MIMS: Mobile Interruption Management System

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by

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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

August 2016

ABSTRACT

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Mobile devices are increasing in an astronomical rate throughout the world. While it is bringing a lot of comfort to the users it is not coming without any hazards. Now a user is susceptible to mobile call interruptions wherever he is, whether he is in the middle of a very important discussion or in a very important task like performing a complicated emergency operation in a hospital. As a result researchers have been studying to find ways to minimize cost of mobile interruptions. In this thesis we have proposed a mobile interruption management system in which callers have been grouped and time intervals of a day have been classified to ascertain whether a call should be allowed to ring, go silent or vibrate. We have also included presence of Bluetooth devices and applications the mobile user is using to decide if the user needs to be interrupted. We have undertaken a survey of mobile users to compare various models and select appropriate default parameter values like caller groups, time intervals, and inclusion of special days/events. We have proposed a matrix containing default values of cost of mobile interruption, which will be adjusted according to contexts the user is in and then this cost is compared with the threshold value. If the cost of receiving the call is less than the threshold value, then device sound profile is set to ring or vibrate otherwise it is set to silent. We have also evaluated our model with existing models and found the system performing well.

ACKNOWLEDGEMENTS

Mohammad Kayes Kaykobad, B.Sc.

It gives me immense pleasure to thank and acknowledge my supervisor, Dr. Praveen Madiraju, who took the pain of guiding this research with patience and wisdom and without whose support the study would have been difficult to bring to a successful end. He has been a great mentor. I would like to particularly thank Dr. Iqbal Ahamed who inspired me and created an opportunity for me of doing higher education. Without his support I might not have been in university campus again. I thank Dr. Thomas Kaczmarek for kindly agreeing to be a member of the thesis committee. I take this opportunity to thank the members of the Ubicomp lab and the environment they have created without which this research would never have been as pleasant and rewarding. I thank other members of Mathematics, Statistics and Computer Science Department of Marquette University for creating an enjoyable and friendly environment for foreign students to pursue their studies away from home. A special thank goes to Amit Kumar Saha, Md Osman Gani, Taskina Fayezeen and Tanvir Roushan for supporting me in this journey. Last but not the least I would like to thank the Bangladeshi community in Milwaukee who have made staying away from my friends and family back home bearable.

I could not have reached this far without the support of my family. My little son Ervin, born only recently during the work, has always been a great source of joy for me as my wife Tanzina Khan. I would also like to thank my father Dr. Mohammad Kaykobad and mother Saleha Kaykobad without whose support nothing would have been possible.

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CHAPTER 1

Introduction

1.1. Introduction

The number of cellphone users is increasing day by day due to advancement in technology that allows cell phones to become affordable and more powerful than ever before. Modern society has already reached a point where cell phones are no longer a luxury but a necessity. As people are becoming more dependent on these handheld devices the negative effects of cellphone disruption is becoming increasingly apparent. Armed with arrays of sensors, today's devices are capable of identifying disruptions by exploiting location, calendar and other contextual data. The objective of a Mobile Interruption Management System is to maximize productivity of users by minimizing disruption. The application should intercept calls, calculate the probability of interruption and change the audio profile of the device based on it. This will facilitate avoiding distractions whenever unwanted or less wanted calls intercept important busy times, and at the same time attention is drawn to more important mobile calls for which loss in disruption is well compensated by the benefits from an important mobile call.

1.2. Motivation

The rate at which cell phones are increasing all over the world is astronomical. The following data have been collected from ITU website.

Table 1. Mobile Cellular Telephone Subscription (In million and /100 inhabitants)

Country	2000	2002	2004	2006	2008	2010	2012	2014
Australia	9/44.5	13/64	16/81.5	20/94.7	22/102.2	22/100.4	24/105.6	31.2/126
Bangladesh	.28/.21	1.1/.78	2.8/2	19/13.2	45/30.2	68/44.9	97/62.8	127/80
Canada	8.7/28.4	11.9/38	15/47	18.7/57.5	22.1/66.2	25.8/75.7	27.7/79.6	28.8/81.1
China	85.3/6.7	206/15.9	332/25.6	451/34.8	678/47.8	896/63.2	1146/80.8	1307/92.2
India	3.6/.34	13/1.2	52/4.7	179/14.5	365/29.5	772/62.4	865/69.9	944/74.8
Indonesia	3.7/1.8	11.7/5.4	30.3/13.7	63.8/28	14.8/60	21.7/87.8	28.2/114.2	32.6/128.8
USA	119/38.5	151/48.9	194/62.6	236/76.3	274/85.2	294/91.3	304/96	355.5/110.2

