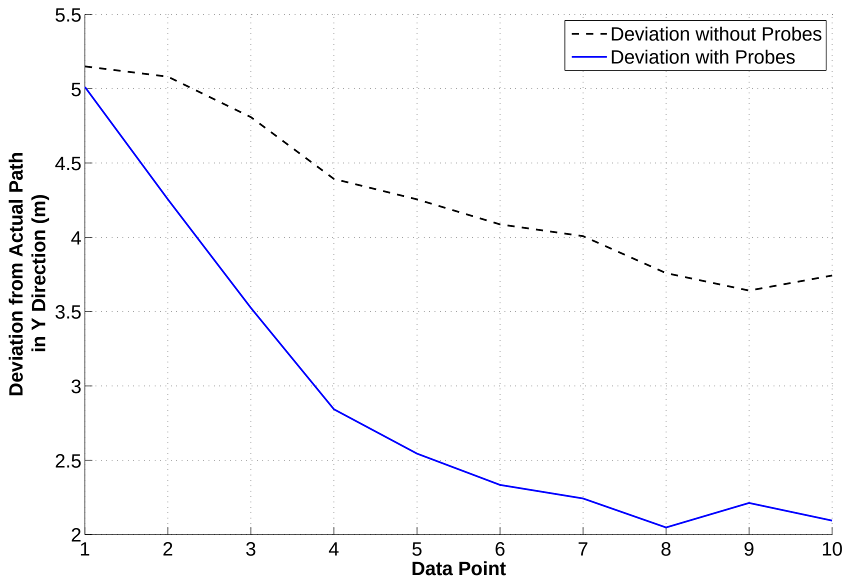
Figure 7.13: Snap of marks made on a tree by an elephnat on Day 3 of the foreset experiment. Observation location was recorded for further reference.

probe technique can be clearly identified. Our technique has located elephants within 30 m to the elephant tracks whilst error in conventional methodology extends over 70 m. The evidence gathered indicates the real localization accuracy attained through our technique. In addition, the results indicate that under the forest environmental condition, the performance of a conventional localization system can be significantly impacted even under a modest temperature and wind velocity variations.

Our system was able to localize elephants over 500 m margin from the village boundary. This implies that, with some modifications to the hardware system such as integrating additional amplifiers the system may perform well above this distance. This fact suggests that similar system can be utilized to monitor elephants noninvasively for behavioural aspects. In a broad sense, our system which costs around $2750 can be utilized to protect a village area of around 2 km^2. However, the system needs to be modified for continuous power requirement in an alerting system. The challenge of battery power constraints can be overcome incorporating hybrid solar and battery power system. Similar methodology use in natural disaster notification which uses Short Message Ser-

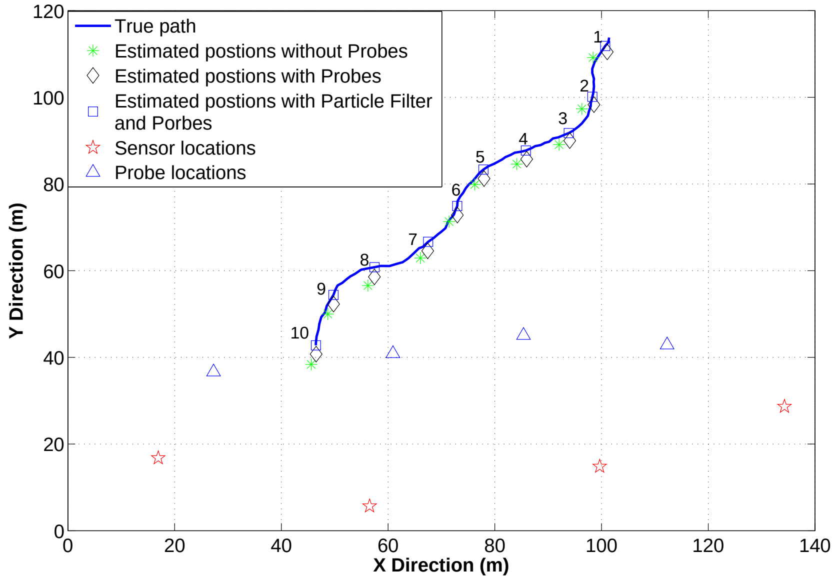


(a) The average temperature during the experiment was 27.4 °C and average wind velocity 6.9 ms^{-1} during the experiment. The estimated localization positions of the Surrogate Elephant closely follow the actual path whilst the probe technique correction was made.

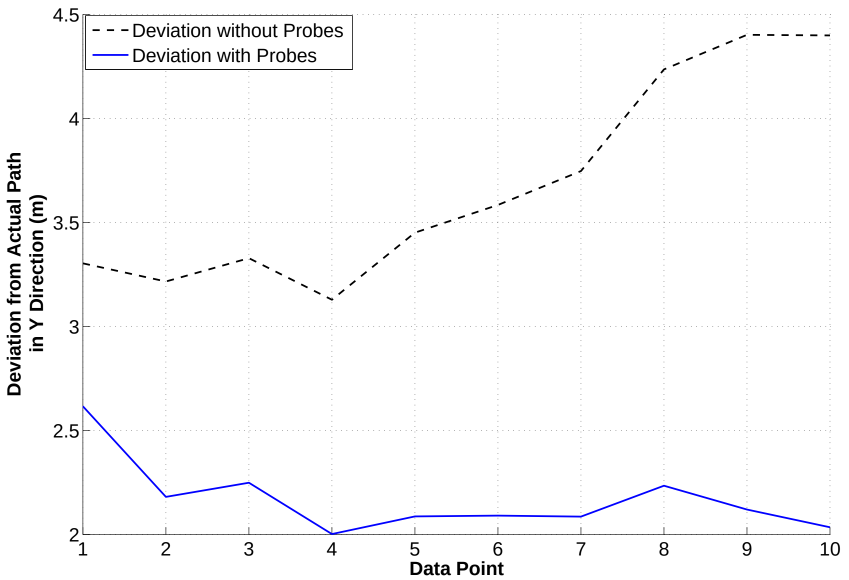


(b) Surrogate Elephant localization error estimation for Data Set 1. The error is calculated deviation in Y direction from the actual path. Note that the ES is moved towards the sensors and 1st data point represent the furthest point from the sensors.

Figure 7.14: Localization of Surrogate Elephant; The analysis results from the Data Set 1 acquired from the real experiment.

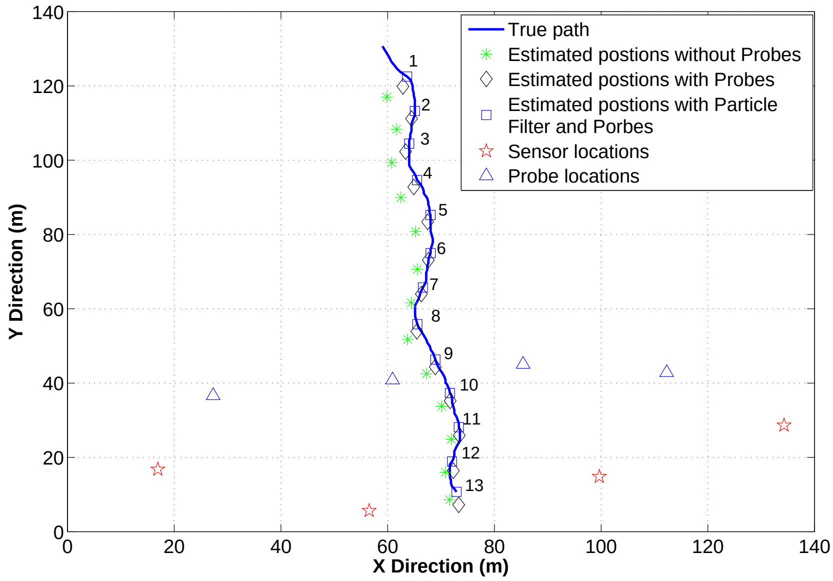


(a) The average temperature during the experiment was 29.3 °C and average wind velocity 8.7 ms^{-1} during the experiment. The estimated localization positions of the Surrogate Elephant closely follow the actual path whilst the probe technique correction was made.

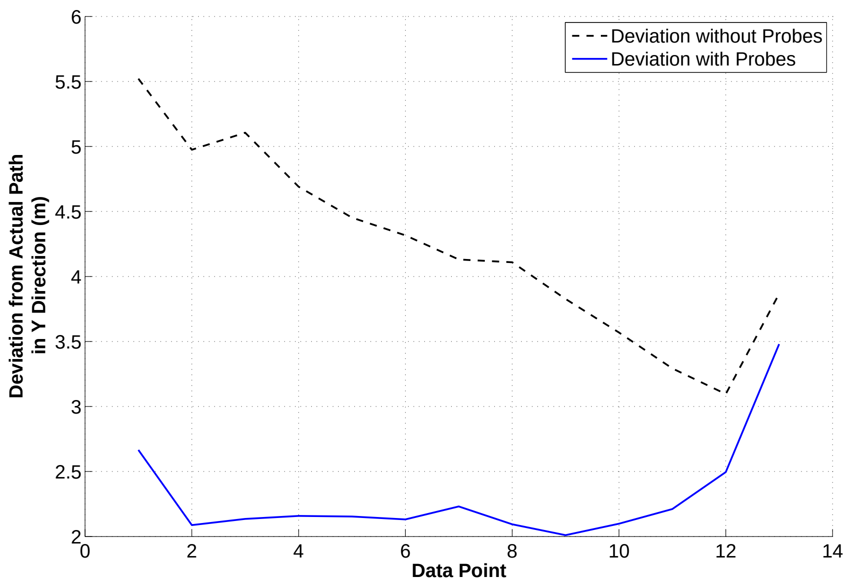


(b) Surrogate Elephant localization error estimation for Data Set 2. The error is calculated deviation in Y direction from the actual path. Note that the ES is moved towards the sensors and 1st data point represent the furthest point from the sensors.

Figure 7.15: Localization of Surrogate Elephant; The analysis results from the Data Set 2 acquired from the real experiment.

