Modeling Cost of Interruption (COI) to Manage Unwanted Interruptions for Mobile Devices

Sina Zulkernain
Marquette University

MODELING COST OF INTERRUPTION (COI) TO MANAGE UNWANTED INTERRUPTIONS FOR MOBILE DEVICES

by

Sina Zulkernain

A Thesis submitted to the Faculty of the Graduate School,
Marquette University,
in Partial Fulfillment of the Requirements for
the Degree of Master of Science

Milwaukee, Wisconsin

December 2011

ABSTRACT
MODELING COST OF INTERRUPTION (COI) TO MANAGE
UNWANTED INTERRUPTIONS
FOR MOBILE DEVICE

Sina Zulkernain

Marquette University, 2011

Unwanted and untimely interruptions have been a major cause in the loss of productivity in recent years. It has been found that they are mostly detrimental to the immediate task at hand. Multiple approaches have been proposed to address the problem of interruption by calculating cost of it. The Cost Of Interruption (COI) gives a measure of the probabilistic value of harmfulness of an inopportune interruption. Bayesian Inference stands as the premier model so far to calculate this COI. However, Bayesian-based models suffer from not being able to model context accurately in situations where a priori, conditional probabilities and uncertainties exist while utilizing context information. Hence, this thesis introduces the Dempster-Shafer Theory of Evidence to model COI. Along the way, it identifies specific contexts that are necessary to take into account. Simulation results and performance evaluation suggest that this is a very good approach to decision making. The thesis also discusses an illustrative example of a mobile interruption management application where the Dempster-Shafer theory is used to get a better measurement of whether or not to interrupt.

ACKNOWLEDGMENTS

Sina Zulkernain

First of all, I thank God for letting me have this opportunity to finish my Masters. I am extremely grateful to my advisor Dr. Praveen Madiraju for being kind, helpful and above all patient with me. I also thank Dr. Sheikh Iqbal Ahamed for helping me throughout the entire program. Dr. Karl Byleen deserves a special gratitude for participating in my committee. The work on the topic was initiated by Karl Stamm from which I took over and I am deeply grateful to him for his work that has led to this thesis. I also thank my family and friends; and finally the Graduate School and all of the Marquette University administration.

TABLE OF CONTENTS

CHAPTER 1: INTRODUCTION

We have all witnessed, at least more than once, situations in which a loud ringing phone interrupts a meeting. The caller hopefully would not have interrupted only if he or she knew the receiver is unable to take a call. All this would have been avoided if the receiver were to put the phone in silent mode to begin with. However, humans tend to forget. Hence, mobile phones have become the most hated device that people cannot live without. For its primary usage as a communication device, it has surpassed any other medium. But it comes with a high price, interruption, anywhere, anytime. Considering receiver's unavailability, it is possible to manage cell phone disruptions using advanced features like sensing capability, ubiquitous computing and context aware systems. But most often or not, we deliberately look to get interrupted, we want somebody to call us, talk to us, send us a message, and overall, communicate with us. So we need a measure which determines the adversity or the benefit of an interruption. One such trait is the Cost Of Interruption (COI). This gives us a probabilistic value whether an interruption is detrimental or welcoming. However, the calculation of COI is not a straightforward process. It involves the uncertainty factor when trying to measure its probability. As with any other uncertain situations, it requires to identify the specific parameters to work with. The task of finding the parameters falls into the realm of context which is a broad horizon itself. This thesis introduces the Dempster-Shafer Theory of Evidence for calculating the Cost Of Interruption (COI). It deviates from traditional probability approach using Bayesian Inference because Bayesian is not equipped to handle events where the a priori or conditional probabilities are unknown. In this thesis, we compare our results with the Bayesian ones. A prototype application is also built to see how the outputs of the algorithm can improve interruption situation. User surveys provide ample evidence that a significant improvement can be made if we use the Dempster-Shafer over the Bayesian Inference.

A cell phone is an electronic device used for mobile telecommunication i.e. telephony, text messaging and data transfer over a cellular network. Mobile phones have gained importance in the sector of information and communication technologies for development only since early 2000s. According to an estimate by the International Telecommunication Union, mobile cellular subscriptions worldwide had already reached approximately 4.6 billion by the end of 2009 [57]. Never ever before in history did a device reach so many people in such a quick time! Not only in mobile phones and smartphones, there has been a tremendous growth in cell phone applications too. Recent statistics indicate there are over 100,000 active iPhone applications [61]. Cell phone has become a necessity in our daily life. A University of Michigan study [59] shows that 83% people think cell phones make life easier and they choose it over the Internet. Mobile phones have the obvious benefit of all the moment communication. Irrespective of time and place, we can expect a phone to ring. But a ringing phone interrupting at an inopportune moment can be very disruptive to the current task or social situation [20]. According to the National Highway Traffic Safety Administration, 3 percent of drivers are talking on hand-held cell phones at any given time [60]. Also, a recent study by the Insurance Institute for Highway Safety reveals that drivers using phones are four times as likely to get into crashes serious enough to injure themselves [56]. In a survey of 1000 senior executives, it was reported that undesirable interruptions constitute 28 percent of the knowledge worker's day, which translates to 28 billion wasted hours to companies in the United States alone [46]. It results in a loss of 700 billion dollars per year, considering an average labor rate of $25 per hour for information workers [55]. A University of Oxford experiment suggests that in cognitively demanding situations, the advantage that 18-21 year olds enjoy over 35-39 year olds is reduced by an interruption caused by electronic communication technology [34]. Hence, to alleviate the aforementioned problems associated with interruption, in this thesis we propose a Smart Interruption Management System (SIMS).

Several research studies have investigated the issue of interruption management in general [8, 17, 19, 24] and also specific to mobile devices [12, 20]. Dekel et al. in 2009 built an application that minimizes mobile phone interruptions by changing profile settings intelligently [12]. Savioja addressed different kinds of alarms for different types of interruptions in control room environments [40]. Khalil & Connelli used calendar information of the phone to minimize disruptions [32]. Marti & Schmandt devised an application for a group setting where a phone had to get all of the members' votes before ring [36]. Also a methodology and design process for building interruption aware system is proposed in [17]. The distinguishing aspect of our work in comparison to the aforementioned ones is that we have built a mathematical model using sophisticated theory to calculate the cost of interruption and have showed that it outputs correct decision almost every time.

Whether an interruption is beneficial or harmful depends on the surroundings of the user i.e. the context. An autonomous system cannot be certain if its decisions are consistent with user preferences because of missing or unreliable context information. Therefore, machine learning and probabilistic approaches are viable options. Some researchers have considered dependencies among the contexts and how they affect the outcome of an interruption, and proposed models using Bayesian Inference [25, 26, 49]. But measuring COI is a problem dependent on user's contexts where it is unrealistic to calculate the a priori and conditional probabilities beforehand needed by Bayesian approach. Furthermore, the problem of interruption management brings in the uncertainty factor where different contexts may lead to conflicting decisions or when some context data is missing. Hence, we use the Dempster-Shafer's Theory of Evidence and Rule of Combination [13, 43] in our model as the mathematical underpinning for calculating COI. The model needs consistent and restricted amounts of inputs for enhanced performance. This has prompted me to optimize the number of contexts to consider which will be used as the input parameters in the model.

Karl Stamm's Master thesis in 2009, "Mobile Intelligent Interruption Management (MIIM): A Context Aware Unavailability System", laid out the foundation for this thesis. Stamm, in his work, vividly described the inauspiciousness of an ill-timed and inconvenient cell phone disturbance. His thesis identified the characteristics necessary for a system to fit in and run on a mobile system. Therefore, the thesis described an architecture that is suitable for handheld devices. Along with a decision tree heuristics, the thesis' simulation results showed that the prototype application met all the characteristics requirements. This thesis is an extension to that. Here, the focus point is to measure the Cost Of Interruption. If we are able to measure the value of an incoming call precisely, both benefit and harmfulness, the system will be more stable and cater to the user needs better. The system will be confronted with a lot of conflicting and uncertain scenarios. To tackle those, this thesis has used the Dempster-Shafer Theory of Evidence and built a mathematical model that can generate a precise value for the Cost Of Interruption.

The contribution of thesis goes a long way for this kind of field of research. To our best of knowledge, this thesis is the first one to address the uncertainty factor in managing interruptions and dealt with it through using Dempster-Shafer theory. The notable accomplishments are:

I. Identified specific contexts
II. Addressed the uncertainty factor using the Dempster-Shafer theory of evidence
III. Built a mathematical model on top of the theory to tackle the problem
IV. Developed a prototype application
V. Evaluated the system with large simulation data
VI. Showed how the solution is programmatically cheap to sit on a mobile platform

The rest of the thesis is organized as follows. The next section describes the motivation that has been the driver for this kind of research. Background section describes all the preliminaries and definitions to comprehend the rest of the thesis. The previous and similar works on the topic and their comparisons are put in the related works section. In the generic function chapter (Chapter 5), a mathematical model has been established to solve the interruption problem. An easy to implement method has also been given to get this model alive into the software arena. The illustrative example (Chapter 6) shows how the Dempster-Shafer theory can be applied to interruption situation with great success. The prototype application and the user response to this application are briefed in chapter 7. Simulation results from Chapter 8 give an idea of how this system is going to behave with large and diverse combinations of data. Finally, the conclusion section summarizes the whole thesis and paves the way for future work.

CHAPTER 2: MOTIVATION

Cell phones have been a tremendous inclusion to our day to day lives. It certainly has made the world smaller to us. But along with every other genius inventions, it comes up with its flaws: the ability to distract, interrupt and disrupt without any prior notification. But again, our research just does not stop at inventing and discovering something new. It is a continuous process where not only we look for new ideas and objects, but also thrive to make every existing idea and objects go better than their previous editions. In case of technological advancements, this is probably truer than any other field of research. We have embraced cell phones and we certainly have gained the capability to minimize its flaws.

To understand the adverse effects of interruption, first of all we need to discuss the outcomes of an interruption. Then we show real life scenarios to strengthen our points.

Cell Phone Interruption

We get interrupted at every phase of our life. In our everyday life, we wake up by a ringing alarm clock. Throughout the day we are interrupted by a door bell, knock on the door, fire alarms, street lights, announcements in a public transport, schools, offices, barking dogs, someone calling by name, a baby screaming, the list just goes on and on. It is impossible to think of a day where nothing has deviated us from our chain of thoughts. Modern day interruptions include tv and radio announcements, email notifications, instant messages, social networking news feeds and most prominent of all, a cell phone ringing. In most of the cases, interruptions are not really thought of as a bad thing or a harmful one. It is so common that people do not even think of its benefits or adversity. However, recent studies have suggested that this is not true in all the cases. Especially with cell phone disruptions, it is way more detrimental than any other interruptions. However, people just love cell phones and they rank it as a better invention than the Internet [59]! But a ringing phone distracts one from an ongoing task and disrupts social situation [20]. Cell phone interruptions actually constitute in a loss of billions of dollars every year [46, 55]. The larger portion of the population that is used to cell phones is mostly the teenagers. But it has been shown that these young and fresh minds lose their effectiveness and cognitive advantages over elders just because of cell phone disruptions [56]. The reason is that an interruption causes a person to make twice the number of errors and uses up a significant percentage of more time to complete the task at hand [5]. Cell phone disruptions are also proving to be fatal. According to National Highway and Traffic Safety Administration, ten percent of the drivers are on the handheld or hands free cell phone on any given hour of the day [63]. This is dangerous as Harvard Center for Risk Analysis assesses that every year, 2600 people die of accidents due to cell phones and 330,000 people get injured [63]. These staggering numbers just speak for themselves how grave a mobile phone interruption can be.