In each cell of Table 1 first number is number of mobile phones in millions whereas the second number is its number per hundred inhabitants. It is evident that number of mobile phones is increasing at exponential rate not only in advanced countries but also in developing countries. It is noteworthy that in advanced countries in 14 years number of mobile phones per hundred inhabitants increased only 3 folds whereas in developing countries like Bangladesh, China, India and Indonesia the corresponding figures are respectively 160, 14, 210 and 70. Since developing world has over 3/4ths of the population of the whole world we have a lot to worry about bad impact of unnecessary interruptions of the mobile phones on our society.

Table 2. Fixed Telephone Subscription (In million and /100 inhabitants)

Country	2000	2002	2004	2006	2008	2010	2012	2014
Australia	10/52.2	10/52.8	10/51.2	9.9/47.6	9.4/43.3	10.6/47.4	10.5/45.4	9.2/38.9
Bangladesh	.49/.37	.60/.44	.83/.59	1.1/7.8	1.34/.9	1.28/.85	.96/.62	.98/.61
Canada	20.8/67.9	20.6/65.9	20.5/64.4	18.2/55.9	18.2/54.7	18.4/53.9	17.7/50.9	16.4/46.2
China	145/11.3	214/16.5	312/23.8	368/27.7	340/25.4	294/21.6	278/20.2	249/17.9
India	32.4/3.1	41.4/3.8	46.2/4.2	40.8/3.6	37.9/3.23	35.½.9	31/2.5	27/2.1
Indonesia	6.7/3.2	7.8/3.6	10.4/4.7	14.8/6.5	30.4/13	40.9/17	38/15.4	26.2/10.4
USA	192/67.6	189/65.2	178/60.1	167/55.6	163/53.1	150/47.9	138/43.6	128/39.8

Table 2 shows that number of fixed telephone lines per hundred inhabitants is declining implying that people are now more interested in mobile phones and not on fixed lines. This means that we must reduce bad impact of mobile phones including mobile interruption to have a healthy society enriched with the virtues of technology and not its vices. Introduction of mobile phones has not only brought a lot of comfort to our everyday life, it has also had a nuisance value. Unfortunately with the exponential growth of mobile phones a user is now susceptible to interruption anywhere and anytime. This was not possible in the days of fixed telephony which caused interruption only when both the receiver and sender of telephone calls were near the telephone sets. Now that even in developing countries like Bangladesh with 160 million people they have as many as 100 million mobile sets, potential of interruption is obvious. In a pace of only 15 years the dramatic increase in mobile phones has simultaneously caused an indifferent and unremarkable stagnancy in the number of fixed telephony indicating the indifference with which users treat fixed telephone sets and enjoy the comfort of having mobile phones.

However, there are times when receiver is deeply engaged in performing an important task, and a mobile phone may very well distract him/her to the extent that it may ultimately slow down his thoughts and deeds, and significantly reduce his/her productivity. So time has come to measure cost of interruption and possibly organize management of interruption in order to reducing the involved cost. According to The Washington Post [39] work interruptions can cost 6 hours a day and it can take 23 minutes 15 seconds to get back to where a worker left off. Back in 2005 [40] interruptions consumed 28% of a worker's day which must be a lot higher today since many individuals are connected to social media and social network notification services on browsers and mobile devices are better than ever before. Jonathan Spira, author of "Overload! How Too Much Information Is Hazardous To Your Organization," estimates that interruptions and information overload eat up 28 billion wasted hours a year, at a loss of almost $1 trillion to the U.S economy [40]. Reference [41] contains interesting statistics of distraction of drivers caused by mobile phones. Distraction contributes to 22% of car crashes and near crashes and 71% of truck crashes (and 46% of near crashes) in naturalistic driving studies. Using a mobile phone whilst driving is highly distracting and increases your risk of a crash four-fold. Despite the dangers and illegality, roughly 25% of recently surveyed Queensland drivers reported using their hand-held mobile phone on a daily basis to answer or make calls, as well as read text messages, while 14% reported using their hand-held phone to send a text message on a daily basis. Another report [41] says that a number of researches indicates that using a mobile phone while driving is a significant distraction, and substantially increases the risk of the driver crashing.