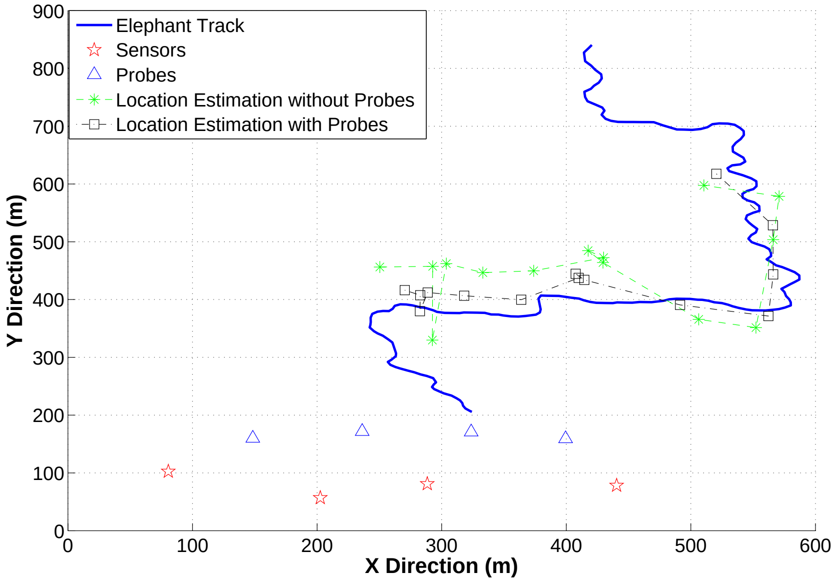


(a) The average temperature during the experiment was 28.1 °C and average wind velocity 10.1 ms^{-1} during the experiment. The estimated localization positions of the Surrogate Elephant closely follow the actual path whilst the probe technique correction was made.

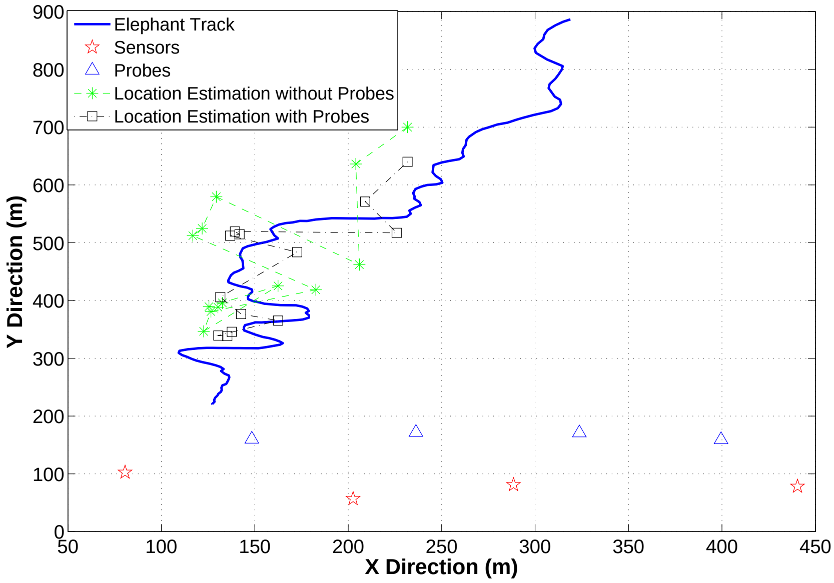


(b) Surrogate Elephant localization error estimation for Data Set 3. The error is calculated deviation in Y direction from the actual path. Note that the ES is moved towards the sensors and 1st data point represent the furthest point from the sensors.

Figure 7.16: Localization of Surrogate Elephant; The analysis results from the Data Set 3 acquired from the real experiment.



(a) The analysis result of the data collection from the Day 1 in real forest experiment. The average temperature was 29.5°C and average wind velocity was 4.2 ms^{-1} during the experiment.



(b) The analysis result of the data collection from the Day 3 in real forest experiment. The average temperature was 28.1°C and average wind velocity was 7.1 ms^{-1} during the experiment.

Figure 7.17: Analysis results of the real forest experiment. Observations were associated to different tracks in Day 1 and Day 3. The estimated elephant localization positions closely follow the elephant tracks. Evidently, the probe technique has significantly improved the localization accuracy despite the complex terrain.

vice (SMS) alerting system [128] can be utilized for warning villagers regarding elephant threats.

In [124], acoustic monitoring of elephants is mentioned as a valuable noninvasive research tool. However, the predicted area of detection depends upon the atmospheric acoustic state. This acoustic state is mainly affected by meteorological effects such as temperature and wind velocity. It is necessary to have real-time knowledge of atmospheric condition to accurately locate the calling elephant [124]. Our proposed methodology addresses exact same problem and adjust the sound speed for atmospheric bias which results greatly improved localization accuracy.

Mayilvaganan et al. have proposed direction of arrival estimation methodology with partial hyperbolic circular array to localize elephants [129]. They also identified that wind velocity and temperature variation significantly affects the localization accuracy. In fact, their analysis shows that localization error could be more than 28 m under narrow wind condition of 2.2 ms^{-1} whilst four sensors and the source is deployed in a 100 m $\times$ 100 m small-scale area. In comparison, analysis results indicate that our methodology performs far better than the above approach in locating elephants even under much stronger wind conditions.

The implemented hardware system is an economical approach for actual elephant localization system. By means of a centralized data collection system, we were able to eliminate the clock synchronization problem which is a main concern in distributed data collection schemes in similar applications. In addition, the inexpensive and effective methodology of utilizing probe technique remarkably increases the localization accuracy.

The sound signal at the receiver itself models the propagation channel characteristics. In our proposed technique this phenomenon is effectively utilized to estimate the sound propagation speed which is affected by temperature and wind variations. Further, information from sensors and probes which represent different spatial regions evidently assists for better sound speed estimation. Besides, the remarkable advantage of this approach is that it does not need both wind and temperature sensors in the network. In addition, we make use of the existing acoustic sensors for sensing probe signals and the elephant calls.

7.6 Chapter Summary

In this chapter we have presented hardware implementation on sensor network that employs a sound probe technique. We have further investigated the feasibility of enhancing the accuracy in elephant localization system by utilizing the sound generating probe technique in practical environment. The inexpensive hardware platform implemented is utilized to evaluate the proposed methodology in an outdoor environment under equivalent elephant localization scenario. Finally, the system was deployed in a real forest environment to localize wild elephants in Sri Lanka. The outdoor experimental implementation verified the significant improvement in accuracy whilst using the probe technique, in a surrogate elephant localization system. Further, the real forest implementation successfully localized elephants over 500 distance. The results confirmed the success of our methodology by enabling to localize wild elephants within 30 m accuracy to their natural walking paths in the real forest implementation.

Chapter 8
Conclusion

8.1 Summary of Contributions

THIS thesis focused on providing an engineering solution to mitigate human-elephant conflict by proposing a methodology to accurately localize the elephants before they move into the village areas. The findings are important not only to ascertain the importance of animal behavioural studies in conservation projects, but also to identify the challenges in animal localization using acoustic sensor networks. The contributions of this thesis are presented in Chapters 4, 5, 6 and 7. The thesis provide details evaluation of useful elephant behavioural patterns in mitigating HEC, the feasibility of using passive acoustic sensor network to localize elephants, mathematical modelling and comparative study of different source localization algorithms, challenges affecting elephant localization accuracy due to environmental effects and novel methodology to improve localization accuracy.

Chapter 2 briefly outlined the earlier researches carried out on habitat monitoring using sensor networks. It also discussed current methodologies used in mitigating HEC and the concerns related to these approaches in terms of effectiveness and availability of resources.

In Chapter 3, we discussed the structure of the elephant society and the behavioural patterns of these highly social animals. The behavioural patterns that ensue HEC and reasons concerning the impossibility of entirely illuminating HEC are emphasized in this chapter. The ability of elephants to adapt in a broad range of ecological conditions always reassure that they will move into village areas for the need food requirements. However, their behavioural tendency to use same corridors allows our approach to locate them in certain known paths which then can be passed into the authorities and villages to take preventive measures. This chapter also discusses the long-range elephant communication call pattern called "rumbles" which is the key in locating elephants in far away distance and presented analysis of rumble signals in frequency and time domain.

Chapter 4 describes detail approach in localizing elephants using timing observation measurements. We outlined two mathematical modeling approaches for elephant localization system framework and derived elephant positioning estimators using BLUE and MLE. The performances of the models are analysed defining a simulation framework and resulted are illustrated in the chapter. The analysis suggested that there is no significant advantage in increasing the number of sensors above certain number to attain successive convergence of the algorithm for elephant location. Similar framework can be defined, and analysis can be performed in future research to identify the required scale of the sensor network with respect to the application. Finally, the chapter presents the statistical bounds of localization error on above mathematical models using FIM and covariance ellipses.

In Chapter 5, we investigated environmental constraints and results of SNR variations on elephant localization accuracy. The elephant rumble calls are the signal for our passive acoustic sensor network and signal travel through the air. Sound propagation in air is affected by various meteorological parameters such as temperature, humidity, water vapour mole fraction and CO_2 content. However, the speed of sound mainly depends on temperature and effect of other parameters are negligible. Consequently, in this chapter we mainly focused on the effect on temperature variations on elephant localization accuracy. In addition, sound signals are longitudinal waves and wind carry the medium that sound signal travels. Therefore, we investigated the effect on changes in wind velocity on our localization accuracy. Moreover, the sound signal intensity is inversely proportional to distance of travel and therefore, SNR varies based on the distance. In this chapter we further investigated the SNR dependency on the elephant localization accuracy. We defined a simulation framework and performed extensive simulation analysis to examine significance on above parameters on elephant localization system that we propose. The findings illustrated that SNR is an important fact that affects the localization accuracy. The system to converge into a source position the SNR need to be above certain marginal level. This has been given as -12 dB with respect our simulation framework discussed in the chapter. In addition, analysis has illustrated uniform temperature variation has insignificant impact on localization accuracy. In contrast, the variation in temperature between source$-$sensor path significantly impact localization accuracy. Wind velocity over the observation area also negatively impact on localization accuracy even the variation is uniform. For instance, a uniform wind velocity of 20 ms^{-1} results in about a 100 m (20%) error at a distance of 500 m. An additional temperature variation of 4 °C can result in an increase in the error to over 175 m (35%). Therefore, chapter concluded mentioning the importance of implementing wind and temperature compensation mechanism in a real implementation of elephant localization and similar system.

Following the extensive analysis on the feasibility of using acoustic sensor network for elephant localization in Chapter 4 and Chapter 5 and the impact on wind and temperature variations on positioning accuracy of such system, in Chapter 6 we propose novel technique to improve the elephant localization accuracy. Sound generating probes are introduced into the passive acoustic sensor network which interns act as a probe that provide a means to estimate accurate sound speed over the observation area. In Chapter 6, the effectiveness of incorporating sound probes into the system in terms of localization accuracy is widely analysed using simulation framework. Comparison models with temperature and wind velocity sensors also introduced for comparative assessment of the probe methodology. The findings suggested that the technique can limit the mean estimation error under 0.06 throughout the interested observation area regardless the non-uniformity of temperature and wind speed of the area. Sound signal travel through the medium itself models the propagation channel characteristics. We introduced probes and an algorithm to effectively utilize this phenomenon to estimate sound propagation speed which is affected by temperature and wind variations. The remarkable aspect of this approach is that it does not need both temperature and wind velocity sensors in the network and we make use of the existing acoustic sensors for sensing probe signals and the elephant calls.