Interruptions are rarely useful to a person who is engrossed in his/her current workflow. It has been assessed that an untimely interruption is harmful to immediate task and if we could schedule it for a future time, it greatly improves performance [2]. Therefore, interruption comes up with a cost. We can term this as the Cost of Interruption (COI). COI can be thought of as function of the user’s concentration level at the current task at hand and it returns a probabilistic value. If the returned value is on the high side, we should defer interruption, if it is on the lower side we let it through. Measuring COI is a research challenge along with how we interpret its output. An automated system can use sensors and find a probabilistic measure but that does not ensure that the output will actually be the outcome the user would prefer. For example, a person may be fully focused and does not want to get interrupted for any reason; but for one or two special people in her life, she is more than willing to take the call. This goes true for the reason of the call also. Hence, the measurement of COI and interpretation of its output involves uncertainty and ignorance. So we are using the Dempster-Shafer Theory of Evidence [13, 43] to calculate COI and its effective interpretation.

Practical Scenario

Let us talk about a few real life scenarios to emphasize the importance of interruption management. Our hypothetical user is Jessica who is a student graduating soon. She is also a marketing intern at an engineering firm. We are going to talk about a day when she has both her classes and work. To help create the scenario, we assume her work place and school are 20 miles apart. She drives a car to commute to both the places from her home.

In the morning, before she goes to school, she intentionally puts the phone into vibration mode. She does not want to get disturbed while she is driving. It is a usual school day, but later at work she has to present at work. Because the phone is in vibration mode, she keeps it on her desk. The first few classes go fine. During the last class, which is an important math course, the teacher is explaining a complicated theorem and all the students are really focused. At that moment Jessica’s phone vibrates and being on the desk it makes a very small noise. But it was loud enough to gather everyone else's attention. Even the teacher gets distracted. Jessica has an apologetic look on her face. So for a minute or so she does not do anything. It was a text message and in the back of her mind, Jessica was wondering who that might be. So after a while, while the class is still on, she picks up her phone and finds that her boss at work needed a simple clarification about the presentation she is supposed to give. Jessica replies and again puts the phone on her desk. This whole 3-4 minutes she was physically in the class but her mind got deviated from the context of the class. So she tries to refocus and try hard to understand what she has missed.

There are two important things to notice here. First, whenever we know we got a notification, we feel an urge to get to the bottom of that. Second, she could have replied after the class which ends in 20 minutes anyway and no harm would have been done. But still she replied and most of us behave the same way too.

Let us go back to our scenario and now we are adding up a new interruption. Jessica has already put the phone in silent mode because of previous embarrassment and was looking at her phone periodically anticipating a new text from her boss. Five minutes later, her phone blinks a light and Jessica knows she has got a text. This time she is almost certain that it is her boss. Wondering whether her clarification was good enough, she picks it up and finds that one of her friends wants to know if she would go out shopping after work. Jessica gets excited reading that and they keep texting each other the whole time until the class ends.

This is a scenario that tells us although the interruption was unnecessary in a way that it could have been dealt with later after class, but still Jessica liked it and kept going with it. She lost the valuable portion of the lecture which is very important for the upcoming exam.

Her school ends for the day and Jessica is in a hurry to go to her office. Before she leaves, she puts her phone on loud ring. While she is driving, Jessica gets a call. She tries to get it out of her purse while driving with one hand. On the freeway, while she was attempting to reach the phone, she gets slightly out of the lane and the car behind honks to alert her. Jessica realizes the mistake and gives up reaching for the phone up until she reaches the parking lot of her office.

Although nothing bad happened in this scenario, presumably that is not the case all the time. We already mentioned that a number of road accidents that occur due to cell phones are becoming more and more common.

At the office while Jessica is presenting, her friend again texts her to know whether Jessica will be able to pick her up from her house. Jessica forgot to put the phone in silent mode and now she looks really embarrassed. She apologizes and turns her cell phone off. But her boss becomes a bit annoyed at her and thinks she still needs to improve on her professionalism.

This scenario tells us that although usually we do remember what to do with the phone, humans tend to forget and that is exactly what happened to Jessica. Because she is looking for a job after graduation, this small incident could be detrimental to her career.

Jessica’s rest of the presentation goes well and she is happy. When she is returning home, her mom calls her for an important reason. But the phone being turned off, Jessica does not get to know about it up until she returns from shopping.

Sometimes interruptions are important. If the phone could somehow know Jessica's routine for the whole day and if it could behave in an intelligent manner, Jessica would certainly have had a better day.

We need to think about how we can improve our phone's capabilities with the current features. Most of today's phones are smartphones. They have a very good microphone that is capable of detecting surrounding noises. They contain a camera that can capture the ambient lights. Most of them have GPS enabled that can certainly know about the user's current location. Also, these phones can access a user's online calendar to know his schedule. Other capabilities include accelerometer, gyroscope, etc., which can certainly facilitate other important features.

Therefore, we have all the sensors necessary to detect the current state of the user. We just need some way to accumulate all these information and develop an interruption management system that will mitigate the flaws of cell phone interruptions.

CHAPTER 3: BACKGROUND

Context

In general, “context” encompasses a large number of bodies. We narrow it down to a finite number that will be fed into our model. Any interruption is considered welcoming or a disruption based on the time of its occurrence. Rather than portraying time itself as a context, we make it an independent variable upon which other contexts depend on. In a general form of presentation, we write interruption related context C_I as a function of time t i.e. $C_I(t)$.

To understand what users usually consider before picking up a call, we arranged a survey among 68 people. More than half (37) were working professionals, 19 junior and senior students, 9 graduate students and 3 faculty members. Instead of preparing generic contexts, we put specific ones that they consider as irritating feature of a call. We asked them to rate them on the scale of 1 to 10. We averaged the ratings and results are summarized in the histogram of Figure 1. We are not showing the contexts like mental state, workloads as their average ratings were below 5.

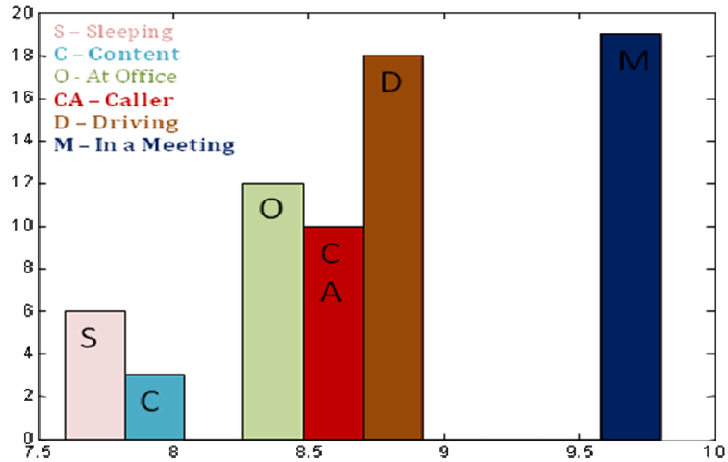

Figure 1: Histogram of user survey

After generalizing the contexts from the survey results, we have identified the following three important ones:

i) User's Location $C_L(t)$

ii) User's Schedule $C_S(t)$

iii) Interruption Feature $C_F(t)$

It is quite natural to find them as functions of time as well. To keep things concise, we term $C_I(t)$ as C_I.

Let S be a set of contexts, S = $\{C_L, C_S, C_F\}$

Then C_I ε any of the subset of S except for the null (Φ) set. The presence of any subset of S will give us the context for interruption.

Each of the three contexts C_L, C_S and C_F can be further broken down as shown in figure below.

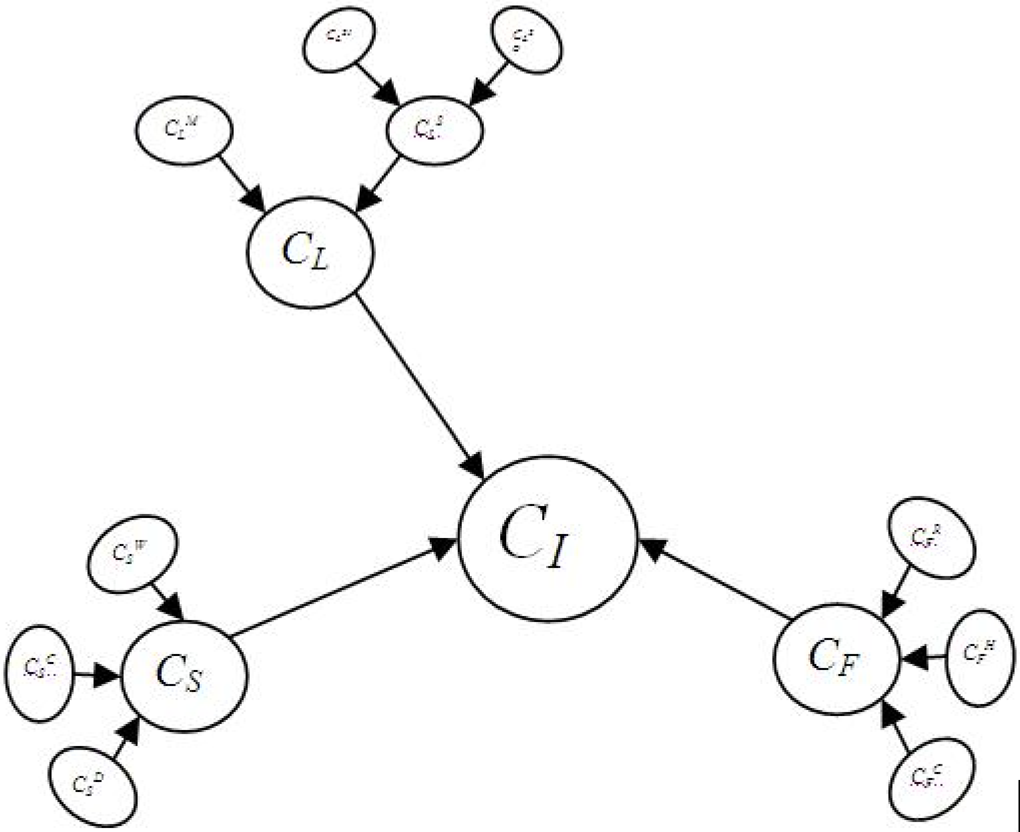

Figure 2: Contexts leading to decision

Context-Location (C_L)

Location can be classified into two major divisions:

i) In-Motion Location (C_L^M)

ii) Static Location (C_L^S). Static location is also branched out as Outdoor Static Location (C_L^{SO}) and Indoor Static Location (C_L^{SI}).

Context-Schedule (C_S)

User's schedule can be determined from using any sort of calendar info (C_S^C). In case of user not putting his/her schedule on anything, simple Day of Week (C_S^W) and/or Time of Day (C_S^D) could be used as this context.

Context-Interruption Feature (C_F)

Another important context from the user survey is the Interruption Feature. There are three constituents of this context:

i) Interrupter-User Relationship (C_F^R)

ii) Interaction History with the Interrupter (C_F^H)

iii) Interruption Content (C_F^C)

We use the above context information to build a model for calculating cost of interruption.

Cost Of Interruption (COI)

The Cost Of Interruption (COI) gives a probabilistic measure of how detrimental an interruption is to a user. If the Cost Of Interruption is low, the user may be willing to get interrupted, and if it is high, the user may not want to be interrupted. An intuitive approach to measure the Cost Of Interruption (COI) is to take the probabilistic measures of the contexts supporting the deference of the interruption and then take a weighted sum. So if *w(t)* is the weight function for the contexts then,

$$COI(t) = P(C_L(t)) * w_L(t) + P(C_S(t)) * w_S(t) + P(C_F(t)) * w_F(t)$$

Intuitively we also measure the individual probability of each context from a weighted sum of their branch probabilities e.g.

$$P(C_L) = P(C_L^M) * w_L^M + P(C_L^S) * w_L^S$$

Rather than measuring only the cost of interruption (COI), Grandhi and Jones measure the Predicted Interruption Value (PIV) [18]. Because some interruptions are actually for the user's own good, the authors show that PIV is a result of the cost along with the benefit evaluation of an interruption. We modified their model for PIV to make it fit into our own model with the new set of contexts.

$$PIV(t) = P(C_L(t) – B_L(t))*w_L(t) + P(C_S(t) – B_S(t))*w_S(t) + P(C_F(t) – B_F(t))*w_F(t)$$

Here *B(t)* and *w(t)* are the context specific interruption benefit and weight respectively.