Drivers using a mobile phone, whether hand-held or hands-free:

- are much less aware of what is happening on the road around them, and fail to see road signs
- fail to maintain lane position and speed are more likely to 'tailgate' the vehicle in front
- react more slowly, take longer to brake and longer to stop
- are more likely to enter unsafe gaps in traffic
- feel more stressed, anxious and frustrated.

They are four times more likely to crash, injuring or killing themselves and other people. Using a hands-free phone while driving does not in any way contribute to reduction of the risks because the problems result mainly for the mental distraction and divided attention of taking part in a phone conversation at the same time as driving.

These facts and statistics have motivated us to undertake research on how to manage mobile interruption, and ensure effective and more productive use of technology and reduce hazards for the benefit of common mass.

1.3. Scopes and Objectives of the Research

While mobile telephony has been introduced very recently its exponential growth has already caught attention of scientists and researchers to ascertain its bad impact in the society and individual life. In this thesis we studied existing literature, and proposals for reducing bad impact of mobile telephony through distraction of our attention from possibly more important tasks at hand. We also carried out a survey to determine the important features of a mobile interruption management system users would like to enjoy. Based upon the survey we propose a mobile interruption management system, and develop its prototype. In particular we have:

a. Identified important contexts that can help detect unwanted calls

b. Implemented them in the prototype

c. Created a new model to calculate predicted level of interruption

d. Implemented the new model

e. Evaluated the new model, the model (Weighted sum with adjustable weights) introduced in previous works on the same topic and Hidden Markov Model(HMM), which to our knowledge has never been used before.

1.4. Organization of the Thesis

Chapter 1 introduces the problem and some statistics that act as motivating factors for selecting such a topic and scopes and objectives of the thesis. Chapter 2 contains survey of literature in the area of mobile interruption management, some proposals for reducing bad impacts of mobile interruption. It also adds some new contexts that are yet to be considered for mobile interruption management. In Chapter 3 we introduce a model for Predicted Level of Interruption (PLI). Chapter 4 contains details of our implementation. Chapter 5 contains comparison of the proposed system with other existing systems. Chapter 6 contains conclusions and suggestions for future study. The thesis ends with a bibliography and annexure containing the details of survey that was carried out to ascertain important parameters of the developed system.

CHAPTER 2

Previous Research

While introduction of mobile phones to the society is pretty new, and is only entering the second decade the huge number of papers appearing in literature does indicate the concern of researchers on its negative impact, and urge for fighting against the probable havoc that can cause by the exponential growth of gadgets involving mobile communications.

2.1. Literature Review

Zulkernain, Madiraju and Ahamed [36] and Zulkernain, Madiraju, Ahamed and Stamm[37] studied the problem of interruption. Cutrell, Czerwinski and Horvitz [10] studied how instant messaging (IM) can affect ongoing computing tasks so badly especially during fast, stimulus-driven search tasks. Moreover, they show that interruptions coming early during a search task are more likely to result in the user forgetting the primary task goal than interruptions that arrive later on. Needless to say that for mobile phones disruptions will affect more seriously since it has to be addressed really instantaneously while for IM you can still have breathing space. Gillie and Broadbent [11] made a series of experiments that use a novel computer-based adventure-game methodology to investigate the effects of the length of the interruption, the similarity of the interruption to the main task, and the complexity of processing demanded by the interruption. Horvitz and Apacible [19] present methods for inferring the cost of interrupting users based on multiple streams of events including information generated by interactions with computing devices, visual and acoustical analyses, and data drawn from online calendars. Adamczyk and Bailey [1] measure effects of interrupting a user at different moments within task execution in terms of task performance, emotional state, and social attribution. They developed task models using event perception techniques, and the resulting models were used to identify interruption timings based on a user's predicted cognitive load. Their results show that different interruption moments have different impacts on user emotional state and positive social attribution, and suggest that a system could enable a user to maintain a high level of awareness while mitigating the disruptive effects of interruption. They also discuss implications of these results for the design of an attention manager. Dekel, Nacht and Kirpatrick [8] proposed to minimize mobile phone disruption via smart profile management. Fogarty, Hudson, and Lai [10] examined robustness of sensor-based statistical models in ascertaining human interruptibility. Grandhi and Jones [11] proposed a theoretical framework for conceptualizing interpersonal interruption management. Guzman, Sharmin and Bailey [15] addressed the issue of deciding whether to communicate over mobile phones based upon prevailing contexts. A host of studies ([3], [5], [14],[15], [17], [18], [24], [25], [26], [32]) have addressed different aspects of interruptibility caused by mobile calls. Researchers have been concerned with minimizing bad impacts of mobile interruptions.