HEC is a real-world problem and it requires practical implementations to reduce the occurrences of conflict. Chapter 7 presents the hardware systems constructed, and the real-world implementation deployed to prove the concepts proposed in previous chapters. Sensor network incorporating the sound probes was built, and experiments were conducted under different ecological conditions in an outdoor environment using surrogate elephant which replicates elephant rumbles. Then the identical experiment setup is deployed in a forest environment to localize wild elephants in Sri Lanka. The analysis results suggest that probe technique has performed efficiently in this outdoor environment as well as heterogeneous forest environment. Our inexpensive methodology proved its effectiveness by enabling to localize wild elephants within 30m accuracy to their natural walking paths in the real forest implementation.

8.2 Future Research

In this thesis, we investigated the feasibility of using acoustic sensor network to localize the elephants. The hardware system is presented for sensor network and data was collected for very limited period. The extended behaviour of the sensor network has not been studied due to project time limitations. Considering the sensitivity of the issue, if the network is deployed as the primary source of information for alerting villages, the extended behaviour of our system framework need to be studied and potential concerns should be identified. This will require further research on areas such as sensor power optimisation and designing standalone sensors and probe units that capable of long-term operation.

This thesis limited the consideration of implementation for a single sensor network that operates in an observation area about 2 km^2. This assumption of observation area is made based on the signal transmission distance of the elephant rumbles and the application requirement of identifying elephants in a location closer to the villages. In practical consideration, this could probably be covering single village area, and each affected village will need a separate elephant localization framework. This leads sensors to have cross-talk effect especially at the boundaries of sensor networks. However, this could be eliminated by incorporating sensor scheduling algorithms and cell planning methodologies yet to be confirmed through careful investigations with respect to the application.

The sensors introduced in this research acts as listening and continues transmission devices whilst the signal processing is conducted at the central processing unit. This approach increases sensor power consumption which interns a major concern in long-run in terms of sensor maintenance. If the sensors made smart to transmit the signals only when the rumble signals are identified, the sensors could run in standby mode for a longer period while increasing the sensor life cycle. This approach requires the development of standalone smart sensors which has signal processing capabilities. With the development of present hardware processing units such as graphics processing units (GPU) this should be feasible, however rigorous design research procedures need to be followed.

The thesis concerns only on identifying the presence of elephants. It has been identified that some of the elephants are more problematic than others. On the other hand, similar to individual human voices, elephants may have distinctive spectral features in their calls which could lead to identify individual elephants. Through extensive data collections and by incorporating speech recognition techniques such as classification and feature extraction or principle component analysis (PCA), this should be feasible. If the elephants can be distinctively identified, this information can be utilised by the authorise to make informed decisions based on prior characteristics of the individual elephant.

In addition, thesis does not consider to distinguish the number of elephants present in the observation area. If it is assumed individual elephant calls have distinctive features it may be possible to estimate the number of elephants moving towards the village area. This problem is similar to the well-known "cocktail party problem" however in a much more challenging environment. Techniques such as independent component analysis (ICA) and blind source separation may be useful in resolving above problem.

Other future research directions would be to define algorithms for optimal placement of probes and sensors. This will be a complex research problem considering it needs to incorporate terrain information as well as signal transmission models and distance constraints. The problem can be further extended by amalgamating elephant track information into the system and assessing the optimal placement of both sensors and probes, knowing the elephant tracks.

Appendix A

Propagation Constraints in Elephant Localization Using an Acoustic Sensor Network

A.1 Introduction

The content of the thesis has been partially published in an international conference and a journal. Appendix A presents the published material in international conference:

Chinthaka M. Dissanayake, K. Ramamohanarao, M. N. Halgamuge, B. Moran, and P. Farrell "Propagation Constraints in Elephant Localization Using an Acoustic Sensor Network" , IEEE 6th International Conference on Information and Automation for Sustainability (ICIAfS'12), pp 101-105, Beijing, China, 27-29 September 2012

A.2 Published manuscript

ICIAfS'12 1569626399

Propagation Constraints in Elephant Localization Using an Acoustic Sensor Network

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***Abstract*—In this paper we discuss elephant localization framework using acoustic sensor network. We further analyze the effect of various meteorological parameters in elephant vocalization propagation and their consequential effects on elephant positioning accuracy. In addition, we present the effect of signal-to-noise ratio (SNR) on detection of vocalization signal which consequently affects the localization accuracy. Extensive simulation results reviled that the uniform distribution of the temperature throughout the localization area does not defect the localization accuracy. Our results show that temperature variations between sensors and wind velocity and direction have significant effect on positioning accuracy of the system. Regardless of this, it is revealed that the localization accuracy decreases enormously once the SNR level fall under certain marginal level.**

I. Introduction

Elephants and human were built with a long tradition of interdependence up until contemporary times. However, today human-elephant conflict (HEC) has become one of the most significant socio-ecological problems in some parts of the world. The conflict primarily is a consequence of frequent attacks from crop riding elephants on the rural agricultural communities. The consequences of HEC made loss of human lives or permanent disability, damage to the properties and cultivation while making negative attitude towards the elephants [1]. Subsequently, elephant deaths resulted from retaliatory killing by people has become ever increasing number during past few years, making Asian elephants (*Elephas maximus*) categorised as Endangered in the International Union for Conservation of Nature (IUCN) Red List [2].

Traditionally, several approaches have been taken to mitigate HEC such as lighting fires and fire crackers and using electric fencing systems. Recently, technological progression leads to use radio and Global Positioning Systems (GPS) collars to detect the presence of elephants [3]. However, these techniques suffer from various drawbacks including non-availability of resources and operational difficulties. Therefore, interest has been growing in detecting elephant through their low frequency elephant calls called rumbles [4]. Previous experiments carried out have shown that these elephant calls travel over a range of at least two kilometres [5]. In this work, we focus on utilizing acoustic senor network to detect and localize elephants through rumble signals. Consequently, we quantitatively analyze the effects of various environmental parameters on the positioning accuracy of the system.

The remainder of the paper is organized as follows. In section II we discuss about the sound propagation in air as the basis for understanding the environmental effects. Section III we analyze the localization algorithm that utilized in our framework. In Section IV we explain the simulation setup and Section V outlines numerical results and discuss it, further. Section VI concludes the paper.

II. Sound Propagation in Air

The accuracy of elephant localization and detection significantly depends on the characteristics of sound propagation in the air. The sound propagates through the air as longitudinal waves and the propagation is affected by the properties of the medium. For instance, the variations in the metrological parameters such as temperature, wind, relative humidity ect. results in the sound propagation variations in terms of intensity and speed. In this paper we basically focus on temperature and wind effects on the speed of sound.

A. Sound Propagation Model

Elephant vocalization generation can be assumed as a point acoustic source and if the medium of air is assumed to be homogeneous, the sound propagation is considered to be spherical. Therefore, the sound intensity in certain direction is inversely proportional to the expanding surface area of the sphere. The sound pressure level (SPL) at distance r is given by $SPL = SWL_{point} - 10log(4\pi r^2)$ dB where SWL_{point} represent the sound pressure level measured at one meter from the source. The model can be simplified to $SPL = SWL_{point} - 20log(r) - 11$ dB which is often referred as the standard inverse square law for point source sound propagation [6]. In summary, relative sound intensity is reduced by 6 dB per doubling of distance. Depletion in sound intensity reduces the SNR levels at the sensors. Consequently, signals of interest which concealed in the background noise become difficult to detect.

B. Temperature Effect

The speed of sound in air changes with respect to variations in several phenomena such as temperature, water vapour mole

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fraction, pressure and CO_2 content in the air. Cramer [7] has proposed a closed form equation for the relationship between speed of sound and the above environmental factors. However, the speed of sound mainly depends on temperature and effects of other variables are insignificant. Therefore, the speed of sound in air can be expressed in terms of temperature as $C_{Sound_T} = C_{Sound_0}\sqrt{(1+\frac{T}{273.15})}$ where $C_{Sound_0} = 331.45$ ms^{-1} is sound speed at 0^0C [8]. In general, per degree Celsius rise in temperature, the speed of sound increases by 0.61 ms^{-1}.

C. Wind Effect

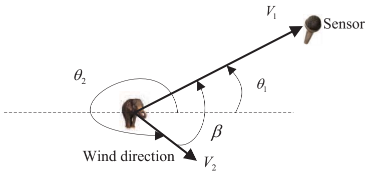

Fig. 1. Wind effect on sound speed in the direction of propagation. Effective component of V_2 along the elephant−sensor direction should be incorporated.

Sound propagation medium of air itself is in a motion due to the wind. The sound propagating through the air will be transported by the moving air mass. Therefore, when the sound propagates towards the direction of the wind, the sound speed will decrease. On the otherhand, if the sound propagates along wind direction, the speed of sound will increase. In a situation, wind makes an angle with the sound path it is necessary to take the vector component along the sound path. In our application, sound path is the elephant−sensor path and Fig. 1 depicts a situation where wind flows in an angle of $\beta(= |\theta_2 - \theta_1|)$ with respect to sound path. Let V_1 be the speed of sound without wind effect, and V_2 be the wind speed. Then, the resultant sound speed V in the direction of source−sensor is given by

$$V = V_1 + V_2 cos(\beta).$$

In the follwoing section we present the localization algorithm utilized in our framework.

III. Localization Algorithm

Once an elephant (source) generates a vocalization, the sound signal propagates through the air following the model discussed in Section II. The sensors at the vicinity of the source receive the attenuated and noise corrupted signal. In our analysis, we assume that all the sensors in our deployment receive the elephant vocalization generated at our interested observation area. Then, we obtain the time difference of arrival (TDOA) information by performing pair−wise cross-correlations between observation signals at each sensor pair.