Uncertainty

Uncertainty applies to the prediction of future events or unknown [21]. Uncertainty is classified into two types:

a) *Aleatory Uncertainty*: If random behavior is expected from the system, we then term this kind of uncertainty as Aleatory Uncertainty. It is also known as Objective Uncertainty or Stochastic Uncertainty.

b) *Epistemic Uncertainty*: When lack of knowledge about a system gives rise to some uncertain behavior, then we term it as Epistemic Uncertainty. It is also known as Subjective Uncertainty, State of Knowledge Uncertainty or Ignorance. Epistemic Uncertainty will be the focus of our attention for the interruption management.

Currently, traditional probability theory is used to deal with both kind of uncertainty. With frequentist approach, it works fine considering Aleatory Uncertainty. But in recent years, it has undergone some criticisms when it comes to dealing with Epistemic Uncertainty. The three main reasons that advocate the criticism are:

1. When all the information about the system i.e. all the a priori probabilities about the system are known, then traditional probability uses Bayesian Inference rule.

2. In absence of the a priori probabilities, it uses Uniform Distribution function justified by Laplace's Principle of Insufficient Reason [41].

3. An additional assumption is that all the probabilities that are specific to one particular property must add up to 1. This makes it feasible to know about the complement of an event when only the knowledge about the event is known.

To explain the factor of uncertainty, we now provide two examples. The first example [62] is about coin toss. If someone is given a "fair" coin and then asked about what is the probability of getting a head after a toss, the reply would be naturally 0.5. Now, if the person is not given any prior information about the coin i.e. no information about whether it is "biased" or "fair" and then with the same test his or her reply will be understandably 0.5 again. Because we are so used to use Laplace's Principle of Insufficient Reason that we cannot differentiate between knowledge or ignorance when assigning probability.

In another example [42], let's assume 3 components A, B and C can independently cause a system failure. Now an expert only on A knows A can cause the failure with probability of 0.3. Although having total ignorance about the other two components, the expert will assign probability of (1 – 0.3) / 2 = 0.35 to each of the other two. If another expert only on B knows B can cause the failure with 0.5, using traditional approach s/he will assign (1 – 0.5) / 2 = 0.25 probability to other two components. This gives rise to the conflicting probability assignments because of the partial knowledge about the system. Considering these conflicting situations, Dempster-Shafer approach is different from the traditional approach by : (i) considering the measure of probability as an interval or set, (ii) not looking for precise measurements, (iii) not imposing the principle of insufficient reason, and (iv) not applying the axiom of additivity.

Evidence

Evidence includes everything that can precisely determine or demonstrate the TRUTH of an assertion. Dempster-Shafer Theory is a theory of evidence and it looks at probability as a set. It mainly deals with four kinds of evidence [42]:

1. When evidences form like a tree structure i.e. when all the elements from a smaller set are included in the next larger set

2. When all the evidences have a common subset

3. When the evidences have some common subsets but not one particular for all of them

4. When none of them share any common element

Limitation of Bayesian

To explain the limitation of Bayesian Inference when dealing with uncertainty, let’s start with an example [10]. Suppose in a system, three sensors A, B and C are independently providing information about the consistency of another sensor X. If *P(X)* is the probability measure of X being a consistent sensor and e_A, e_B and e_C are the evidences from A, B and C respectively, then the conditional probability of X being consistent based on the evidences,

$$P(X \mid e_A, e_B, e_C) = [P(e_A, e_B, e_C \mid X) P(X)] / [P(e_A, e_B, e_C \mid X) P(X) + P(e_A, e_B, e_C \mid X') P(X')]$$

where X' denotes X is not consistent. Because all the evidences are independent, hence

$$P(e_A, e_B, e_C \mid X) = P(e_A \mid X) * P(e_B \mid X) * P(e_C \mid X)$$

So to find $P(X \mid e_A, e_B, e_C)$, we need to know all the a priori and conditional probabilities. It shows the limitation of Bayesian Inference clearly as:

1. Bayesian approach requires the complete knowledge of the system with all the a priori and conditional probabilities. But in practical scenarios, they are very hard to determine beforehand.

2. Empirical data or Uniform distribution is traditionally used to measure the a priori probabilities. Outcomes also reflect these assumptions. Hence, this method is not at all equipped to handle the state of ignorance effectively.

Dempster-Shafer Formalities

Dempster-Shafer uses three functions:

1. Basic Probability Assignment (bpa or m)
2. Belief Function
3. Plausibility Function

Basic Probability Assignment

If our universal set is S then bpa defines a mapping of the power set of S to the interval between 0 and 1. bpa of the null set is 0 and all other subsets' bpa add up to 1. So formally,

$m: power(S) \rightarrow [0, 1]$

$m(\Phi) = 0$

$\sum m(A) = 1$ *where the sum is over all subsets A of S*

Belief Function

Belief for a set A is defined as the sum of the bpa's of all the subsets of A.

$Bel(A) = \sum m(B)$ *where the sum is over all subsets B of A*

Plausibility Function

Plausibility of a set A is the sum of the bpas of all the sets B that share some common elements with A.

$Pls(A) = \sum m(B)$ *where the sum is over all subsets B of S such that* $B \cap A \neq \Phi$

Now if Â is the complement of A then we can derive,

$Pls(A) = 1 - Bel(\hat{A})$

So, from any of the given measures, *m(A), Bel(A)* or *Pls(A),* it is possible to derive the other two.

Dempster's Rule of Combination

To summarize the data that is coming from a single or multiple sources, aggregation of information is necessary. Examples of common aggregation techniques are: arithmetic, geometric and harmonic averages, maximum and minimum value, etc. From set perspective, there are mainly two types: Conjunction (AND – based on set intersection) and Disjunction (OR – based on set union).

Dempster's Rule of Combination [13, 43, 44] is based on three key points:

1. Belief and Plausibility are derived from combined bpa's

2. Multiple Belief functions are combined through their m's

3. The rule of combination is purely a Conjunctive (AND) operation

The combination, referred to as joint m_{12}, is calculated as the aggregation of two bpa's m_1 and m_2 in the following way:

$m_{12}(\Phi) = 0$, *if* $A \neq \Phi$,

$m_{12}(A) = (\sum m_1(B)\, m_2(C))/(1 - K,)$ *where the sum is over all ordered pairs (B, C) of subsets of S such that* $B \cap C = A$,

and, $K = \sum m_1(B)\, m_2(C)$, *where the sum is over all ordered pairs (B, C) of disjoint subsets of S*

CHAPTER 4: RELATED WORKS

Our aim is to build a management system to control cell phone interruptions using sensors on the phone. When a call is made, the system decides all by itself whether it should or should not let the call go through. To do this, we need to measure the cost of an incoming call. The system will take various user states as parameters and return a probabilistic value between 0 and 1. A pervasive system deals with context scenarios which is a significant portion of our research. Hence, the survey of literature spans into areas related to COI, interruptions, context aware systems and of course, interruptions associated with mobile devices.

Cost Of Interruption (COI)

In 2004, Adamczyk and Bailey measured the effects of interruption in terms of task performance, emotional state and social attribution [1]. Their study suggests that relationship between interruption and task is crucial in certain conditions. It also aims to find the most suitable time to interrupt the user. Several researchers have addressed the issue of Cost Of Interruption [4, 29, 19]. Mark et al. measured the COI based on additional time required to reorient back to the primary task and mental stress brought upon the interruptee [35]. The authors suggest that COI differs for different individuals. The results show that openness to interruptions and quickness in handling them can lower the cost of disruption. Bailey and Iqbal approached interruption by measuring the value of delivering information against the cost of interrupting the primary task [4]. To compute COI, the authors used non task specific cues e.g. desktop activity, visual and acoustical analysis of the environment and user’s scheduled activity. To understand work load changes during task execution, the authors used pupil size. A user's pupil size increases due to the mental processing efforts and there is an upper bound on how much it can grow. Bailey showed that this could be a possible way to measure a user's mental stress [4]. Hence, it would be possible to decide whether interruption could be detrimental or a bit refreshing. The bottom line is to prevent interruption when COI is high, and do the opposite when it is low.

Researchers have built mathematical models that can measure the cost of interruption. Most of these approaches used the Bayesian Probability model [25, 26, 27, 49, 50]. But a shortcoming of these works has been that they have not taken into account the value of an interruption. Again, the decision to overrule interruption involves factors in uncertainty. Several factors may lead to uncertainty: unknown and variable number of contexts, absence of sensors to provide context data, inaccurate weight assignments, conflicting context outputs that measure the COI, little or no information available about the system beforehand, etc. The abovementioned research work did not shed any light on these matters either. Hence, our research differentiates by exploring uncertainty factor for managing interruption and by introducing a new mathematical model based on the Dempster-Shafer theory [13, 43].

Interruption Management

To manage interruption, first we need to specify the factors that make interruption a burden. Horvitz described a system that builds decision-theoretic models by asking users about their perceived interruptibility during a training phase [27]. Ho and Intille considered 11 factors that impact the perceived burden of interruption [24]. These are activity, emotional state and social engagement of the user, social expectation in a group environment, user's control over the device and task efficiency rate, importance of the message to the user, medium and frequency of interruption and, user's previous and future activities and also history and likelihood of responses. The authors further suggested that an exhaustive model of interruptibility should include a weighted sum of these factors.

Next, we need to use context aware services to manage interruption. Abundant body of literature has studied the issue of context management for personal computers [15, 28, 9]. Baladauf et al. presented a survey of context aware systems [6]. The typical contexts included are: location, time, day, and proximity. In relation to interruption management, several researchers have proposed other meaningful contexts. Petersen mentioned the challenges to face when pervasive computing becomes a reality and a part of our everyday life [38]. The authors discussed the problem of interruption in pervasive aware systems and identified different roles that software agents can play supporting it. Godbole and Smari considered three types of contexts to solve the interruption problem [17]. They considered interruptor-interruptee relationship, interruptor's context and interruption content such as relational context, interruptee's local environment factors e.g. place, people around as social context and, interruptee's cognitive level of involvement in tasks and interruption's effects on task performance as cognitive context.

A context aware system knows about its surroundings and can notify about various updates and reminders. Ziebart et al. analyzed the complexity to map these systems' outputs to everyday lives [52]. They also worked on to bridge this gap. In [11], context awareness is extended into the service oriented architecture. After configuration, a service oriented system is accessible to any sort of request and it also provides extensibility and scalability in the enterprise setting. In [33], interpersonal relationships in regard to data privacy preferences have been addressed. Automated preference control on mobile devices has been tackled in [7]. So far the road seems smooth for us to build an interruption management system.