2.2. Proposals for Addressing the Interruptibility Issues

Interest has been growing in opportunities to build and deploy statistical models that can infer a computer user’s current interruptibility from computer activity and relevant contextual information. This is also applicable for massively used devices like mobile phones. We will be largely concerned on mobile phones. Some researchers propose to train the system that intermittently asks users to assess their perceived interruptibility during a training phase and builds decision-theoretic models with the ability to predict the cost of interrupting the user. The models are used at runtime to compute the expected cost of interruptions, helping a mediator for incoming notifications, based on a consideration of a user's current and recent history of computer activity, meeting status, location, time of day, and whether a conversation is detected. They associate so called cost of interruption with every call depending on the caller's importance to the user, and the state in which the user is to help her decide appropriately. If the cost of interruption is low, for example user is free or the caller is important for the user cost of interruption is low. If the user is busy doing a very important time critical task then cost of interruption may be very high. So depending upon situation the system may help the user in accepting the call for conversation, or the mobile may vibrate to bring the fact of the call to user's attention or simply note down for the user to browse through at a leisure hour and take appropriate steps. Zulkernain, Madiraju and Ahamed [36] discussed the limitations of Bayesian inference in estimating cost of interruption. Bayesian approach demands a) complete knowledge of the system with all the priori and conditional probabilities, which in practical scenarios are very hard to determine beforehand and b) Empirical data or Uniform distribution is traditionally used to measure the priori probabilities. Outcomes also reflect these assumptions. Hence this method is not at all equipped to handle the state of ignorance effectively. They advocated for using Dempster-Shafer formalities that bases on three functions: (i) Basic Probability Assignment (bpa or m); (ii) Belief Function; and (iii) Plausibility Function. On the other hand Horvitz, Koch and Apacible [20] studied the problem for mobile phones, developed personalized model for cost of interruption and packaged the same into the system called *BusyBody*. During a training phase, BusyBody intermittently engages users in assessing their current cost of interruption efficiently. In the background, a rich stream of desktop events is logged continuously. These events, along with information drawn from the user's calendar, wireless signals, and an onboard conversation detector, are combined with the self-assessments to build a case library. BusyBody trains and periodically re-trains Bayesian network models that provide real-time inferences about the cost of notification. The models are linked to programming interfaces that allow other components, such as notification systems to access the expected cost of interruption. BusyBody can be instructed to execute either entirely on a user's personal computer, or to alternatively package the information locally and to communicate its logs to a server when network connections become available. The use of a central server enables the construction of models that consider activity on multiple machines that the user may use at the same or different locations. They seek to infer the cost C assigned by users of being interrupted by different types of disruptions D conditioned on being in particular states S, $C(D_i,S_j)$. In a messaging setting, such costs can be assessed using decision-analytic assessment techniques such as the willingness to pay in dollars to avoid the disruptive component of notifications. Predictive models of user states constructed with training data generate probability distributions over states of interruptibility. Thus, we invoke the principles of expected utility decision making to compute the expected cost of disruptions under uncertainty in taking mediation actions.

2.3. Adding Important Contexts

So far location, time of day, schedule from calendar, driving, caller group contexts have been used to make a decision whether the user should be interrupted or not. These contexts are certainly the most important ones but there are some other contexts that can be helpful in aiding the application to make more informed decisions. The additional contexts that application is going to be aware of are Bluetooth devices in proximity and foreground application running on the device. Using Bluetooth sensors other Bluetooth devices present in proximity can be detected. This can help the application be aware of the people that are in the proximity. Knowing which application is on foreground can also help our system make a decision of whether to let a call through or not. Moreover, personal days like birthdays, marriage ceremonies or similar family events may also contribute to the cost of interruption.