Let the time of arrival measurements at sensor i to be t_i where $i = 0, 1, \cdots, N-1$. The infrasonic acoustic sensors are deployed at pre−determined coordinates (x_i, y_i). It is

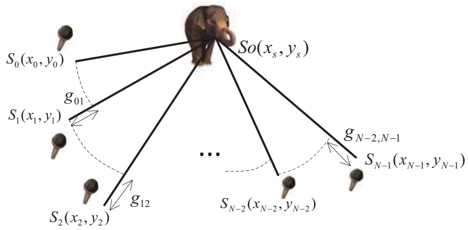

Fig. 2. N number of sensors are deployed at the vicinity of the expected elephant location. Here, the distance difference between source and the p^{th} and q^{th} sensor is defined as g_{pq}.

necessary to locate the source position (x_s, y_s). The arrival time measurements can be modelled by

$$t_i = T_0 + \frac{R_i}{c_i} + w_i \qquad i = 0, 1, \cdots, N-1 \tag{1}$$

where T_0 is the signal emitted time by the source, R_i is the range difference between source and the i^{th} sensor, c_i is the sound propagation speed and w_i is the uncorrelated measurement noise with zero mean and σ^2 variance. It should be noted that the speed of sound between source and each sensor could vary due to the ecological effects discussed in Section II. The distance from source to i^{th} sensor R_i is given by

$$R_i = \sqrt{(x_s - x_i)^2 + (y_s - y_i)^2}. \tag{2}$$

The signal emitted time T_0 in (1) is unknown. Therefore, now we incorporate TDOA measurements to the model. Let the TDOA measurement between p^{th} and q^{th} sensor denoted by Δt_{pq} which is given by

$$\Delta t_{pq} = t_p - t_q + w_{pq} \tag{3}$$

where $p = 0, 1, \cdots, N-2$ and $q = p+1, p+2, \cdots, N-1$. The equation (3) can be written in terms of (2) by

$$\Delta t_{pq} = \frac{R_p}{c_p} - \frac{R_q}{c_q} + w_{pq} \tag{4}$$

which can be explicitly characterized by the non linear model

$$\mathbf{Y} = \mathbf{h}(\mathbf{x}) + \mathbf{w} \tag{5}$$

where

$$\mathbf{Y} = \begin{bmatrix} \Delta t_{01} \\ \Delta t_{02} \\ \vdots \\ \Delta t_{N-2,N-1} \end{bmatrix}$$

$$\mathbf{h}(\mathbf{x}) = \begin{bmatrix} \frac{R_0}{c_0} - \frac{R_1}{c_1} \\ \frac{R_0}{c_0} - \frac{R_2}{c_2} \\ \vdots \\ \frac{R_{N-2}}{c_{N-2}} - \frac{R_{N-1}}{c_{N-1}} \end{bmatrix}$$

$$\mathbf{w} = \begin{bmatrix} w_{01} \\ w_{02} \\ \vdots \\ w_{N-2,N-1} \end{bmatrix}.$$

Solving non linear equation in (5) can be approached with diverse techniques [9] [10]. We appreciate the problem in a geometrical approach as depicted in Fig. 2. Lets assume that the $w_{pq} = 0$ and the $c_p = c_q = c$ for $\forall(p, q) = 0, 1, \cdots, N-1$. Here, Δt_{pq} corresponds to the distance difference between source and the pair of sensors p and q. Let

$$h_{pq} = c \times \Delta t_{pq} \tag{6}$$

and

$$g_{pq} = R_p - R_q \tag{7}$$

where both (6), (7) represent the distance differences. However, g_{pq} consists of the unknown source location. Therefore, the source location can be determined by solving the function defined by

$$f(x_s, y_s) = \underset{x_s, y_s}{argmin} \sum_{p,q} (h_{pq} - g_{pq})^2 . \tag{8}$$

However, the location estimation found by (8) does not consider the measurement errors and the sound propagation velocity variances discussed previously. Therefore, by introducing those constraints externally to the localization routine, we can attain the effect of those parameters. The next section of the paper presents the simulaions of the estimation accuracy that affected by different constraints.

IV. Simulation Framework

The simulation is involved in two major steps. Former part of the simulation is carried out to implement elephant vocalization signal detection at the sensors. This routine also provides the time delay information between each pair of sensors. In this section, the SNR effects on signal detection and acquiring time delay information are also considered. The latter part of the simulation estimate the source position utilizing the time delay information provided by the previos section. The wind and temperature effect on source position estimation is considered in this section.

A. Vocalization Detection

In real world scenario, once an elephant made a rumble signal, each sensor in the vicinity of the source location hear time delayed and noise corrupted versions of the original signal. This is simulated by shifting and zero padding the original rumble vocalization data file by relevent time delays for each sensor. Then, the noise corruption is incorporated by adding white Gaussian noise to time shifted signal. Now at the receiver, if the signal is cross−correlated with signature rumble vocalization signal, it is possible to find the peak cross−correlation coefficient at number of samples which represent the original time delay information. We perform multiple cross−correlations between each pair of sensors' observation signals to find the time delay information represented by Δt_{pq} in (6).

B. Sensor placement and Source localization

In this part of the simulation several real world aspects are taken into the consideration. We chose 2000 m $\times$ 2000 m square as our analysis area which represent the woodland. We assume that coordinate axis $y = 0$ as our village boundary. Countermeasure can be taken only if the elephants are localized at least before they enter into the 500 m margin from the village boundary. Therefore, we choose interested source observation area as the rectangle bounded by coordinates $\{(0, 500), (0, 2000), (2000, 500), (2000, 2000)\}$.

Sensors might need occasional maintenance for instance, to replace the batteries, to sensor health checks etc. Practically people could not frequently move into deep forest area which is not pleasing in terms of risk and the cost of visit. Therefore, the sensors need to be placed close to the village boundary. We decide that the sensors should be placed within 200 m distance from the village boundary. Consequently, the sensor deployment area is a rectangle bounded by coordinates $\{(0, 0), (0, 200), (2000, 0), (2000, 200)\}$. However, sensors need to be placed optimally so that they avoid the redundancy and provide maximum accuracy. We, considered several options, such as placing sensors randomly, homogeneously, in a line and in a curvature. In the line deployment, we selected centre line of the chosen sensor deployment strip ($y = 100$ m) and we deployed sensors in equidistance separations. In curvature deployment, proper arc is found as follows. First, we drew a circle centred at $(1000, 2000)$ and radius 2000 m. Then we select the arc which is laid inside the sensor placement strip. Then the sensors are placed such that they are separated each other by equal arc distances. In our simulations we used four sensors which have identical capabilities. It is identified, by means of several simulation experiments that the curvature sensor placement outperforms other methods in source localization. Therefore, it is chosen as the sensor placement criteria for the results presented in this work.

The effect of each constraint discussed in Section II is attained by placing the source at different positions in the interested observation area and calculating the estimation error. Initially, the rectangular observation area is divided into 100 m $\times$ 100 m small girds. Then, the source is placed 100 times randomly inside the small grid and the source position is estimated according to the algorithm discussed in Section III. However, each of position estimation obtained here is affected by different parameters such as wind, temperature and SNR and thus they are erroneous. We compute the error for each random source position by calculating the Euclidean distance between actual and the estimated source locations. Then the mean estimation error is calculated for the above 100 source placements. The computed mean error is considered as the average inaccuracy in positioning when the source is located at the area represented by that particular grid. The above process is repeated for each grid in the observation area. The effects of different meteorological parameters and SNR are presented in the subsequent section.

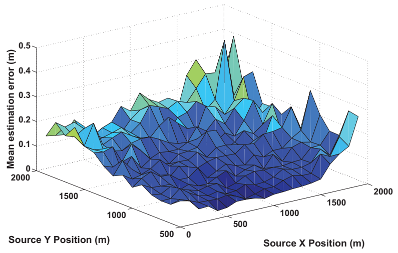

Fig. 3. The source localization error variation at different source positions within the observation area. Four sensors are deployed in curvature with equal arc length separations as discussed in Section IV-B. The $\mathbf{T = 22\ ^0C}$ uniform throughout the area. $V_2 = 0$ ms^{-1}, $\theta_2 = 270^0$, SNR= 10 dB

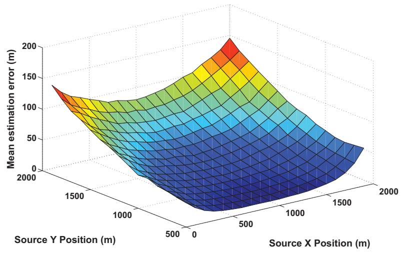

Fig. 5. The source localization error variation at different source positions within the observation area. The sensors are deployed in curvature with equal arc length separations as discussed in Section IV-B. The Temperature varies between each sensor path. $\mathbf{T_{S1} = 25\ ^0C}$, $\mathbf{T_{S2} = 23\ ^0C}$, $\mathbf{T_{S3} = 22}$ $\mathbf{T_{S4} = 24\ ^0C}$. $V_2 = 0$ ms^{-1}, $\theta_2 = 270^0$, SNR= 10 dB

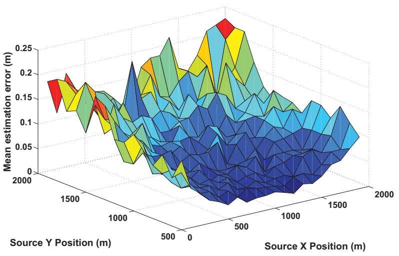

Fig. 4. The source localization error variation at different source positions within the observation area. Four sensors are deployed in curvature with equal arc length separations as discussed in Section IV-B. The $\mathbf{T = 30\ ^0C}$ uniform throughout the area. $V_2 = 0$ ms^{-1}, $\theta_2 = 270^0$, SNR= 10 dB

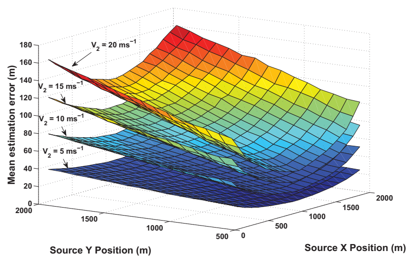

Fig. 6. The source localization error variation at different source positions within the observation area for wind velocities $\mathbf{V_2 = 5}$ ms^{-1}, $\mathbf{V_2 = 10}$ ms^{-1}, $\mathbf{V_2 = 15}$ ms^{-1}, $\mathbf{V_2 = 20}$ ms^{-1}. Four sensors are deployed in curvature with equal arc length separations as discussed in Section IV-B. The $T = 22\ ^0C$ uniform throughout the area. $\theta_2 = 270^0$, SNR = 10 dB.

V. Results and Discussions

The simulation setup discussed in the Section IV is obtained using Matlab 7.9.0 (R2009b) development environment for the analysis. The effect of individual parameter is analyzed via simulations while keeping the other parameters constant. Figures 3$-$5 show the temperature effects on the source positioning. Initially, it is assumed that the temperature is uniform throughout the area. Results for the instances of temperature 22^0C and 30^0C are depicted in Figs. 3, 4, respectively. The maximum mean estimation errors in these incidents are less than one meter throughout the observation grid. Therefore, the increase in the temperature equally, does not affect the source positioning accuracy significantly. Then, we varied the temperatures at each node such that $\mathrm{T}_{S1} = 25^0$C, $\mathrm{T}_{S2} = 23^0$C, $\mathrm{T}_{S3} = 22^0$C, $\mathrm{T}_{S4} = 24^0$C, and execute the simulation again. Figure 5 shows that in this scenario the positioning error increases, drastically.