Interruption with Mobile Devices

There have been several works on how to manage interruption at inopportune moments using smartphones. Yu et al. defined user preference, terminal capability, location, time, activity and so on as context dimensions for smartphones [51]. In [39], the authors suggested that an interruption technology adapting its response considering a person's feelings is likely to improve people's experience with that technology. Godbole and Smari surveyed the type and extent of desired information about the incoming cell phone call [17]. Their findings show that the desired information is highly unknown and often misattributed by the user. Guzman et al. studied the context information users consider when they make a call and also the context information they wish others consider when they receive a call [20]. The study shows that the key points are: Location, Time, Physical Ability, Social Availability, Task Status and Emotional Availability. In addition, the authors showed that some users do not even consider any of these issues whereas some others consider something else. In [48], the authors grouped the strategies for interruption management by filtering calls based on caller's identity, situation and time, and, status message sharing e.g. current location, activity etc. As users tackle interruption by taking some actions themselves, Toninelli et al. suggested that the intelligent system should monitor how the users act in different situations, learn from them and later take actions according to them [48].

To summarize the diverse areas that have been explored to build the basis of this thesis, here is a graphical presentation of the literature studied.

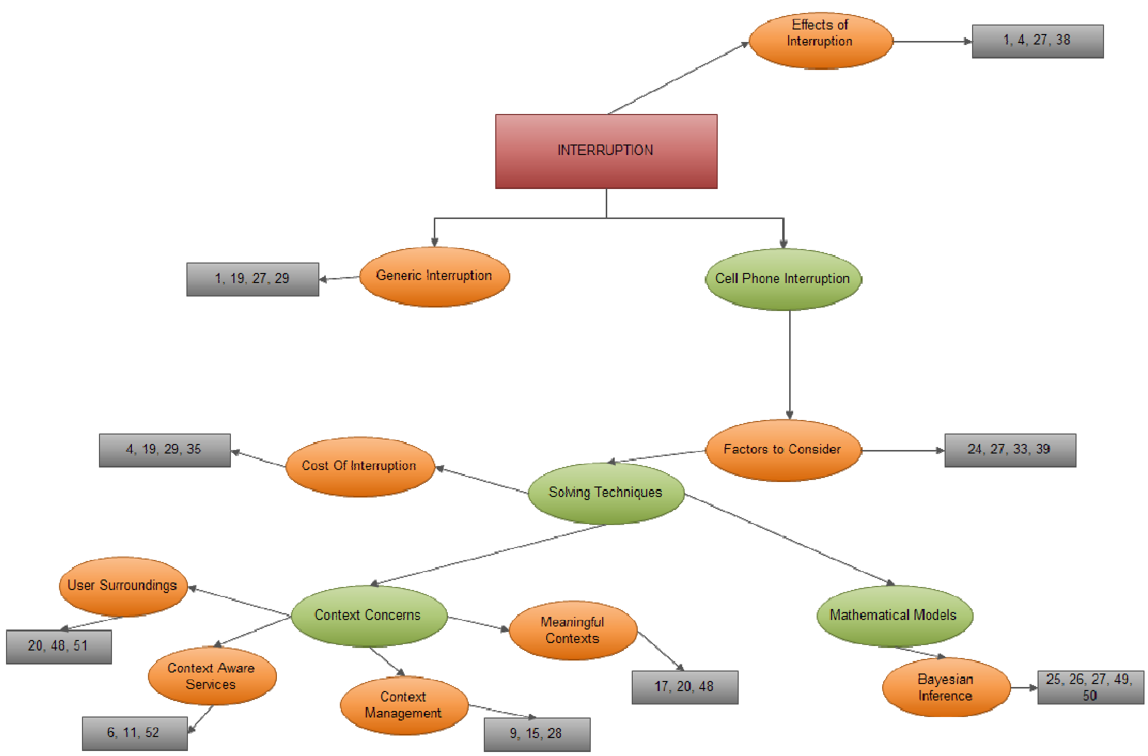

Figure 3: Exploration of different areas of Interruption

The tree above illustrates different sectors of interruption that needed to be looked into. First of all, it is imperative for us to know both beneficial and adverse effects of interruption. Then comes the types of interruption. We categorized them primarily into two parts: generic and cell phone related. Our focus was solely on to the smartphone related ones. Factors that make interruption a burden are the next issue. Then we searched for the techniques or ideas that tried to minimize the bad effects. We zoomed into the topic that could show the light at the end of the interruption tunnel, Cost Of Interruption. If we can measure the interruption effect by some sort of numerical value, it becomes easier to map it to a mathematical model. For this, we also had to research through the context horizon. Though this is a vast area of research in itself, we focused only on the context aware services and context management methodologies. From there, it was easy to find the meaningful contexts to consider for cell phone disruptions. Finally, we looked into the mathematical models that may be inadequate in fulfilling all the requirements, but give us a solid platform to work on for our desired model to attack mobile phone interruptions.

Now, to overview how this thesis differentiates from earlier works on the topic, here is a comparison table.

	Specify Factors & Contexts	Measure Cost of Interruption	**Consider Uncertainty Factor**	Build a Mathematical Model	Simulate & Evaluate	Prototype Application
Factors and Contexts [1, 6, 15, 33, 38, 39]	X					
Detriment-al Effects [4]	X	X				X
Cost Of Interrupti-	X	X			X	

on [6]						
Managem-ent Systems [19]	X	X		X		
Context Aware Approach [24]	X			X		
Attention Sensitive [25]				X	X	
Bayesian Approach [49, 50]		X		X	X	
This Thesis	X	X	**X**	X	X	X

Table 1: Comparison table

The above table compares this thesis with previous prominent works that have been done to tackle the same problem. Most of the earlier works delved into finding the factors and contexts to consider. A lot of them also put emphasis on finding the Cost of Interruption. A few of them provided models along with simulations and small applications. But none of them considered that solving interruption problem is a very difficult one due to a lot of uncertain factors. To our best of knowledge, this thesis is the first work to propose a mathematical model that considers the uncertainty factor to face the problem of interruption.

The aforementioned research works give us a solid basis for (i) which contexts need to be considered, and (ii) how to evaluate such contexts. However, the chief distinguishing aspects of this work are (i) Identifying specific contexts, (ii) Building a mathematical model, (iii) Developing a prototype application, (iv) Evaluating the system with simulation results and, (v) Showing how the solution is programmatically very cheap for cell phones.

CHAPTER 5: GENERIC FUNCTION

Different sensors provide different context information as a probabilistic measure. The system is supposed to combine these evidences to make a decision about interruption or non-interruption. But any of these probabilities might not be accurate or precise themselves and thus contribute unreliable evidence. So validity of the context information received from a sensor about a context is also an issue here.

There are several possible approaches we can use to combine the evidences to make a decision about interruption. One simple way is to average the evidences. But averaging ignores the fact that one context may be more important and/or more accurate than others. So without putting appropriate weights on the context values and taking simple averages may lead to erroneous results. Another probable way to go about is to use majority-decision rule. If most of the context values direct toward one outcome, we take that as the final outcome. But in real world, majority just may lead us to the completely wrong result. The Dempster-Shafer theory of evidence addresses this situation by representing uncertainty in the form of belief functions. The essential idea is that a sensor can obtain degrees of belief about a proposition from a related proposition's subjective probabilities. The theory's practical appeal is due largely to Dempster's rule for combining beliefs based on independent pieces of evidence.

Another common technique for combining evidences is to use Bayesian Inference approach. Suppose three sensors A, B and C provide evidences toward non-interruption. So the posteriori probability of Non-Interruption would be

*P(NI | A, B, C) = [P(A, B, C | NI) * P(NI)] / [P(A, B, C | NI) * P(NI) + P(A, B, C | I) * P(I)]* where *I* stands for interruption and P(I) stands for probability of interruption. As the sensors are conditionally independent of each other, then

*P(A, B, C | NI) = P(A | NI) * P(B | NI) * P(C | NI)*

Clearly, the Bayesian approach requires complete knowledge of both prior and conditional probabilities, but in practice this is very difficult to determine. Prior probabilities are usually estimated from empirical data or, in the absence of empirical data, uniform or some other distribution is used. These assumptions are obviously reflected in the outcomes, so critics often point out that Bayesian approach is not well equipped to handle states of ignorance.

Dempster's rule for combination is a process of combining independent pieces of evidences. Two basic probability assignments m_1 and m_2 provided over a common universe X, are combined by Dempster's rule of combination as a joint bpa, denoted by $m_1 \oplus m_2$ over the same universe. If A is the subset of X, then the combined weight

$$\sum_{A_1 \cap A_2 = A} m_1(A_1) * m_2(A_2)$$

This scheme indeed yields a bpa except for the fact that it may assign a non-zero weight to the empty set. Therefore the weight of the empty set is explicitly set to zero and all other weights are normalized by a factor of K^{-1} where

$$K = \sum_{A_1 \cap A_2 \neq \varphi} m_1(A_1) * m_2(A_2)$$

This scheme is generalized to an arbitrary number of bpas. Given a sequence of bpa's $m_1, m_2, \ldots, m_n$, their combination $m = \oplus_{i=1 \text{ to } n}$ is defined as

$m(\Phi) = 0$

for A $\neq \Phi$,

$m(A) = K^{-1} *$

$$\sum_{\cap_i A_i = A} m_1(A_1) * m_2(A_2) * \ldots * m_n(A_n)$$

where

$$K = \sum_{\cap_i A_i \neq \varphi} m_1(A_1) * m_2(A_2) * \ldots * m_n(A_n)$$

Dempster's rule is extended in the following way. The combination of two belief functions Bel_1 and Bel_2, determined by bpa's m_1 and m_2, is defined as

$(Bel_1 \oplus Bel_2)(A) =$

$$\sum_{B \subseteq A} (m_1 \oplus \mathrm{m}_2)(B)$$

We can thus combine more than two belief functions (pair wise) in any order.

Let's see how this generic equation can be used in calculating COI. For each sensor, we have three hypotheses: No-Interrupt (NI), Interrupt (I) and Either Interrupt or No-Interrupt (U). Suppose the probability of sensor A being accurate is α. If sensor A directs toward non-interruption, then the basic probability assignments will be

$m_1(NI) = \alpha$

$m_1(I) = 0$

$m_1(U) = 1 - \alpha$

If sensor A directs toward interruption then the assignments become

$m_1(I) = \alpha$

$m_1(NI) = 0$

$m_1(U) = 1 - \alpha$

Suppose we have n sensors operating. For a second sensor B, we could construct the basic probability assignments m_2 the similar way. We can combine these by using Dempster's rule of combination, $Bel(NI) = m(NI) = m_1(NI) \oplus m_2(NI)$. Because the result will also give us a bpa, for next argument we will combine them similar way. We will keep combining (pair wise) until the number of sensor data is exhausted.

The combination of m_1 and m_2 gives us

$m_1(NI) \oplus m_2(NI) = 1/K * [m_1(NI) * m_2(NI) + m_1(NI) * m_2(U) + m_1(U) * m_2(NI)]$

$m_1(I) \oplus m_2(I) = 1/K * [m_1(I) * m_2(I) + m_1(I) * m_2(U) + m_1(U) * m_2(I)]$

$m_1(U) \oplus m_2(U) = 1/K * m_1(U) * m_2(U)$

where $K = m_1(NI) * m_2(NI) + m_1(NI) * m_2(U) + m_1(U) * m_2(NI) + m_1(I) * m_2(I) + m_1(I) * m_2(U) + m_1(U) * m_2(I) + m_1(U) * m_2(U)$

We can similarly combine the result with m_3, the next result with m_4 and so on up to m_n.

To weigh and combine A and B's direction toward Non-Interruption, Dempster-Shafer must know the probability of A and B being accurate. If we compare this with Bayesian, it would require the prior probability of *P(NI)* when there is no evidence present and also all the conditional probabilities. So Bayesian looks for much more information which is almost non-existent in our context.