Using Bluetooth: Bluetooth devices in proximity can be scanned and decisions can be made from that data. Let us consider a scenario where one does not want the phone to ring when in presence of a particular person. After an interval the Bluetooth scans other Bluetooth devices in proximity and automatically switches to silent mode if that particular person is nearby. There can also be a group of people one does not want to speak with in front of anybody that belongs to another group. For example one may not want to talk to a family member in front of colleagues. One thing to note is it is not important for the device owner to know the names of the Bluetooth devices, the application installed can get this data from the server. One drawback is everyone has to use the same application so that whenever people sign into the service the server will know who is who and send information to the phones so that the installed application can make decision using the available information. For instance this assumption is not outrageous~~,~~ in corporate world, it is often assumed the employer who provides access to mobile phones to their employees has a corporate server authentication system (example, exchange server) for email access and in the same vein, can have the server identify the devices

Application in Foreground: Information on activities in social media can also help make decision whether one should be interrupted or not. For example a person uploading pictures on Instagram, putting statuses on Facebook may not mind being interrupted. To detect social media activity we have employed detection of application running in foreground.

CHAPTER 3

Model for Predicted level of Interruption (PLI)

In this chapter we propose a model for predicted level of interruption, and then apply it in mobile interruption management system. While in literature the phrase *probability of interruption (POI)* is in use the term probability must satisfy some conditions like sum total of probabilities of all possible events of a sample space must be 1, probability cannot be negative, in POI models so far developed this has not been well maintained. So we would like to introduce the phrase *Predicted Level of Interruption (PLI)* indicating cost or more specifically standardized cost to be incurred in attending a call on mobile phones or tab or any other gadget while we are involved in a process.

3.1. Calculating PLI

For probability of interruption let us consider the following situation. Any person usually belongs to one of several groups, like family members, friends or colleagues with whom he has comparable communication. His scale of interruption depends upon his place of presence like at home, in the office, on a tour or in any other special places like hospital, time of day like in the morning, in the daytime or in the evening. Quite often he may like to be communicated with a particular person if there is some special business with him/her. Usually he will set standard probability of interruption. So there will be a standard cost for communication with each group depending upon time of day or location. So we can have a matrix with columns representing time of day, say morning, office/work time and evening, and rows can represent different groups like family, friend, and colleague. Each entry of the matrix will represent standardized cost of interruption.

Let c_i be threshold of interruption, that is, if cost of interruption exceeds this threshold then it will be too costly for the user to take the phone call. If cost>c_1 then the call will not be addressed, else if it is >c_2 then it will be processed at a later more convenient time, else it will remain unanswered. However, on a particular day or time we may like to increase or decrease these probabilities manually say in the morning, or according to the location the user is in. This can be done by "if then else" type or case type structures. It is also possible that we can increase or decrease the cost of interruption for individual caller for a particular day. The Lower the value of Threshold c_i is, less likely it is for the phone to ring. It may be noted here that in our implementation we have used a single threshold value to decide whether to change the sound profile to ring or silent.

3.2. A Matrix Model for PLI

Consider 4 groups such as family, friend, colleague and an extra group to cover any other collection of people having mobile communication with the user. So these will be numbered from 1 to 4 respectively. In respect of time of day let us have time period 1 for 10 pm to 6 am (Night), 2 for 6 am to 9 am (Morning) then 3 for office time 9 am to 5 pm (Office time) and 4 for 5 pm to 10 pm(Evening) . These time periods will be customized by individual users considering his/her own daily routine. The following probability of interruption matrix indicates that p_{ij} indicates the probability of interruption for any member of group i during time period j.

Table 3: Matrix Model for PLI

	10pm-6am Night	6am-9am Morning	9am-5pm Office time	5pm-10am Evening
Family	p_{11}=0.4	p_{12}=0.2	p_{13}=0.5	p_{14}=0.3
Friend	p_{21}=0.8	p_{22}=0.4	p_{23}=0.6	p_{24}=0.2
Colleague	p_{31}=0.9	p_{32}=0.4	p_{33}=0.2	p_{34}=0.7
Extra	p_{41}=0.9	p_{42}=0.2	p_{43}=0.2	p_{44}=0.2

In addition we can give input for reduction or increase of threshold values at a particular time depending on the type of busy period we are passing. With if then else structure we can also adjust this cost depending upon location. If it is a birthday we can decrease POI for family members and friends. If, for example, 3 consecutive calls come from the same caller we should probably consider it important irrespective of caller's weightage, even unknown, and time of day the call has been made since this may really be an emergency situation for the receiver.