The wind has very significant effect on localization accuracy as depicted in Fig. 6. Rise in the wind velocity increases error in positioning especially towards the boundaries of x axis. In lower wind velocities, perhaps the error margin of $\pm$ 20 m at 500 m might not exceed; however, inaccuracy at higher velocities cannot be tolerated. Faster wind velocities toward the sensors, will increase the sound velocity while decreasing the time-of-flight (TOF) of signal from source to the sensor. The TOF is higher when the source is far away from the sensors. Therefore, the error in time delays increase with the distance resulting higher positioning errors at far away source locations from the sensors.

The SNR has much more considerable effect on the source localization accuracy in our algorithm. Figure 7 depicts the distribution of mean estimation error throughout our observation grid, while the SNR is set to -15 dB. Note that in our analysis we add the noise from uniform distribution, assuming noise is equivalent even for far away distances from the sensors. However, this assumption does not follow the actual scenario. Accoding to the discussion in Section II-A the sound intensity depletes with the distance, resulting lower SNR levels at the sensors when source is far away. Therefore, it can

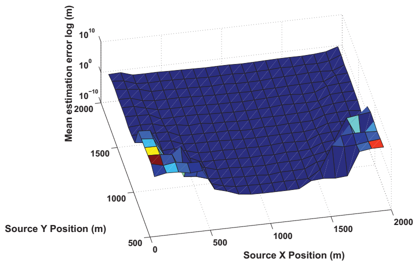

Fig. 7. The source localization error variation at different source positions within the observation area. Four sensors are deployed in curvature with equal arc length separations as discussed in Section IV-B. The T $= 22\ ^0C$ uniform throughout the area. $V_2 = 0$ ms^{-1}, $\theta_2 = 270^0$, **SNR = -15 dB.**

be expected higher SNR levels while the elephants are closer to the sensors. The SNR level has substantial effect when the source is placed in the XY corners of the observation area. This results from inaccurate time delay information provided by correlation routine, at lower SNR levels. The inaccuracy is significant once sensors are spatially in closer to source. These erroneous time delays subsequently cause the minimization algorithm to estimate enormously inaccurate source positions as depicted in Fig. 7. The effect was further analyzed by increasing the SNR level in steps. The inaccuracy disappeared at the SNR level of -12 dB. We identified this as the marginal SNR level that is necessary for the system to provide proper localization estimation in this simulation setup.

VI. Conclusion

In this paper we have analyzed major propagation constraints that could affect the elephant localization framework. Our results show that the impact of the temperature for the accuracy of source localization is insignificant if the temperature is uniform over the considered area. In contrast, the temperature variation between each source$-$sensor path significantly affects the source positioning error. Therefore, in real implementation integrating temperature measurements to the system will vastly improve the localization accuracy. In addition to this, our results show the influence of the real time wind velocity data in to the sensor network. The SNR levels at the sensors also play major role in localization error. The system provides enormously inaccurate position estimations once the SNR level drops under certain marginal level. More precisely, this level is -12 dB with respect ur simulation framework discussed in this paper. Therefore, in actual implementation, incorporating signal processing techniques for noise reduction will increase the overall performance of the system.

Acknowledgment

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Appendix B

Improving Accuracy of Elephant Localization using Sound Probes

B.1 Introduction

The content of the thesis has been partially published in an international conference and a journal. Appendix B presents the published material in international journal:

Chinthaka M. Dissanayake, K. Ramamohanarao, M. N. Halgamuge, and B. Moran, "Improving Accuracy of Elephant Localization using Sound Probes", Applied Acoustics, Volume 129, pp 92–103, 2018

B.2 Published manuscript

Applied Acoustics 129 (2018) 92–103

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Improving accuracy of elephant localization using sound probes

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ABSTRACT

Localization of elephants in the vicinity of villages is an important issue in mitigating human-elephant conflict. This paper proposes an inexpensive, effective and non-invasive framework that employs a sound probe technique with an acoustic sensor network to localize elephants. Incorporation of probes in our sensor network eliminates the requirement to explicitly measure temperature and wind velocity for accurate determination of sound velocity. A sensor network has been built and experiments performed by replaying recorded elephant sounds under three different environmental conditions. The results overall show that the system is capable of providing remarkable accuracy under distinct wind and temperature conditions. An identical experimental set up was used to localize wild elephants in Sri Lanka. Our approach enabled localization of wild elephants at a distance of over 500 m from the sensors to within 30 m, providing adequate time for the villages to take appropriate safety measures.

1. Introduction

Changes in social and ecological conditions precipitated by human needs are resulting in serious depletions in certain animal populations. Human-elephant conflict (HEC) is one such problem resulting in deaths of members of both species. Humans are clearing large areas of land for food production, increasing pressure on traditional elephant habitats. This results in migration of elephants to villages to fulfil their food requirements and ensuing HEC. In Sri Lanka, HEC has is causing more than 60 human deaths and over 200 killings of elephants, annually [1].

Various strategies have been implemented to mitigate HEC. These include implementing electric fencing systems and using satellite imaging and radio and Global Positioning Systems (GPS) collars to detect the presence of elephants [2].

Electrified wire fences are used to restrain elephants into the forest areas. This is an expensive option due to high installation and maintenance cost. In practice, the long-term success with anti-elephant fences has often fallen well below expectation. This is basically because of deficiencies in meeting the considerable demands of meticulous routine maintenance. In addition, wild elephants have low resistance to these barriers as they have learned to demolish the fences using tree branches and thereby enter into the protected areas [3].

Tagging elephants with radio and GPS collars for understanding the behavioural aspects is presently conducted in many parts of the world. However, this methodology is impractical for real-time monitoring of wild elephants due to the battery power limitations in collar systems and the cost of GPS data retrieval. In addition, capturing elephants and fitting GPS collars to these animals is a complex and dangerous procedure which risks lives of both elephants and personals involved. Therefore, it is in practice even impossible to collar elephants which are deemed problematic.

With the advancements in technology, satellite imaging is also proposed as a methodology for tracking wildlife [4]. However, thick vegetation and environmental factors hinder this sophisticated and expensive technology for real-time monitoring of wild elephants.

Recently, interest has grown in the detection of elephants through their low-frequency calls, commonly referred to as "rumbles" [5]. This technique is a safe, practical and non-intrusive methodology to detect these highly social animals that use rumbles for long distance communication. Once the elephants are detected at a sufficient distance from the village boundaries countermeasures such as the use of firecrackers, broadcasting of noise through loudspeakers, and warnings to the local population can be deployed.

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However, the variations in environmental conditions seriously affect the performance of such systems [6,7]. This is due to the sound speed dependency on several environmental phenomena such as temperature, water vapour mole fraction, atmospheric pressure and CO_2 content in the air. Cramer [8] has proposed a closed form equation for the relationship between speed of sound and the above environmental factors through a laboratory experiment. However, the speed of sound mainly depends on temperature and effects of other variables are insignificant. The speed of sound in air can be expressed in terms of temperature as $C_{Sound_T} = C_{Sound_0}\sqrt{(1+\frac{T}{273.15})}$ where $C_{Sound_0} = 331.45\ \mathrm{ms}^{-1}$ is sound speed at 0 °C [9]. In addition, wind causes to movement of the propagation medium which effectively alters the propagation sound speed between sound source and the receivers [10].

In [6] the possibility of using an acoustic sensor network to detect and localize elephants has been extensively analysed. Wind and temperature variations are identified as the main cause for the deterioration of the performance of the above approach [6,7]. For instance, a uniform wind velocity of 20 ms^{-1} results in about a 100 m (20%) error at a distance of 500 m. An additional temperature variation of 4 °C can result in an increase in the error to over 175 m (35%) [6].

In this paper we propose a technique to correct the errors arising from variations in sound speeds due to environmental effects. We propose a system to implement the algorithms that have been developed and describe the results of experiments, under three different environmental profiles, using a sensor network system that we designed. Then, we implement our system in a village area in Sri Lanka and test it for the real application of wild elephant monitoring. Our contribution is to present an effective solution that significantly improves localization accuracy over a conventional acoustic sensor network, and which does not require explicit wind and temperature sensors to compensate for the environmental effects on sound speed.

The remainder of the paper is organized as follows. In Section 2 we summarize the localization algorithm that will be utilized in our proposed system. In Section 3 the technique used to correct the speed of sound to mitigate temperature and wind velocity effects is described in detail. In Section 4 we describe the corresponding experimental setup for tests we conducted in open field and forest environment. Section 5 outlines the experimental results and discusses them further. Section 6 concludes the paper.

2. Localization algorithm

We consider an acoustic sensor network with N sensors that listen to elephant vocalizations. In consideration of the long propagation range of infrasonic rumble signals [11], it is assumed that all sensors receive an attenuated and noise corrupted replica of a call generated by an elephant (source). Let the time of arrival measurements at sensor S_i be t_i where $i = 0, 1, \cdots, N-1$. The infrasonic acoustic sensors are deployed at predetermined coordinates (x_i, y_i). It is necessary to locate the source position (x_s, y_s). The arrival time measurements at sensor S_i can be modeled by $t_i = T_0 + R_i/c_i + \epsilon_i$ where T_0 is the signal emitted time by the source, R_i is the distance between source and the ith sensor, c_i is the sound propagation speed and ϵ_i is the normally distributed measurement noise with zero mean and σ^2 variance. It should be noted that the c_i between the source and each sensor could vary because of environmental effects such as wind and the temperature. The distance from source to ith sensor R_i is given by $R_i = \sqrt{(x_s - x_i)^2 + (y_s - y_i)^2}$. The time T_0 of signal emission is unknown, and so it is appropriate to perform a time-difference-of-arrival (TDOA) estimation. TDOA information is obtained by performing pair-wise cross-correlations between the observation sound signals at each sensor pair. TDOA measurement between the pth and qth sensors denoted by Δt_{pq} is given by $\Delta t_{pq} = t_p - t_q + \epsilon_{pq} = R_p/c_p - R_q/c_q + \epsilon_{pq}$, where $p = 0, 1, \ldots, N-2$ and $q = p+1, p+2, \ldots, N-1$, $\epsilon_{pq} = \epsilon_p - \epsilon_q$ (see Fig. 1).