In our interruption management system, we are dealing with specific contexts: Location (C_L), Schedule (C_S) and Interruption Feature (C_F). If U stands for either interruption or non-interruption then,

$m_1(NI) = P(C_L)$ $\quad$ $m_1(I) = P(C_L')$ $\quad$ $m_1(U) = 0$

$m_2(NI) = P(C_S)$ $\quad$ $m_2(I) = P(C_S')$ $\quad$ $m_2(U) = 0$

$m_3(NI) = P(C_F)$ $m_3(I) = P(C_F')$ $m_3(U) = 0$

Again,

$m_1(NI) \oplus m_2(NI) = P(NI_{LS})$

$m_1(I) \oplus m_2(I) = P(I_{LS})$

$m_1(NI) \oplus m_2(NI) \oplus m_3(NI) = P(NI_{LSF})$

$m_1(I) \oplus m_2(I) \oplus m_3(I) = P(I_{LSF})$

So if we consider combining Location and Schedule contexts first, then K becomes,

$K = P(C_L) * P(C_F) + P(C_L') * P(C_F')$

$P(NI_{LS}) = 1/K * P(C_L) * P(C_F)$

$P(I_{LS}) = 1/K * P(C_L') * P(C_F')$

With these values if we combine the values for Interruption Feature context, then we come up with the final outcome of probability of non-interruption using all the contexts, $P(NI_{LSF})$. Interesting thing to notice here is $P(NI_{LS}) = 1 – P(I_{LS})$ and final outcome $P(NI_{LSF}) = 1 - P(I_{LSF})$. So only calculating either the probability of non-interruption or probability of interruption is necessary. The values can be derived from each other. Also, the other most important thing is, although we deviated from the traditional probabilistic measures slightly in dealing with uncertainty, the final outcome definitely follows traditional probabilistic rule.

So the final question is how we interpret our results. The approach taken here is

If $P(NI) > P(I)$:	No Interruption
Else:	Interrupt

Now, let me put the whole calculation in a programmatic way. Here, the function will take a context array as an input. It will return the probabilistic context value as its output. The intermediate value of each iteration will be saved in a temporary variable.

```
decimal MeasureCOI(decimal arrayContext[])
{
      //temporary storage for intermediate value
      decimal temp = 0;

      for int i = 1 to length(arrayContext) - 1
      {
            decimal k;

            //consider two context values at a time (one of them
            is the //value gathered from previous iteration)

            //for first iteration, pick the first two contexts
            instead //of the temp. Because there's no temp for
            the first //iteration
            if i == 1 then
                  a = arrayContext[i];
            else
                  a = temp;

            b = arrayContext[i + 1];

            //calculate the normalizing factor
            k = a * b + (1 - a) * (1 - b);

            //finally calculate COI for these two values
            temp =  (1/k) * a * b;
      }

      //return the outcome after all the contexts is exhausted
      return temp;
}
```

The system will be put on a cell phone with low computational power and limited memory storage. So the system requires to be efficient computationally and miserly regarding resource usage. Therefore, the system needs to bear the following properties:

- **Decisive**

In most cases, the system should be able to produce a result that is decisive whether or not to let a call go through. A value that lies in the middle around 0.5 has a very high chance of producing a wrong result. On the other hand, a probabilistic value, that is either low or high, generates a better decision making output.

- **Scalable**

The system should not be constrained only to a fixed number of inputs. Inputs can vary from the number of contexts to various combinations of fixed contexts.

- **Computationally Efficient**

As the system will be taking decisions when a call comes in, it needs to take the decision in a fraction of a second. This is a highly desired property that must be met.

- **Requires Small Storage**

The system needs to fit on a cell phone. The system itself should not consume more than a few kilobytes. Again, the memory space it will be using should be very low.

The system should be able to meet the criteria described above. Otherwise, it will lack what an ideal cell phone system should be.

CHAPTER 6: AN ILLUSTRATIVE EXAMPLE

Here we provide a case study of a sample application where a corporate sends all its sales employees performance metrics each hour. These metrics represent their manufacturing, marketing, sales, customer response and the employee's current rank compared to their peers. The institution uses it to make its sales force competitive within the company and also in regard to its competitors. Each sales person has a designated work area and each of them carry a mobile device for office notifications only. The management plans to force its sales personnel to acknowledge the notification with some feedback within 20 minutes of receiving it. Their idea is to stay up to date on an hourly basis. Although most of the sales staff works outdoors, some of them work indoors and they are mostly in the positions of managers. Now even though a sales person may be in his/her work area, s/he might be busy in a meeting with the customers or briefing his/her supervisor. Whenever the sales person is in some scheduled event the management does not want to send the metrics. The company is looking for an automated system that will take all the factors into consideration before popping up a notification. Here we apply the context based Dempster-Shafer theory to this example.

The notification problem is entirely context dependent. It is intuitive to see how our classification of context from Section II falls into this model. First of all, the role of the interruption feature (C_F) context is negligible here because we can presume every notification to be of high importance. So we leave that out for any consideration.

The other two contexts, Location (C_L) and Schedule (C_S) play the significant role here. The mobile device each employee carries has a built in GPS. It can correctly specify an employee's current location at any given time only if s/he is out on the streets but fails to provide a precise location in case of working indoor. The device can certainly remember the last detected location and hence provide us with a probabilistic idea of the employee's whereabouts. It is also a company policy following highway safety rule not to interrupt the employee when s/he is in motion i.e. driving.

The system on the mobile device can look at the employee's calendar for the schedule of events for the day e.g. a meeting with a prospective or existing customer. The management mentioned that these events may start on time but hardly finish right on schedule. According to their observations, almost 60% of the time they go for 20-30 minutes extra and 27% of the time 10 minutes or less. Again, it is the company's policy to consider the 15 minutes period before these events as meeting preparation time for the employee. Hence, void entry in the calendar at a particular moment does not necessarily mean it is okay to interrupt the person.

The system needs to decide whether to interrupt or not based on aforementioned context data. Let's consider a situation where the system detected the employee's location 1 hour ago and the points of interests in the 2 mile radius of that location include an existing customer office. There are also nice lunch places situated in the vicinity. Again, according to his/her calendar entry, the employee is supposed to be out from a meeting half an hour ago. To keep brevity of the things, we now denote the probability of a context as the probability of a context in against of a notification. So a high probability outcome will mean not to make any disruption.

A $P(C_L) = 0.8$ gives a high probability of employee being busy but a moderate $P(C_S) = 0.4$ denotes the employee may be eligible to receive the notification. This is a perfect conflicting scenario to apply Dempster-Shafer theory. If we prefer to go with the location context, then the probability of Non-Interruption based on Location $P(NI_L)$ becomes

$$P(NI_L) = [P(C_L) * P(C_S')] / [1 – (P(C_L) * P(C_S))]$$

$$= [(0.8) * (0.6)] / [1 – (0.8) * (0.4)] \approx 0.7$$

Here, $P(C_S')$ is simply the complement of the probability $P(C_S)$.

So C_L puts a high 0.7 degrees of belief toward not interrupting. Likewise, if we go with the schedule context, the probability of non-interruption based on schedule becomes

$$P(NI_S) = [(0.4) * (0.2)] / [1 – (0.4) * (0.8)] \approx 0.1$$

This suggests a low degree of belief toward non-interruption or a high degree of belief toward interruption. The probability that we cannot interrupt based on neither of these contexts, $P(NI_O)$ is

$$P(NI_O) = 1 – (0.7 + 0.1) = 0.2$$

This value is inside the range of 0.1 and 0.7. So the bound Dempster-Shafer Theory puts on no-interruption scenario here is *[0.1 0.7]* instead of traditional probability bound of *[0 1]*.

Now if we put weights on these probabilistic measures of context outcomes, we use the just deduced Dempster-Shafer bound and take a weighted average, it leads us to a more accurate decision of whether or not to interrupt. So, the probability of Non-Interruption $P(NI)$ becomes,

$$P(NI) = [P(NI_L) * w_L + P(NI_S) * w_S] / (w_L + w_S)$$

where w is the weight of the different contexts providing information about non-interruption. Note that we have left out $P(NI_O)$ from our consideration, because we do not know the weight of this and in this uncertain scenario Dempster-Shafer just uses the upper and lower bound only.

CHAPTER 7: PROTOTYPE APPLICATION

Here we provide a case study implementation where a company (anonymous for privacy reasons) wants to send all its sales employees performance metrics each hour. These metrics represent their production, sales and the employee's current rank compared to others. They use it to make their sales force competitive within the company. Each sales person has an area specified as their work area and the company wants to send the metrics to a sales person whenever they are in the work area. Some sales people work indoors and they are mostly in the positions of managers. Now even though a sales person may be in his/her work area, s/he might be busy in a meeting with their superiors. Whenever the sales person is in some scheduled event the company does not want to send the metrics to him/her. Based on these requirements, we developed the prototype application. Whenever the sales person is in their designated area, not busy in a scheduled event and also when the time is between their work hours, we show the metrics on the device. But when any of the cases fail, we do not show him/her the metrics.

Implementation

For now, the prototype is developed on the Android, the operating system of a new class of smartphones which was designed primarily at Google in participation with the Open Handset Alliance. The reason for choosing Android is that it is open sourced. Most importantly when there is no call (in this case when no data is sent from the server); our application can run as a background process using minimal CPU or battery resources. The application needs to be installed in the receiver phone and Android is the only platform that allows full control of the ringer actions i.e. the interrupter. In the future, we also plan to implement it on other platforms as well. For the prototype, we used three contexts: location, schedule, and interruption feature. We used Google Calendar as our scheduler. The assumption is that whoever uses the system will have some sort of scheduler where the application can query into. To find the location, we used the GPS service provided by Google. So it had to be a smartphone. Some mock data have been used to setup the interruption feature context i.e. the importance of this interruption. Now we show step by step screen shots to explain how our application is working.

First, we need to gather the location information of the user. Figure 4 shows the pinpointed location of the user for the last one hour.

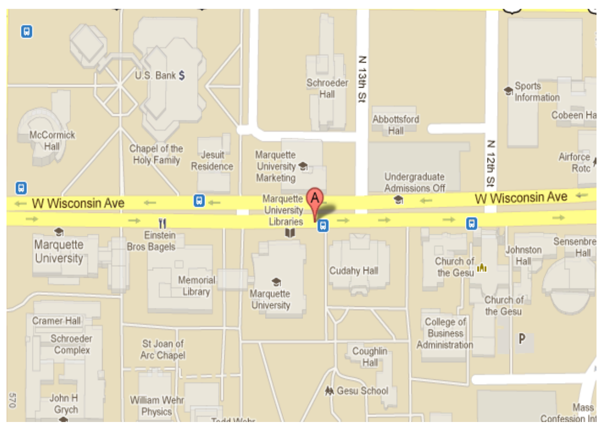

Figure 4: Get location data

Next context on the list is to collect the schedule of the user at a certain time. Different calendars can be used to retrieve this information. For this application, we used the Google calendar that is associated with the phone. Figure 5 gives a sample look at the calendar at a specific time.

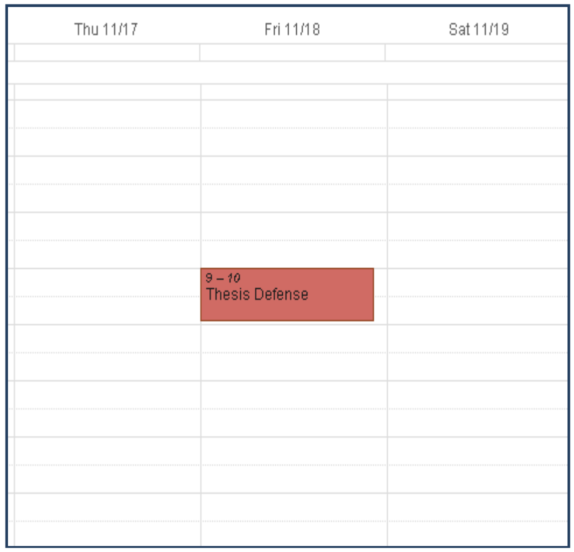

Figure 5: Get schedule information

The last context that needed to be figured out is the caller importance. The application looks at the call log for last seven days and sees how many calls have been made to the caller and how many have been received. Based on this information, it determines the caller importance when the call comes in.