The system will have standard p_{ij} values where i stands for group and j stands for time of day. On any day the user can update these costs of interruption setting it higher on a day or at a particular time of the day not suitable for accepting mobile calls or lower on a more relaxing day. Say on a birthday user might expect to decrease POI for family and friends. Factor d adjusts POI for driving, e stands for factor for personal events, b presence of Bluetooth or similar devices. If one has an important assignment with a group of people on a particular day then possibly an extra group can be created and corresponding POI should be reduced by a factor. If the user drives and does not want to be interrupted by calls then factor d will be smaller. Or even if user is in terms of proximity near her boss that may be recognized through Bluetooth or other devices she would like to avoid receiving calls. We are assuming that these values will be so for any time of that particular day. It may be noted here that in order to avoid updating these factors every now and then some standard values can be set at the start and used thus relieving the user from the burden of inputting these numbers. However, users can customize groups, time periods and other factors as per their choice.

Initially Bluetooth factor b, driving factor d, event factor e, location factor l and application running in foreground context a, are all set to 1. We have specified some default values of these factors. However, user can prefix these values to her choice. In our implementation we have assumed these values are fixed and independent of group or time interval. If driving then d= 0.7, if it is a special personal/family day then e=.7, l stands for location factor. If one will remain very busy during time period j_1 and j_2 then e can be set a different value for that duration. c_i is the standardized threshold for group i. So if a call is desirable from a group this standardized cost will be less, otherwise more. Initially for a normal day all c_i can be set to 0.5.

So the pseudo code goes as follows:

Algorithm 1: Calculate the Threshold Value

Set b, d, e, l and a to 1

Value of p is taken from Table 1.

If within Bluetooth region of an important person then

    b=0.6

endif

If driving then

```
        d=0.7
endif
If special day then
        e=0.7
endif
endif
If app in foreground is Facebook or Twitter then
        a=0.7
endif
factor = bdel
for i=1 to m do
    c'i=factor*ci
enddo
if pij< c'i then
        change to appropriate sound profile(ring)
        else
                generate a standard uniform random number  z
                If pij>z then
                        set appropriate sound profile (reject the call)
                else
                        Store the call for later attention
                endif
        endif
```

endif

At the end reset b, d, e, l, a to 1

Basically the standard threshold value is updated, in fact, decreased based upon the scenarios the recipient is in. However, at the end calculation the values are rest again to standard values.

3.3. Calculating PLI Dynamically

3.3.1 Implementing Bayesian Model to Correct User Input/PLI

Bayesian models are used to predict the outcome of a situation given that the same situation has occurred before and the previous outcomes are known. The more the sample data we have the better the predictions are going to be theoretically. To implement a Bayesian Model we need to have the following data: For each location profile we need to have a matrix that contains number of calls per week/month where the rows represent caller groups and columns stand for Time of Day. In the example given below we are assuming that there are 4 caller groups and 4 times of day.

Table 4: Number of calls per week Matrix (L_1)

	Time of Day 1	**Time of Day 2**	**Time of Day 3**	**Time of Day 4**
Caller group1	5	4	2	3
Caller group2	8	7	6	4
Caller group3	7	6	5	3
Caller group4	3	5	8	9

85 calls

We are going to need another chart that contains no of interruptions per week with again caller groups representing rows and columns representing Times of day.

Table 5: Number of interruptions per week Matrix (L_2)

	Time of Day 1	**Time of Day 2**	**Time of Day 3**	**Time of Day 4**
Caller group1	2	1	1	1
Caller group2	3	3	1	2
Caller group3	2	1	2	1
Caller group4	1	1	2	4

28 Interruptions

We can also calculate a matrix that gives us acceptable interruption denoted by I' by subtracting the second matrix from the first matrix.

Table 6: Number of acceptable interruptions matrix (L_3)

	Time of Day 1	Time of Day 2	Time of Day 3	Time of Day 4
Caller group1	3	3	1	2
Caller group2	5	4	5	2
Caller group3	5	5	3	2
Caller group4	2	4	6	5

57 Acceptable Interruptions

Prior: P(I) = 28/85 (Number of interruptions/number of phone calls)

Bayes theorem states

$P(A/B) = \{P(B/A)\ P(A)\}/\{P(B)\}$

$= \{P(B/A)\ P(A)\}/\{P(B/A)\ P(A) + P(B/A')\ P(A')\}$

Let P(LCT/I) be the conditional probability of being at location L with call from group C and time interval T given that the call is a bad interruption. In our case P(LCT/I) is obtainable from the table above. And we need to be able to compute the value of P(I/LCT) for any combination of location, caller group and Time of Day.

For example, the probability of $P(L_1C_1T_1/I)$ can be obtained from the values given in the table.