Let the measured TDOA ranges be

$$\mathbf{m} = [m_{2,1} \quad m_{3,1} \quad \cdots \quad m_{n,1}]^T = \mathbf{d} + \boldsymbol{\epsilon}$$

where

$$\mathbf{d}(\theta) = [r_{2,1} \quad r_{3,1} \quad \cdots \quad r_{n,1}]$$

and $r_{p,q} = R_p - R_q$. The probability density function [12] of $\mathbf{m}$ given θ is

$$f(\mathbf{m}/\theta) = 2\pi^{-n/2}(\det \mathbf{Q})^{-1/2}\exp\{-J/2\}$$

where

$$J = [\mathbf{m} - \mathbf{r}(\theta)]^T \mathbf{Q}^{-1}[\mathbf{m} - \mathbf{r}(\theta)].$$

The Maximum Likelihood Estimate (MLE) is the $\theta(x_s, y_s)$ that minimizes J. This can be reduced to minimizing the non-linear least square problem [13] of

$$f(x_s, y_s) = \arg \min_{x_s, y_s} \sum_{p,q} (h_{pq} - g_{pq})^2. \tag{1}$$

where $h_{pq} = c \times \Delta t_{pq}$ and $g_{pq} = R_p - R_q$.

The solution to (1) gives the unknown source location. However, to locate the source accurately the above system needs the correct sound propagation speeds between the source and each sensor, which is affected by wind and temperature variations. Our approach to estimate sound speed with mitigated temperature and wind velocity effects is presented in the next section.

3. Average sound speed estimation methodology

Our goal is to estimate the approximate speed of sound that signals propagate with respect to each sensor. In order to build a solution that attains the above sound speeds in a real world environmental scenario we first develop a model assuming uniform environmental conditions. Then the model is extended to real world comparable, non uniform and totally unknown environmental conditions.

To locate the elephants accurately, acoustic sensors and some specific sound (chirp) signal generators are deployed at predetermined location coordinates. These sound generators are referred to as “probes” in the remainder of the paper. The chirp signal generation time schedule is predefined and known to both devices. Therefore, by listening to the signal, each sensor can determine the time of flight (TOF) from probes to the sensor. Then, the approximate speed of sound between the source and the sensors is estimated in two different models as presented below.

Model A: *The temperature over the area is assumed to be uniform but unknown. The wind speed and the direction over the area are assumed to be uniform but unknown.*

Here we estimate the wind information and the uniform temperature over the area completely depending on the probe technique without incorporating additional sensors. Consider that the ith sensor (S_i) receives the signal from the probes P_l, P_m, P_n as depicted in Model A in the Fig. 2. The temperature affected speed of sound between S_i and P_z is $V_{P_zS_i}(T)$ where $z = l, m, n$, and, so the measured speed of sound $V_{P_zS_i}$ between S_i and P_z is given by

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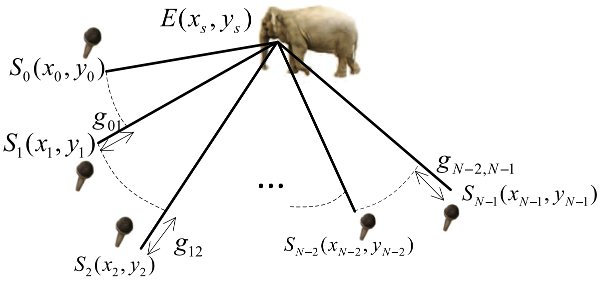

Fig. 1. *N* number of sensors are deployed at the vicinity of the expected elephant location. The distance difference between source and the *p*th and *q*th sensor is defined as g_{pq}.

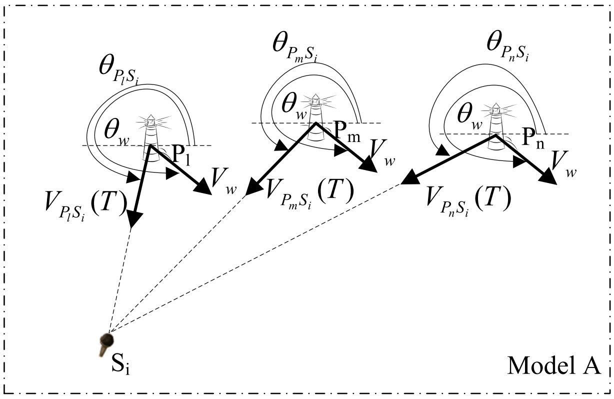

Fig. 2. The *i*th sensor (S_i) receiving the signal from the probes P_l, P_m, P_n. The wind flows with speed of V_w with an angle of θ_w with respect to the horizontal axis. The temperature affected speed of sound between P_z is $V_{P_zS_i}(T)$ where $z = l, m, n$.

$V_{P_zS_i} = V(T) + V_w \cos(\theta_w - \theta_{P_zS_i})$. Thus, by resolving the system of equations for each probe z and sensor S_i, it is possible to estimate the approximate speed of sound in the area by evaluating three unknowns (wind speed V_w, wind direction θ_w, and temperature affected speed of sound $V(T)$). Now the wind direction can be derived as

$$\theta_w = \tan^{-1}\left[\frac{A\sin(\beta) - B\sin(\alpha)}{A\cos(\beta) - B\cos(\alpha)}\right] \tag{2}$$

where

$$A = \left(V_{P_lS_i} - V_{P_mS_i}\right)\sin\left((\theta_{P_nS_i} - \theta_{P_lS_i})/2\right),$$

$$B = \left(V_{P_lS_i} - V_{P_nS_i}\right)\sin\left((\theta_{P_mS_i} - \theta_{P_lS_i})/2\right),$$

$\alpha = \left(\theta_{P_mS_i} + \theta_{P_lS_i}\right)/2$, and $\beta = \left(\theta_{P_nS_i} + \theta_{P_lS_i}\right)/2$. The wind speed V_w is now

$$V_w = \frac{V_{P_lS_i} - V_{P_mS_i}}{\cos(\theta_w - \theta_{P_lS_i}) - \cos(\theta_w - \theta_{P_mS_i})}. \tag{3}$$

By using (2) and (3) we obtain the temperature affected speed of sound $V(T)$ from

$$V(T) = V_{P_lS_i} - V_w \cos(\theta_w - \theta_{P_lS_i}). \tag{4}$$

The temperature and the wind effects compensated sound velocity can then be determined.

Model B: *The temperature over the area is non-uniform and unknown. The wind speed and the direction over the area are also non-uniform and unknown.*

Under the condition where wind and temperature are non-uniform and information is unavailable, it is difficult to produce closed form equations to correct the actual sound propagation speed, because not enough information is available. In this case real world spatial properties of the temperature and wind variations were incorporated. The assumption of slow spatial variation of temperature permits temperatures in adjacent regions to be considered as correlated random variables. We model this variation, therefore, as a two-dimensional Gaussian function. The temperature at particular location coordinates (x, y) is given by $f(x, y) = T_{min} + \Delta T_{Vmax}\exp\left(-\left(\frac{(x-x_o)^2}{2\sigma_x^2} + \frac{(y-y_o)^2}{2\sigma_y^2}\right)\right)$, where T_{min} is the minimum temperature, ΔT_{Vmax} is the maximum temperature variation, (x_o, y_o) is the centre coordinates of the interested area, σ_x, σ_y are the x and y spreads of the temperature blob over the area. In addition, the wind flow is assumed to be a Markov Random Field (MRF). The wind vector at a particular position is determined by values drawn from a normal distribution $\mathcal{N}(\mathbf{V_{wAdj}}, \sigma_w^2)$ where

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$\mathbf{V_{wAdj}}$ is the wind vector in adjacent locations. Now, the probe technique is incorporated to evaluate the approximated actual sound propagation by dividing the interested area into effective isothermal spatial regions. Validity of the above approximation depends upon selection of the spatial region. The smallest region to uniquely estimate the environmental parameters is chosen as the isothermal region. This region is the area depicted as Model A in Fig. 2. The set of equations derived in the Model A can be used to estimate the average sound speed correction within the effective isothermal areas. Sound signals to distinct sensors will experience different speeds of propagation as affected by wind and temperature variations. By efficiently averaging them considering the spatial proximity, approximation to the effective sound speed can be obtained.

4. Experimental setup

4.1. Open field experiment

The hardware system consisted of sensor units which contain microphones (Audio-Technica AT897) and FM transmitters (Fmuser SDA-01A) and sound probes which include chirping devices (see Figs. 3 and 4). Separate laboratory experiment was conducted to investigate the frequency response of the signal sensor microphones detection system. It was confirmed that system performs well in the range of approximately 10–400 Hz and can capture main signal energy components of low frequency elephant calls as shown in [5].

The sensors listen to the sound signals and transmit them in a dedicated FM channel to the centralized receiver in real time. Each sensor was assigned a distinctive FM channel to prevent the interference at the receiver. These channels were carefully selected to avoid interference with the other FM transmissions such as local radio stations and communication within police forces and emergency services. The centralized receiver consisted of a set of FM receivers (Sony CRSW08) which are synchronized to each sensor unit FM frequency. The outputs of these receivers were then streamed into a laptop computer via a USB sound card hub which enabled simultaneous signal recording. Sound signal acquisition is attained through a commercial software program named Cool Edit pro Version 2.0. The signals from each sensor channel was recorded into separate tracks in the software program and subsequently saved and exported into wave files for further analysis. The main feature of the software program that facilitated in our experiment is that it enables synchronized data recording from separate channels. Table 1 provides a cost analysis of the hardware system that utilized in this implementation. The overall cost of the system including a cheap processor is less than \$2750.

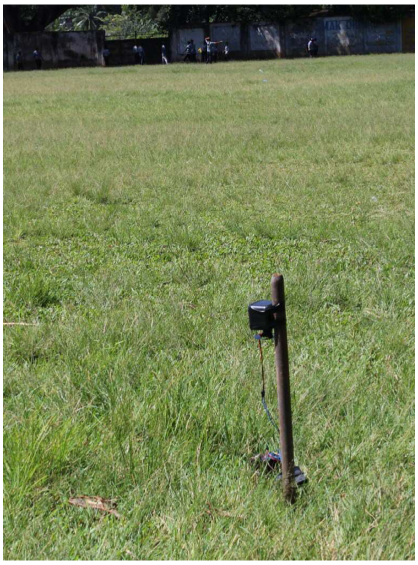


Fig. 4. Snap of Probe unit deployed in the field. The unit consists of sound chirp generator and a controller unit which determines the timing of chirp generation. The unit was powered by a 12 V DC battery.

Fig. 3. Snap of complete sensor unit deployed in the field. The microphone and the transmitter units are mounted on a tripod and units are protected with weather shields. Four sets of similar sensor units are deployed for the experiment. The transmitter units were powered by 12 V DC battery.