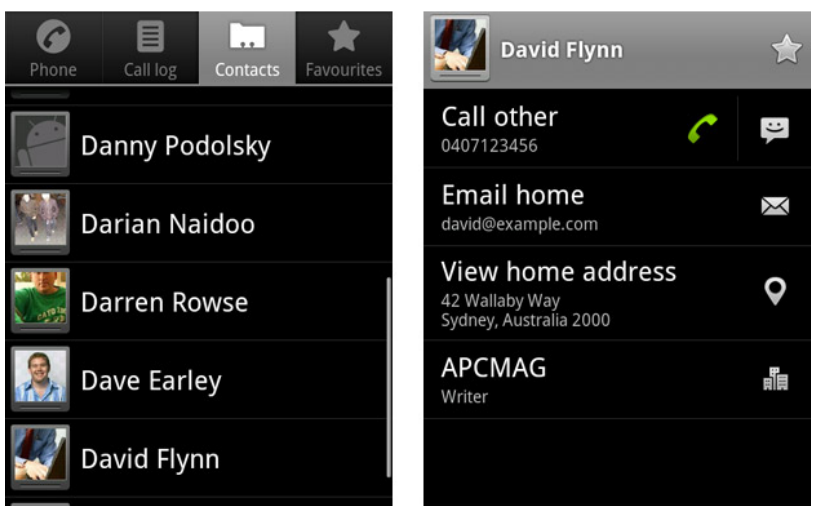

Figure 6: Get caller importance

Now we have got all the context information that will be placed into the model as inputs. But this information needs to be put in such a way that it is represented as some probability value. For this, we will use an external server to send us the values. For now, we made some educated guesses and put probabilities accordingly.

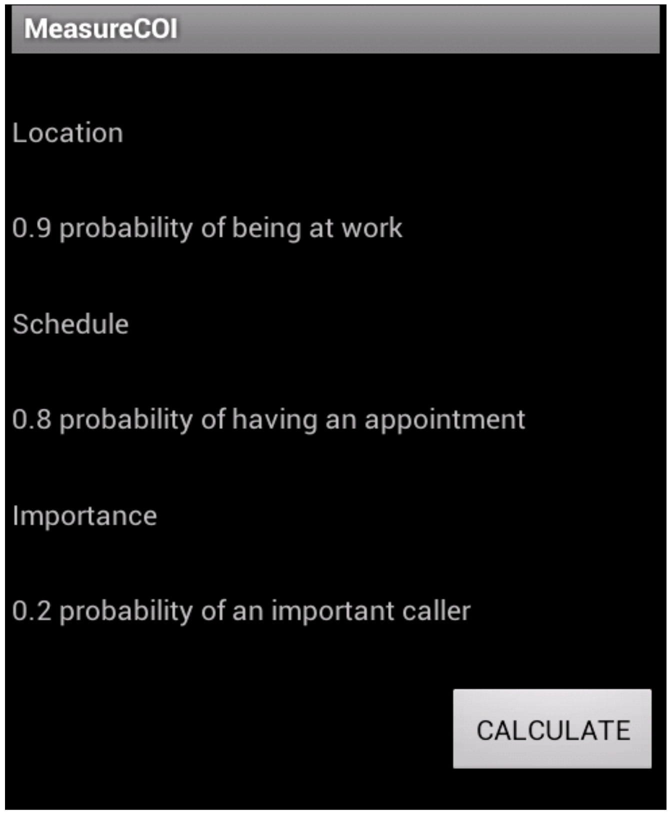

Figure 7: Summary of the contexts

The figure above shows a summary of the contexts the system is going to consider before making a decision. The first context it considers is the location. The probability of the user to be at work is interpreted as 0.9 which is a considerably high probability. The next one is the schedule context. From user's calendar information, the interpreted probabilistic value for the user meeting an appointment is 0.8. Again, another high value comes up that would suggest no disturbance. The last one is the interruption feature context. Here, the importance of this call is set to a very low value of 0.2. When you hit the CALCULATE button, the following screen pops up.

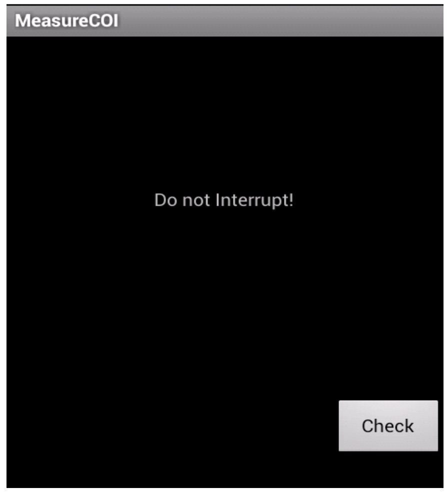

Figure 8: Interruption Decision

The result of non-interruption looks to be a valid output. Two thirds of the inputs were suggesting no interruption and the model behaved exactly the same way. The inputs went through the Dempster-Shafer roller coaster, so to speak, and produced an output which is understandably a correct one.

Figure 9: Interruption Feedback

Finally, the application seeks user feedback. The phone stores all the inputs and also the customer response about the accuracy of the application output. For each “No”, the system will store these values. Next time, when it encounters a similar situation and if the result is hovering around the middle, it will simply do the opposite of what it did before.

Cognitive Walkthrough

To get the proper assessment of our application, we used the cognitive walkthrough strategy. We did a survey on a group of 13 people on the usability and usefulness of the application. First we explained the problem, briefly went over some of the issues addressed in this thesis and then showed the prototype application demo. The distribution of the participants is as follows: 4 graduate students, 7 employees in an organization and 2 pedestrians.

Five questions about the application were handed out to each participant and requested them to answer them on a scale of 1 to 5. The questionnaire for the survey is given below:

1. Overall, how do you rate this application for the service it is providing? (*1 = Very Poor*, *5 = Excellent*)
2. How do you rate the effectiveness of the application? (*1 = Very Poor, 5 = Excellent*)
3. How much user friendly you think the application is? (*1 = Very Poor, 5 = Excellent*)
4. Will you pay to use this application? (*1 = Definitely Not*, *5 = Definitely Yes*)
5. Would you recommend this application to a friend? (*1 = Surely Not*, *5 = Surely Yes*)

The survey results are shown in a chart below:

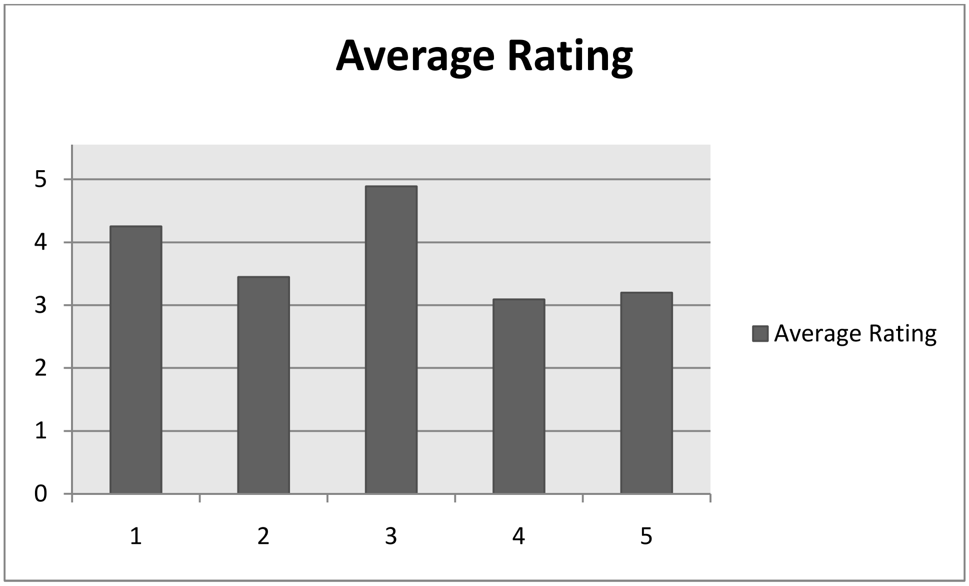

Figure 10: Histogram from the survey

From the graph, it is evident that participants were enthusiastic about the application and its usability. Although the willingness to pay for this application got the worst number, the other questions have achieved good and positive responses. The ease of use and effectively solid application show us how grave the problem of interruption is, and what we have done to get rid of it.

CHAPTER 8: SIMULATION & EVALUATION

Simulation

Example 1

Suppose $P(C_L) = 0.9$, $P(C_S) = 0.8$ *and* $P(C_F) = 0.2$. This is a perfectly conflicting scenario with two of the values suggesting strongly toward non-interruption whereas another one is very strong in suggesting an interruption. So we apply Dempster-Shafer to this scenario. Combining the values for Location and Schedule gives $P(NI_{LS}) = 0.9730$. This is a very high value suggesting no interruption. Now let's combine with the third one, interruption Feature. This gives $P(NI_{LSF}) = 0.9001$. This is also a very high value suggesting no interruption. So Dempster-Shafer in this scenario has discounted the value for interruption Feature context because of having high amount of uncertainty.

The calculation (see appendix) is a mere implementation of the function *MeasureCOI* described in the previous section. Here, there are only three contexts. So, instead of putting them in an array, we have kept them separately in three distinct variables (*l, s, f*). *MeasureCOI* takes two contexts at a time, calculates their normalizing factor and measures the probability of non-interruption using only these two contexts. In its next step, it uses this result to be fed as a new context that is combined with the next one from the array. In the example, we only had three contexts; that means there was only one intermediate value. So, instead of running a loop, we put both those instructions separately with second one using the intermediate value from the combination of the first two contexts.

Example 2

Let's consider the situation in a different way. If all the parameters stay the same way but we put higher weight on Interruption Feature context and relatively low on the other two, the calculation (see appendix) gives us a totally different result.

In this situation, although two higher probabilities indicated no-interruption, higher weight on the third one actually indicates an interruption.

For different $P(C_L)$, $P(C_S)$ and $P(C_F)$:

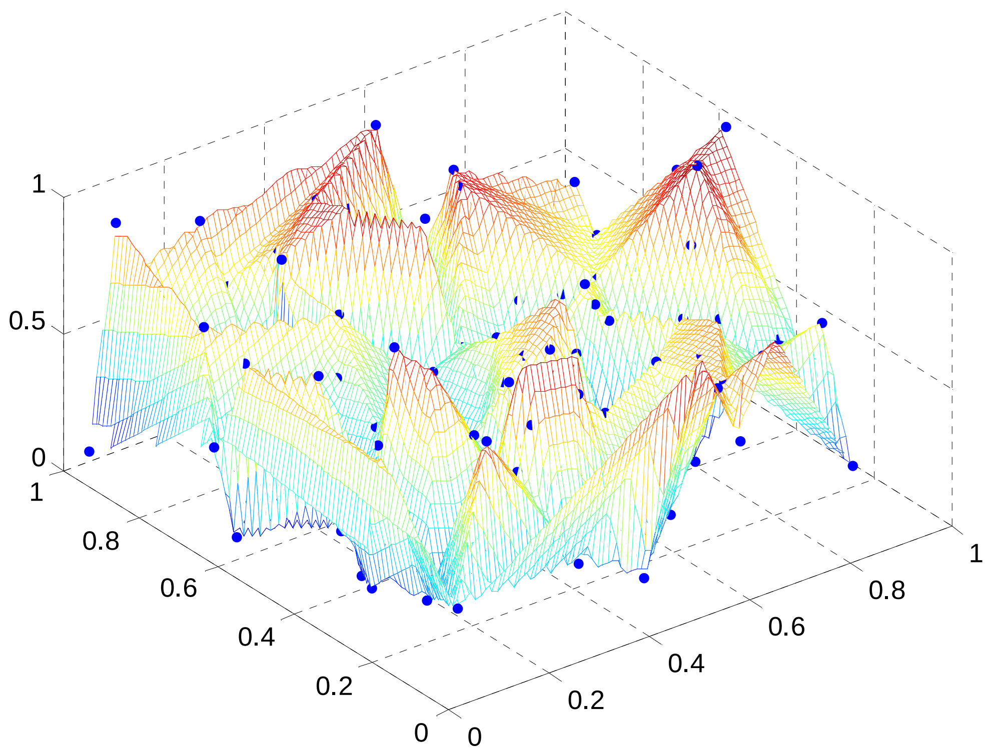

Figure 11: Data in 3D space

Here we generated three random numbers from the uniform distribution 100 times. So there were 100 different combinations of three context probabilities for simulation. The figure above clearly shows how the data was distributed throughout 0 to 1 and how the combinations were dispersed through the entire region.