Conditional: $P(L_1C_1T_1/I) = 2/28$

$P(L_1C_1T_2/I) = 1/28$

$P(L_4C_4T_4)$ can also be calculated in the same manner.

For any given situation we need to be able to calculate P(I/LCT).

$P(I/LCT) = \{P(LCT/I)\ P(I)\}/\{P(LCT)\}$

$= \{P(LCT/I)\ P(I)\}/\{P(LCT/I)\ P(I) + P(LCT/I')\ P(I')\}$

In the above equation all values we need can be obtained from the tables with a little calculation.

For example P(I/L1C1T1) would be:

$P(I/\ L_1C_1T_1) = \{P(L_1C_1T_1/I)\ P(I)\}/\{P(L_1C_1T_1/I)\ P(I) + P\ L_1C_1T_1/I')\ P(I')\}$

$= \{2/28 * 28/85\} / [\{2/28 * 28/85\} + \{3/57 * 57/85\}]$

$= 2/5$

It may be noted that this information is already available in Table 3.

3.3.2 Dynamic PLI Calculation

We can also follow a dynamic model that will accommodate change of group members with time like having more relatives after marriage, having a different set of friends with change of residence, or a different set of colleagues with change of jobs. In these cases rather than guessing the cost of interruption according to some old scenario we can compute it from the recent calls as follows. In order to computing every entry of the matrix let us use the last, say, n calls, and take user's feedback from these calls. If a call is important the user is likely to continue with it happily say for more than 30 seconds. So the mobile will record that cost of interruption for this call is 0. On the other hand if duration of call is less than 30 seconds then the user was not interested in that call and a cost of 1 will be recorded for that call. Moreover, the user may also like to take the trouble of recording the cost by himself. Cost of interruption will be calculated based upon the last n calls, and will be equal to m/n where m is the number of undesirable calls. A call can be addressed in several ways like accepting the call, putting the mobile in vibration mode, bringing the call to the attention of the user at a less busy time. In the remaining cases cost of interruption can be recorded by the user appropriately. Now the calculation can be done in the following way: q - number of calls, m -number of undesirable calls, i is the group caller belongs to and j is the time of day. Call information is stored in a queue with head (h) as front and tail (t) as back. At the start input q=0 should be given.

Algorithm 2: Dynamic PLI Calculation

```
If q=0 then
        m=h=t=0
endif
For each new call
        if q<n then
        q++
        t++
        endif
        if call desirable then
                a_ijt=0
        else
                a_ijt=1
        endif
        If q<n then
        m=m+ a_ijt
```

else

$m=m-a_{ijt}+a_{ijh}$

$h=h+1 \bmod n$

endif

$t=t+1 \bmod n$

$p_{ij}=m/q$

enddo

It may be noted here that basically this gives the same output had we used Bayesian model in this context. So in reality this is an implementation of Bayesian model.

CHAPTER 4

Implementation of the Application

4.1 The Mobile Platform

In implementing our model we consider mobile platform with the following parameters. The application will receive information as to the presence of Bluetooth, other applications the user in using, location and other important parameters.

4.2 Application System Flow

Our application will be working as follows. As soon as an incoming phone call is detected by the broadcast receiver, the application's PLI (Predicted Level of Interruption) calculation module starts running. PLI calculation module fetches calendar, time of day, contact group, Bluetooth and foreground app context data. It also gets Location and driving data using google play services. The user enters PLI of each contact group for each time of day after installing the application.