Our ultimate goal is to utilize the system to localize and track the forest elephants through their rumble signals. In our experiment, we decided to utilize a moving sound source which produces elephant rumble signals such that we can maintain the analogy up to some extent. First, we included rumble signals into a sound player (Sansa® Express™) which consisted of a storage device and connected it to a large speaker through an amplifier (TOA™ A-50 M). The speakers had frequency response of $\pm 3\,dB$ over the range 16–250 Hz and nearly all the elephant calls used for the simulation had acoustic energy within the above range. Then the system is mounted on a wheel cart so that it can easily be moved in the field. We called this system setup as "Surrogate Elephant" (SE) (see Fig. 5).

The experiment site was a playground named Weeguluwathte at the city of Gampola which is located in the Central Province of Sri Lanka. The experiment was performed in three sets during dif-

Table 1
Cost analysis of the hardware system utilized in the real world implementation.

Item	Brand	Model	Unit price	No. units	Cost
Acoustic sensor	Audio-Technica	AT897	$212.00	4	$848.00
Long range FM Transmitter	Fmuser	SDA-01A	$112.00	4	$448.00
Receiver	Sony	CRSW08	$48.00	4	$192.00
Probe	Custom design	Custom design	$40.00	4	$160.00
Battery	B.U.E	3FM-4.0	$25.00	8	$200.00
Recorder software	Cool Edit	Pro V2.0	$300.00	1	$300.00
Processor unit (Laptop)	Toshiba	SATELLITE C50D	$499.00	1	$900.00
Interfacing units and connectors	N/A	N/A	$100.00	1	$100.00
Total					$2747.00

Fig. 5. Picture of the surrogate elephant which is being moved by one of the assistants. The unit consists of sound player connected to a speaker through an amplifier. The system was designed to play previously recorded elephant rumble signals during the experiment.

Table 2
Average wind and temperature measurements during the experiment trials.

Experiment set	Average temperature (°C)	Average wind speed (ms^{-1})
Data Set 1	27.4	6.9
Data Set 2	29.3	8.7
Data Set 3	28.1	10.1

ferent time periods of the day such that natural variation of temperature and wind velocities can be taken into account. The experiment was carried out in a sunny day and humidity was 64%. The average temperature and wind speed with respect to north was obtained using an anemometer (Bentech GM816) during each set and is summarized in Table 2.

The sensors and the probes were deployed in the field as per the reasoning explained in the simulations. The exact locations of the probes and sensors were acquired using eTrex™ GPS device and recorded. In addition, the distance between each sensor and probe was accurately measured via Leica DISTO™ A8 Laser distance meter. Once the probe sensor system was deployed and activated, the centralized data recorder system was positioned in a convenient location to start the recording. Then a GPS data recorder was attached to our Surrogate Elephant (SE) to obtain the actual path where it was travelling. Subsequently, SE is moved at a constant speed towards the deployed probe sensor direction whilst recording sound signals into the centralized data recording system.

4.2. Real forest experiment

Following the open field implementation and identifying the possible challenges, we proceeded to test our methodology in real forest environment. The experimental site was a village called Swaranapaligama which was situated in North central province, Sri Lanka. The village is located adjacent to the border of the Wasgamuwa National Park and a branch of Amban River flows close to the village. The primary occupation of the villages is farming and they mainly cultivate rice and vegetables. As a result of close proximity to the forest and the continual production of crops, wild elephants frequently enter into the village especially during the dry season. Considering the above facts, we conducted our experiment in the end of September 2013 which is the latter period of the dry season.

A similar experimental setup as in the open field experiment described in Section 4.1 was employed in this implementation as well. A set of sensors and probes were deployed at predetermined locations. The probes were kept in the forest area to obtain a better representation of the sound characteristics through the woodland. The sensors are kept close to the village boundary depending on practical considerations. A simplified block diagram of the hardware setup is depicted in Fig. 6. The probe and the sensor coordinates were recorded using eTrex™ GPS devise as in the previous experiment and those coordinates are summarized in Table 3.

During the background information gathering the villagers informed us that in many occasions, elephants come closer to the village shortly after the nightfall. Therefore, we set up equipment targeting to start the data collection during the above period. Owing to constrains in battery life and available resources, successful data collection was done in three consecutive days and typical weather information during the experiments is summarized in Table 4.

Once the experiment was conducted, in the following day we walked through the elephant tracks to verify the presence of elephants during the previous day. The verification process was practically impossible to conduct in real time during the experiment due to safety issues. However, through the evidence such as fresh piles of elephant dung, broken tree branches, signs of browsing grass and foot prints embossed in the ground, we were able to determine the presence of the elephants during the days we conducted the experiment (see Figs. 7 and 8).

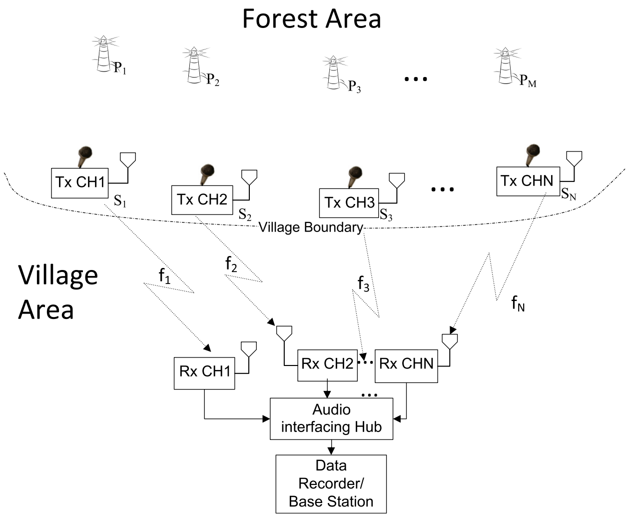


Fig. 6. Simplified block diagram of the system hardware implementation. Each sensor consists of microphone and a FM transmitter. Vocalization data and the probe signals acquired through each microphone is transmitted through a dedicated FM channels to the centralized receiver. Probes are placed in the forest area to get a better representation of the real sound speeds of the observation area.

Table 3
Sensor and probes location coordinates at the real forest experiment.

	GPS coordinates	
	Longitude	Latitude
Sensor 1	80.954352	7.863963
Sensor 2	80.953244	7.864375
Sensor 3	80.952465	7.864156
Sensor 4	80.951085	7.864182
Probe 1	80.953736	7.863446
Probe 2	80.952939	7.863341
Probe 3	80.952146	7.863349
Probe 4	80.951457	7.863455

We obtained the assistance of few villages who were experts in identifying elephant tracks and familiar with the forest area closer to the village to accomplish the above task. We recorded the coordinates of the elephant tracks using eTrex™ GPS device. In addition, GPS coordinates and the description of the signs were manually recorded at the specific locations where we identified as elephants were present. Through these field visits we identified that, out of three days we conducted the experiment, in two days elephants have travelled through the tracks we observed.

5. Results and discussions

5.1. Open field experiment results

The results of the practical implementation of our proposed methodology in an outdoor environment are depicted in the Figs. 9–11 for three different data collection sets. It can be identified that our proposed technique clearly improves the localization accuracy of the sound source under different environmental conditions. The accuracy improves whilst the source is close to the probes. The reason for this is that, when probes and SE are in close proximity, the probes technique represents the actual sound speeds between source–sensor paths. Due to limited space and narrow variation of temperature and wind velocities in the experimental area, the localizations without probe technique correction also follow the path to a certain extent. However, this fact is invalid in a real forest application where environmental condition variation would be much more complicated.

The elephants have a behavioral characteristic of walking in the same particular paths which they have followed throughout the generations. Therefore, it is possible to incorporate these path data as a prior information whilst implementing tracking algorithms. We have implemented a particle filter considering prior information of the path data of the surrogate elephant whilst incorporating probe correction in our posterior analysis. As shown in Figs. 9–11

Table 4
Weather details during the real forest experiment.

Experiment trial	Weather	Average temperature (°C)	Average wind speed (ms^{-1})	Humidity (%)
Day 1	Sunny	29.5	4.2	64
Day 2	Sunny	29.3	8.4	72
Day 3	Sunny	28.1	7.1	68

Fig. 7. A snap shot of recording information on a location where elephants were present in a day that we conducted the experiment. GPS coordinates and information on the observation were recorded manually for further reference.

Fig. 8. Picture of foot print embossed in the ground of an elephant that visited the area in the day which we conducted the experiment. Similar observations were made on fresh pile of elephant dung, broken tree branches, and signs of browsing grass and the observation locations were recorded for further reference.

the outcome of the implementation clearly indicates an accuracy improvement.

5.2. Real forest experiment results

Fig. 12 depicts the localization results from gathered data during the real forest experiment. The analysis revealed that elephant calls were recorded during only two days of the experiment. This is in fact verified through the observations made during the post experimental visits through elephant tracks. The probe technique has performed efficiently in this heterogeneous environment as well. Evidently, it surpasses the observation made without considering the wind and temperature variations. Due to large observation area and variations in the environmental facts, the remarkable performance of the probe technique can be clearly identified. Our technique has located elephants within 30 m to the elephant tracks whilst error in conventional methodology extends over 70 m. The evidence gathered indicates the real localization accuracy attained through our technique. In addition, the results indicate that under the forest environmental condition, the performance of a conventional localization system can be significantly impacted even under a modest temperature and wind velocity variations.

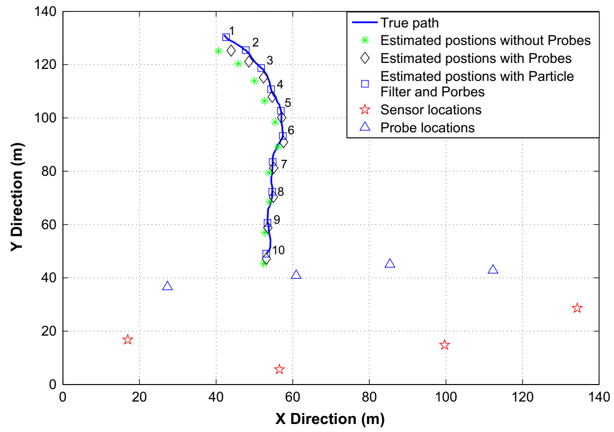
Our system was able to localize elephants over 500 m margin from the village boundary. This implies that, with some modifications to the hardware system such as integrating additional amplifiers the system may perform well above this distance. This fact suggests that similar system can be utilized to monitor elephants noninvasively for behavioural aspects. In a broad sense, our system which costs around $2750 can be utilized to protect a village area of around 2 km^2. However, the system needs to be modified for continuous power requirement in an alerting system. The challenge of battery power constrains can be overcome incorporating hybrid solar and battery power system. Similar methodology use in natural disaster notification which uses Short Message Service (SMS) alerting system [14] can be utilized for warning villagers regarding elephant threats.