The first task is to take the average of the above highly dispersed combinations of data. When the averages were taken and plotted, it came up as a very close normally distributed graph. This was expected though. When the sample space is large and the values are taken randomly, the averages always take up to the normal curve. This means more conglomerations around the middle zones and less on the boundaries.

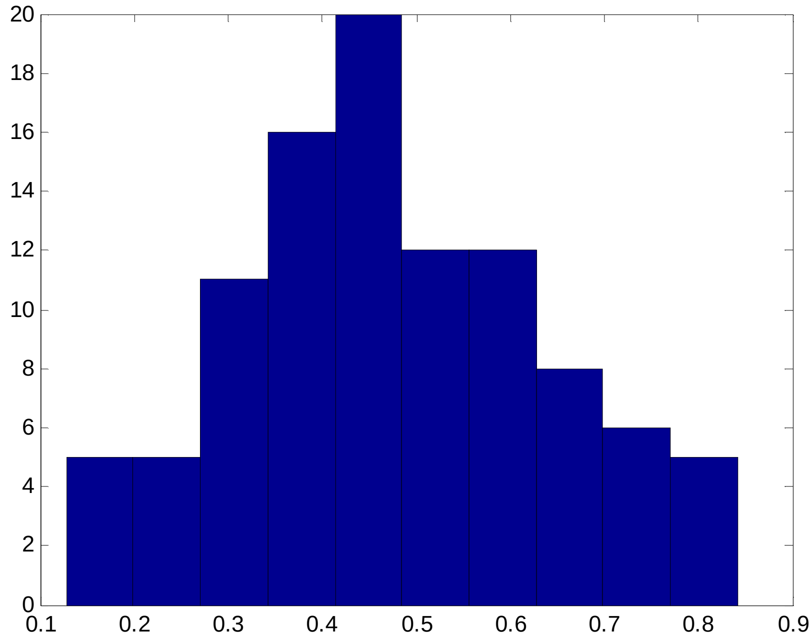

Figure 12: Histogram after taking averages

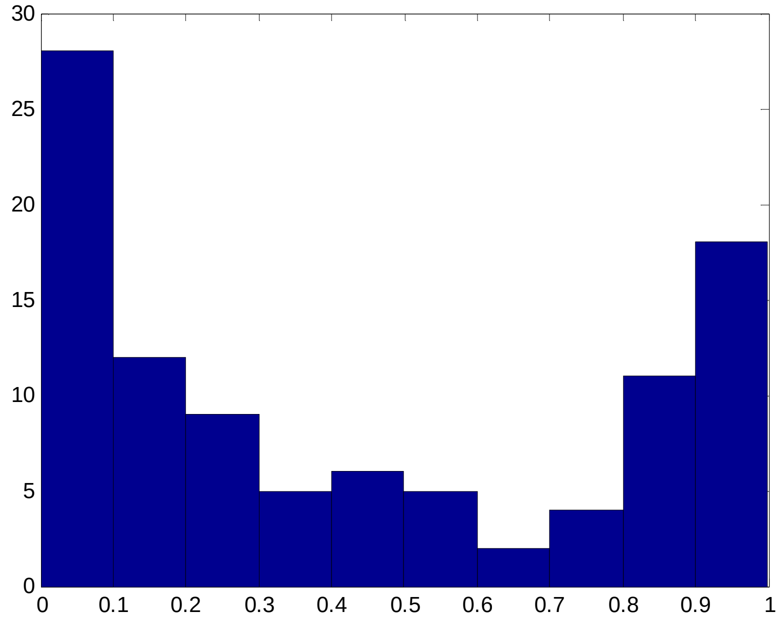

Figure 13: Histogram after applying Dempster-Shafer

Now, the same data was applied to the Dempster-Shafer Rule of Combination. To our surprise, this came up quite different than the previous one. It is almost like the upside down version of the previous graph. But, the result is what we have been longing for; some model that does not hover around the middle, but provide solid results that lie in the boundary to let us make easy decisions. See appendix for the source code to draw the graphs.

Discussion

The graph is almost the opposite of normal graph, where the middle portion has lesser values and higher values are on the boundary. So it helps to take decisions very precisely in most of the cases. Unlike averages, this obviously provides us with a better solution. So clearly Dempster-Shafer helps us find a decision better because it provides outputs in the boundaries.

Evaluation

Our model based on Dempster-Shafer has some positive properties. They are stated below.

- **Decisive**
  - As you can see from the Dempster graph, it’s almost opposite of the Average one. This is good for us, because traditional probability always hover around in the middle part (e.g. normal distribution) which makes it really difficult to take a decision.
  - On the other hand, Dempster’s graph is well poised on the boundary, i.e. most part of it lies on the extremes. So in most cases, it will be easier to take decision from it.
- **Scalable**
  - The solution considers only two contexts at once to get a combined probability. With that it combines the next one and it goes on like that until all the contexts are exhausted. So this system is very scalable without any doubt.
  - In our simulation, we applied a large number of different combinations to see how it behaves. The solution worked very well and generated a

result in no time for each combination. So even in that sense, it is scalable.

- **Convergent**
  - The graph also shows that the method converges to a result most of the time. We applied a large data set and for a very few it was hovering in the middle.
- **Time Complexity**
  - The time complexity of the solution is *O(n).* Here is the reason: For each iteration, the solution only takes two contexts and applies single instructions. Then pairs the result with the next context probability. So for *n* contexts the loop runs for *n-1* times. So the time complexity should be *O(n-1)* or *O(n)* which is considerably small and well suited for cell phone programming.
- **Computationally Efficient**
  - It is evident from the time complexity that the system is not computationally heavy at all. It will be able to take the decision in a mere fraction of a second.
- **Requires Low Storage**
  - The system only stores the context array elements temporarily. It also keeps intermediate result of the two contexts combined to be used as an input to the next iteration. After the decision is made, these values

need not be kept in the storage. So the system will not keep any data on the memory or save anything that will cramp up the memory.

The system meets all the properties we mentioned in the previous section as requirements. Overall, it is perfectly fit for a cell phone.

CHAPTER 9: CONCLUSION

In this thesis, we have proposed a mathematical model for calculating the cost of interruption. We have addressed the uncertainty factor that is associated with cell phone disruptions. To our best of knowledge, this is the first time the state of ignorance for interruptions has been taken into consideration. We have incorporated the Dempster-Shafer theory of evidence into the model to attack this issue. The model has been applied to a prototype application with success. Simulation results show that with different and diverse combinations, the model gives quick and decisive answers. So, the contributions of this thesis are as follows:

- Specific context identification
- Pioneered in addressing the uncertainty factor
- Introduced the Dempster-Shafer Theory of Evidence in this area of research
- Developed a prototype application
- Successful system evaluation with simulation

Untimely interruptions have caused major headaches from the realm of professionalism to day to day life. The irritating nature of a mistimed call is not welcomed at all. But to find the remedy, we cannot just throw away our cell phones. It has become a commodity that we keep with us all the time. So, we needed some way to make it work for us, rather than irritate us. As we have already discussed, it is tremendously hard to judge when and where a call can ring. The issues revolving around this problem are highly complex and somewhat unpredictable in nature. That is why the Dempster-Shafer Theory of Evidence has been used to model the solution to get rid of the uncertainty factor. The results of the model show great improvement in tackling the problem.

We previously implemented a middleware on HTC G1 for the Android platform [54]. To build better and more accurate interruption management systems, we are now working on implementing the full scale operating application described in this thesis. But there are other things still need to be explored here. We need to figure out the probabilities that have been assigned to fit into the model. These probabilities vary for different users and situations. The full scale application will need to have a small database that contains the user feedbacks. So, each time it makes a decision, it needs to update the data storage depending on user's response. Hence, the application will be a self-learning mechanism that will get customized for each user on its own in a small period of time. Furthermore, we will undertake simulations to have a better understanding of how this model performs in comparison with other models using Bayesian. In addition, we are planning to build the application for all the different mobile platforms. Right now the focus is only on the Android platform, but shortly in future, this will be available in iPhone and Blackberry. We would also like to look into different application domains from cell phones to instant messaging, email clients, and social networking. These are some areas which operate by interrupting a user and we plan to associate uncertainty factor to them so that the cost of interruption is kept to a minimum. If a similar model can be applied some of these areas with success, then this model will definitely have a great value in the real world.

BIBLIOGRAPHY

1. Adamczyk, P. D. and Bailey B.P., "*If not now, when? the effects of interruption at different moments within task execution*", in proceedings of the SIGCHI Conference on Human Factors in Computing Systems, 2004, pp. 271-278.

2. Adamczyk P. D., Iqbal S. T. and Bailey, B. P., "*A method, system, and tools for intelligent interruption management*", in the 4th international workshop on Task Models and Diagrams, 2005, pp. 123-126.

3. Ahamed, S. I., Sharmin, M., and Ahmed, S., "*A Risk-aware Trust Based Secure Resource Discovery (RTSRD) Model for Pervasive Computing*", In Proceedings of the Sixth Annual IEEE international Conference on Pervasive Computing and Communications, 2008, pp. 590-595.

4. Bailey B. P. and Iqbal S. T., "Understanding changes in mental workload during execution of goal-directed tasks and its application for interruption management", ACM Trans. Comput.-Hum. Interact. 14, 4, 2008, pp. 1-28.

5. Bailey, B.P., and Konstan, J.A., "*On the need for attention aware systems: Measuring effects of interruption on task performance, error rate, and affective state*", Journal of Computers in Human Behavior, Vol.22, No.4, 2006, pp. 709–732.

6. Baldauf, M., Dustdar, S. and Rosenberg, F., "*A Survey on Context Aware Systems*", International Journal of Ad Hoc and Ubiquitous Computing, Vol. 2, No. 4, 2007, pp. 263-277.

7. Bayley, C., Jernigan, C., Lin, J., Shu, J. and Wright, C., "*Talk Android, http://www.talkandroid.com/android-forums/android-market-reviews/495-locale.html*, 2008.

8. Begole J., Matsakis N. E. and Tang J. C., "*Lilsys: Sensing Unavailability*", in ACM Conference on Computer Supported Cooperative Work, 2004, pp. 511-514.

9. Brown, P.J., "*The Stick-e Document: a framework for creating context-aware applications*", In Electronic Publishing, Palo Alto, 1996.

10. Chen T. M. and Venkataramanan V., "*Dempster-Shafer Theory for intrusion detection in ad hoc networks*", In IEEE Internet Computing, 9(6), 2005, pp. 35–41.

11. Conlan, O., Power, R., Higel, S., O'Sullivan, D., and Barrett, K., "*Next generation context aware adaptive services*", In Proceedings of the 1st international Symposium on information and Communication Technologies, 2003, pp. 205-212.

12. Dekel A., Nacht D. and Kirkpatrick S., "*Minimizing mobile phone disruption via smart profile management*", in the 11th international Conference on Human-Computer interaction with Mobile Devices and Services, 2009, pp. 1-5.

13. Dempster, A. P., “*Upper and Lower Probabilities Induced by a Multivalued Mapping*”, The Annals of Statistics 28, 1967, pp. 325-339.

14. Dey, A. K., “*Enabling the use of context in interactive applications*”, In CHI '00 Extended Abstracts on Human Factors in Computing Systems, 2000, pp. 79-80.

15. Dey, A.K., Salber, D. and Abowd,G.D., “*A Conceptual Framework and a Toolkit for Supporting the Rapid Prototyping of Context-Aware Applications*”, In the Human-Computer Interaction (HCI) Journal, Volume 16 (2-4), 2001, pp. 97-166.

16. Dey, A., Mankoff, J., Abowd, G. and Carter, S., “*Distributed mediation of ambiguous context in aware environments*”, In Proceedings of the 15th Annual ACM Symposium on User interface Software and Technology, 2002, pp. 121-130.

17. Godbole A. and Smari W.W., “A Methodology and Design Process for System Generated User Interruption based on Context, Preferences, and Situation Awareness. Information Reuse and Integration”, in IEEE International Conference, 2006, pp. 608-616.

18. Grandhi S. A. and Jones Q., “*Conceptualizing Interpersonal Interruption Management: A Theoretical Framework and Research Program*”, in the 42nd Hawaii International Conference on System Sciences, 2009, pp. 1-10.

19. Grandhi S.A., Schuler R.P. and Jones Q., “*To answer or not to answer: that is the question for the cell phone users*”, in the 27th international conference extended abstracts on Human factors in computing systems, 2009, pp. 4621-4626.

20. Guzman E. S., Sharmin M. and Bailey B. P., “Should I call now? Understanding what context is considered when deciding whether to initiate remote communication via mobile devices”, in Graphics interface, 2007, pp. 143-150.

21. Helton, J. C., “*Uncertainty and Sensitivity Analysis in the Presence of Stochastic and Subjective Uncertainty*”, Journal of Statistical Computation and Simulation 57, 1997, pp. 3-76.

22. Henricksen, K. and Indulska, J., “*A software engineering framework for context-aware pervasive computing*”, Pervasive Computing and Communications (PerCom) 2004, Proceedings of the Second IEEE Annual Conference, pp. 77 – 86.

23. Henricksen, K. and Indulska, J., “*Modeling and using imperfect context information*, Pervasive Computing and Communications Workshops, 2004. Proceedings of the Second IEEE Annual Conference, pp. 33 – 37.

24. Ho J. and Intille S. S., “*Using context-aware computing to reduce the perceived burden of interruptions from mobile devices*”, in the SIGCHI Conference on Human Factors in Computing Systems, 2005, pp. 909-918.

25. Horvitz E., Jacobs A. and Hovel, D., “*Attention-Sensitive Alerting*”, UAI, 1999, pp. 305-313.

26. Horvitz E. and Apacible J., "*Learning and Reasoning about Interruption*", Proceedings of the International Conference on Multimodal Interfaces (ICMI), 2003, pp. 20-27.

27. Horvitz E., Koch P. and Apacible, J., "*BusyBody: creating and fielding personalized models of the cost of interruption*", in the ACM Conference on Computer Supported Cooperative Work, 2004, pp. 507-510.

28. Hull, R., Neaves, P. and Bedford-Roberts, J., "*Towards situated computing*", In Proceedings of International Symposium on Wearable Computers, 1997.

29. Iqbal, S. T. and Bailey, B. P., "*Leveraging characteristics of task structure to predict the cost of interruption*", In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, 2006, pp. 741-750.

30. Iqbal S. T. and Bailey B. P., "*Effects of intelligent notification management on users and their tasks*", in the 26th Annual SIGCHI Conference on Human Factors in Computing Systems, 2008, pp. 93-102.

31. Jiang, X., Chen, N. Y., Hong, J. I., Wang, K., Takayama, L. and Landay, J. A., "*Siren: Context aware Computing for Firefighting. Lecture notes in computer science*, In Proceedings of Second International Conference on Pervasive Computing, 2004, pp. 87-105.

32. Khalil, A. and K. Connelly, "*Improving cell phone awareness by using calendar information*", In Proceedings of INTERACT 05. 2005.

33. Lederer, S., Mankoff, J. and Dey, A. K., "*Who wants to know what when? Privacy preference determinants in ubiquitous computing*", In CHI '03 Extended Abstracts on Human Factors in Computing Systems, 2003, pp. 724-725.

34. Lee Ju-Hwan, Poliakoff Ellen, and Spence Charles, The Effect of Multimodal Feedback Presented via a Touch Screen on the Performance of Older Adults. In *Proceedings of the 4th International Conference on Haptic and Audio Interaction Design* (HAID '09), 2009, pp. 128-135.

35. Mark G., Gudith D. and Klocke U., "*The cost of interrupted work: more speed and stress*", in the 26th Annual SIGCHI Conference on Human Factors in Computing Systems, 2008, pp. 107-110.

36. Marti, S. and Schmandt, C., "*Giving the caller the finger: collaborative responsibility for cellphone interruptions*", In CHI '05 Extended Abstracts on Human Factors in Computing Systems, 2005, pp. 1633-1636.

37. McCrickard, D. S., Chewar, C. M., Somervell, J. P. and Ndiwalana, A., "*A model for notification systems evaluation—assessing user goals for multitasking activity*", ACM Trans. Comput.-Hum. Interact. 10, 4, 2003, pp. 312-338.

38. Petersen S. A., Cassens J., Kofod-Petersen A. and Divitini M., "*To be or not to be aware: Reducing interruptions in pervasive awareness systems*", in the 2nd

International Conference on Mobile Ubiquitous Computing, Systems, Services and Technologies – UBICOMM, 2008, pp. 327–332.

39. Picard W. R. and Liu K. K., "*Relative subjective count and assessment of interruptive technologies applied to mobile monitoring of stress*", International Journal of Human-Computer Studies; volume 65, issue 4, 2007, pp. 361 – 375.

40. Savioja, P., Alarms – Necessary Interruptions? Seminar on User Interfaces and Usability, HUT, Sober IT, 2004, 121-900.

41. Savage, L.J., "*The Foundations of Statistics*", New York, Dover Publications, 1972.

42. Sentz, K. and Ferson S., "*Combination of Evidence in Dempster-Shafer Theory*", Sandia National Laboratories, New Mexico, 2002.

43. Shafer, G., "*A Mathematical Theory of Evidence. Princeton*", NJ, Princeton University Press, 1976.

44. Shafer, G., "*Probability Judgement in Artificial Intelligence. Uncertainty in Artificial Intelligence*", in L. N. Kanal and J. F. Lemmer, New York, Elsevier Science, 4, 1986.

45. Sharmin, M., Ahamed, S. I., Ahmed, S., & Li, H. SSRD+, "*A Privacy-aware Trust and Security Model for Resource Discovery in Pervasive Computing Environment*", Computer Software and Systems Conference, 2006, pp. 67-70.

46. Spira J.B. and Feintuch J.B., "The Cost of Not Paying Attention: How Interruptions Impact Knowledge Worker Productivity", Basex, 2005.

47. Stamm, K., Ahamed, S. I., Madiraju, P. and Zulkernain, S., "*Mobile Intelligent Interruption Management (MIIM): A Context Aware Unavailability System*", In Proceedings of the 25th Annual ACM Symposium on Applied Computing, 2010.

48. Toninelli A., Khushraj D., Lassila O. and Montanari R., "*Towards Socially Aware Mobile Phones*", 7th International Semantic Web Conference, 2008.

49. Turney P., "*Exploiting Context when Learning to Classify*", in the European Conference on Machine Learning, 1993.

50. Turney P., "*Robust Classification with Context-Sensitive Features*", in the 6th International Conference on Industrial and Engineering Applications of Artificial Intelligence and Expert Systems, 1993.

51. Yu Zhiwen, Zhou Xingshe, Zhang Daqing, Chin Chung-Yau, Wang Xiaohang and Men Ji, "*Supporting context-aware media recommendations for smart phones*", Pervasive Computing, IEEE, Volume 5, Issue 3, 2006, pp. 68 – 75.

52. Ziebart, B. D., Roth, D., Campbell, R. H., and Dey, A. K., "*Learning Automation Policies for Pervasive Computing Environments*", In Proceedings of the Second

international Conference on Automatic Computing, June 13 - 16, 2005, pp. 193-203.

53. Zulkernain S., Stamm K., Madiraju P. and Ahamed S. I., “*A Context Aware Interruption Management System for Mobile Devices*”, in the proceedings of the third International ICST Conference on MOBILe Wireless MiddleWARE, Operating Systems, and Applications (Mobilware), 2010 (Springer Lecture Notes of ICST).

54. Zulkernain S., Stamm K., Madiraju P. and Ahamed S.I., “A Mobile Intelligent Interruption Management System”, in Journal of Universal Computer Science, Vol. 16, No. 15, 2010, pp. 2060-2080.

55. Bureau of Labor Statistics, http://www.bls.gov/

56. Disruptive communication and attentive productivity, http://www.iii-p.org/research/disrupt_comm_report_v2.pdf

57. International Telecommunication Union, http://www.itu.int/newsroom/press_releases/2009/39.html

58. MIT press release, http://web.mit.edu/invent/n-pressreleases/n-press-04index.html

59. Cross-cultural cell phone study, http://www.ur.umich.edu/0607/Apr02_07/02.shtml

60. Statistics and facts about distracted driving, http://www.distraction.gov/stats-and-facts/

61. App Store Metrics, http://148apps.biz/app-store-metrics/

62. Dempster-Shafer Theory, http://en.wikipedia.org/wiki/Dempster-Shafer

63. Cell phone accidents, http://cellphones.org/blog/cell-phone-accidents/

APPENDIX

Calculation for Simulation Example 1

```
l = 0.9;
s = 0.8;
f = 0.2;

k1 = l * s + (1 - l) * (1 - s);

ni = (1/k1) * l * s;

k2 = ni * f + (1 - ni) * (1 - f);

nif = (1 / k2) * ni * f;

ni = 0.9730
nif = 0.9001
```

Calculation for Simulation Example 2

```
l = 0.9;
s = 0.8;
f = 0.2;

wl = 2;
ws = 1;
wf = 7;


k1 = l * s + (1 - l) * (1 - s);

niw = wl * ws / (wl + ws);

ni = (1/k1) * l * s * niw;

k2 = ni * f + (1 - ni) * (1 - f);

nifw = niw * wf / (niw + wf);

nif = (1 / k2) * ni * f * nifw;

ni = 0.6486
nif = 0.1922
```

Source code for the Simulation graphs

```
clear
clc

for count = 1 : 100
    l(count) = rand;
    s(count) = rand;
    f(count) = rand;

    k1 = l(count) * s(count) + (1 - l(count)) * (1 - s(count));

    ni(count) = (1/k1) * l(count) * s(count);

    k2 = ni(count) * f(count) + (1 - ni(count)) * (1 - f(count));

    nif(count) = (1 / k2) * ni(count) * f(count);

    average(count) = (l(count) + s(count) + f(count)) / 3;
end

ti = 0 : 0.01 : 1;
[XI, YI] = meshgrid(ti, ti);
ZI = griddata(l, s, f, XI, YI);

mesh(XI, YI, ZI), hold
figure(1)
plot3(l, s, f, '.'), hold off

figure(2)
hist(average)

figure(3)
hist(nif)
```