In [7], acoustic monitoring of elephants is mentioned as a valuable noninvasive research tool. However, the predicted area of detection depends upon the atmospheric acoustic state. This acoustic state is mainly affected by meteorological effects such as temperature and wind velocity. It is necessary to have real-time knowledge of atmospheric condition to accurately locate the calling elephant [7]. Our proposed methodology addresses exact same problem and adjust the sound speed for atmospheric bias which results greatly improved localization accuracy.

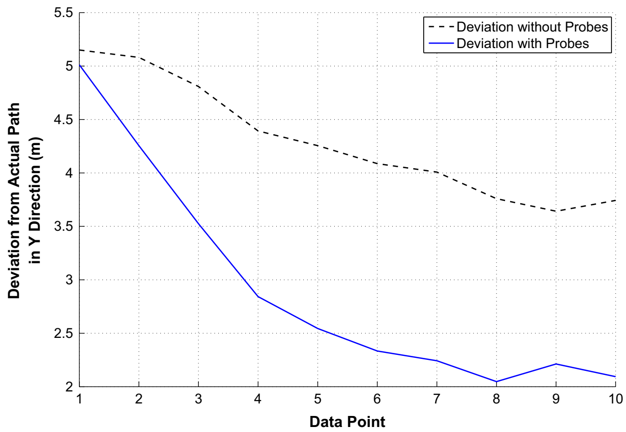
Mayilvaganan et al. have proposed direction of arrival estimation methodology with partial hyperbolic circular array to localize elephants [15]. They also identified that wind velocity and temperature variation significantly affects the localization accuracy. In fact, their analysis shows that localization error could be more than 28 m under narrow wind condition of 2.2 ms^{-1} whilst four sensors and the source is deployed in a 100 m $\times$ 100 m small-scale area. In comparison, analysis results indicate that our methodology performs far better than the above approach in locating elephants even under much stronger wind conditions.

The implemented hardware system is an economical approach for actual elephant localization system. By means of a centralized data collection system, we were able to eliminate the clock synchronization problem which is a main concern in distributed data collection schemes in similar applications. In addition, the inexpensive and effective methodology of utilizing probe technique remarkably increases the localization accuracy.

The sound signal at the receiver itself models the propagation channel characteristics. In our proposed technique this phenomenon is effectively utilized to estimate the sound propagation speed which is affected by temperature and wind variations. Further, information from sensors and probes which represent different spatial regions evidently assists for better sound speed estimation. Besides, the remarkable advantage of this approach is that it does not need both wind and temperature sensors in the network. In addition, we make use of the existing acoustic sensors for sensing probe signals and the elephant calls.

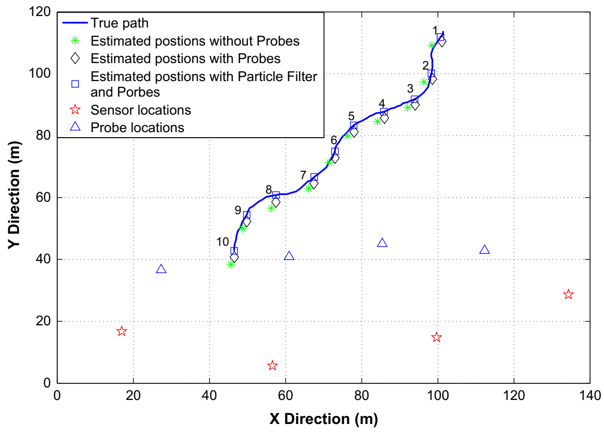


(a) The average temperature during the experiment was 27.4 °C and average wind velocity 6.9 ms^{-1} during the experiment. The estimated localization positions of the Surrogate Elephant closely follow the actual path whilst the probe technique correction was made.

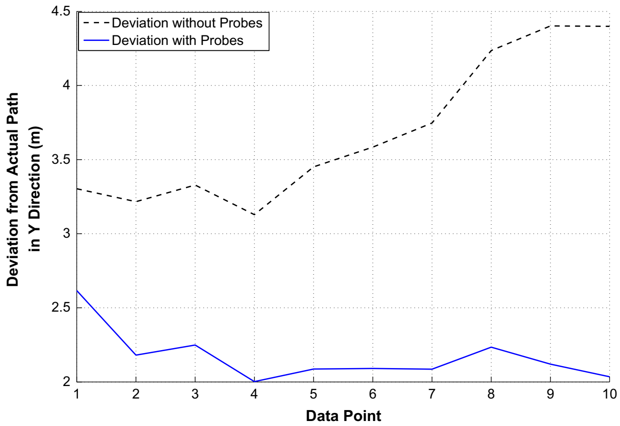


(b) Surrogate Elephant localization error estimation for Data Set 1. The error is calculated deviation in Y direction from the actual path. Note that the ES is moved towards the sensors and 1st data point represent the furthest point from the sensors.

Fig. 9. Localization of Surrogate Elephant; the analysis results from the Data Set 1 acquired from the real experiment.

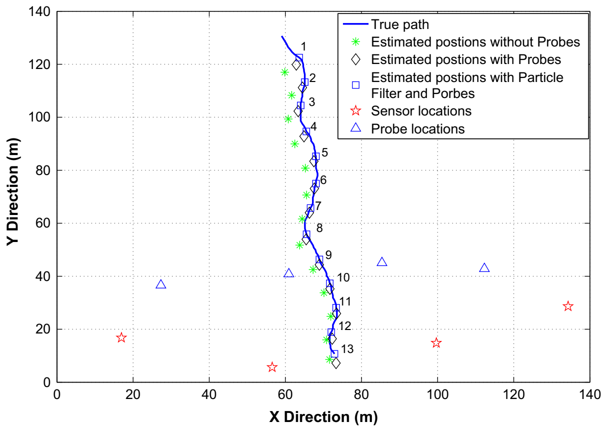


(a) The average temperature during the experiment was 29.3 °C and average wind velocity 8.7 ms^{-1} during the experiment. The estimated localization positions of the Surrogate Elephant closely follow the actual path whilst the probe technique correction was made.

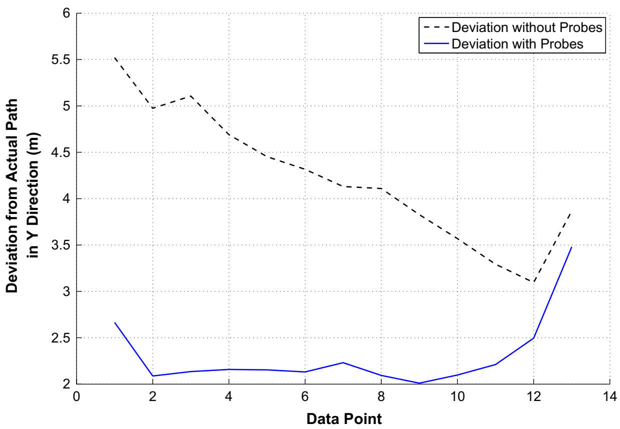


(b) Surrogate Elephant localization error estimation for Data Set 2. The error is calculated deviation in Y direction from the actual path. Note that the ES is moved towards the sensors and 1st data point represent the furthest point from the sensors.

Fig. 10. Localization of Surrogate Elephant; the analysis results from the Data Set 2 acquired from the real experiment.

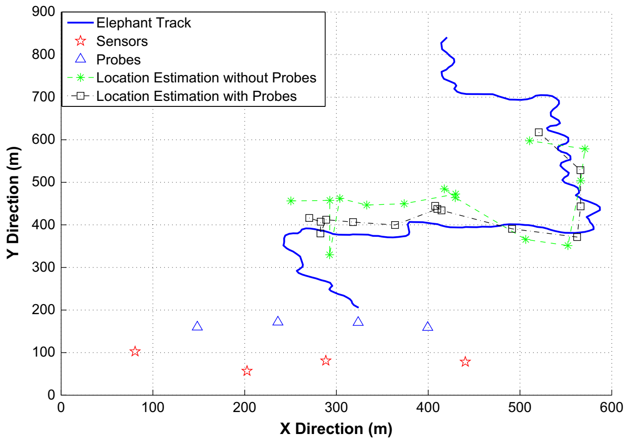


(a) The average temperature during the experiment was 28.1 °C and average wind velocity 10.1 ms^{-1} during the experiment. The estimated localization positions of the Surrogate Elephant closely follow the actual path whilst the probe technique correction was made.

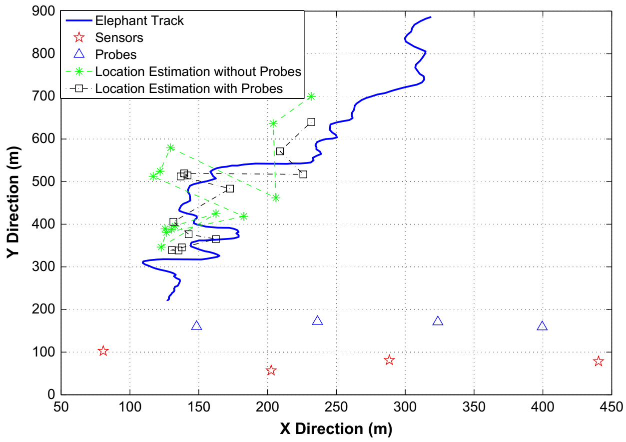


(b) Surrogate Elephant localization error estimation for Data Set 3. The error is calculated deviation in Y direction from the actual path. Note that the ES is moved towards the sensors and 1st data point represent the furthest point from the sensors.

Fig. 11. Localization of Surrogate Elephant; the analysis results from the Data Set 3 acquired from the real experiment.



(a) The analysis result of the data collection from the Day 1 in real forest experiment. The average temperature was 29.5°C and average wind velocity was 4.2 ms^{-1} during the experiment.



(b) The analysis result of the data collection from the Day 3 in real forest experiment. The average temperature was 28.1°C and average wind velocity was 7.1 ms^{-1} during the experiment.

Fig. 12. Analysis results of the real forest experiment. Observations were associated to different tracks in Day 1 and Day 3. The estimated elephant localization positions closely follow the elephant tracks. Evidently, the probe technique has significantly improved the localization accuracy despite the complex terrain.

6. Conclusion

In this paper we have investigated the feasibility of enhancing the accuracy in elephant localization system by utilizing a sound generating probe technique. An inexpensive hardware platform is implemented to evaluate the proposed methodology in an outdoor environment under equivalent elephant localization scenario. Finally, the system was deployed in a real forest environment to localize wild elephants in Sri Lanka. The outdoor experimental implementation verified the significant improvement in accuracy whilst using the probe technique, in a surrogate elephant localization system. Further, the real forest implementation successfully localized elephants over 500 distance. Moreover, our methodology enabled to localize wild elephants within 30 m accuracy to their natural walking paths in the real forest implementation.

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