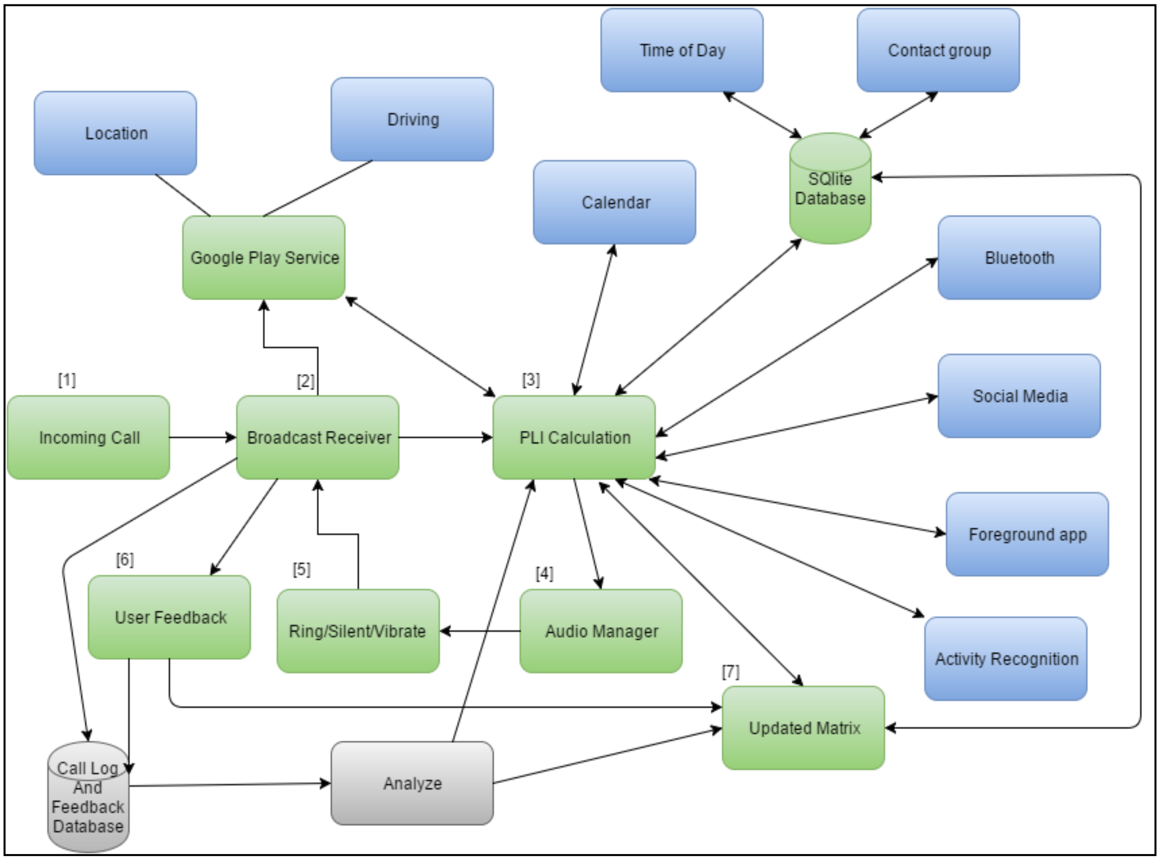

Figure 1: Application System Flow

Since our model utilizes weights (factors) to calculate the final PLI, user must input these factors for Location, Driving and Bluetooth. The entry in the updated matrix module is retrieved by the caller group name and time of day. The PLI calculation module fetches context data from Bluetooth, foreground app, location, driving and calendar and uses them to calculate final PLI. Based on the final PLI the audio manager changes the sound profile of the device. The output we get is the phone goes into Ring/ Silent or vibrate mode. After the user hangs up the broadcast receiver message box pops up that asks the user whether the user considers the interruption as a good one or bad one. The user's review is stored in an SQLite database and is also used to update the matrix so that over time the matrix improves itself. The matrix is updated using a Bayesian formula which calculates PLI for a caller group for a certain time of day. Storing feedback in internal database allows the application to improve the matrix offline. Feedback, caller group and time of call are also saved to an online database so that more complex patterns can be identified. The feedback database is then analyzed and can be used for PLI calculation. So PLI calculation module can utilize machine learning in 2 ways. One way is to use analysis performed on call log and feedback database. The other way is to use the updated matrix module in the app. The benefit of storing updated matrix in phone is the application will continue to work offline.

4.3 Determining the Preferred Method of Interruption (PMI)

If the PLI is above .5 the PLI calculation module instructs audio manager to change the sound profile to ring or vibrate. We assume that it is okay to vibrate if it is okay for the phone to ring. The user can choose the preferred method of interruption for each context. By default for each context PMI is set to vibrate. If all of the measurable contexts have PMI set to ring the phone will ring. If even one of the measurable contexts has its PMI set to vibrate the phone will vibrate.

4.4 Obtaining and Setting Preferences for the Contexts

4.4.1 Location Preferences

Manage Locations UI allows the user to create location profiles. The user begins with naming the location profile after that the user can select location, probability of interruption, preferred method of interruption for each saved location profile. When the user enters a location it is matched against google maps database and some addresses are suggested. The user can pick one from the suggested addresses. One thing to be noted here is Locations can be entered only when there is an active internet connection. A SQLite database stores longitude, latitude and user preferences.

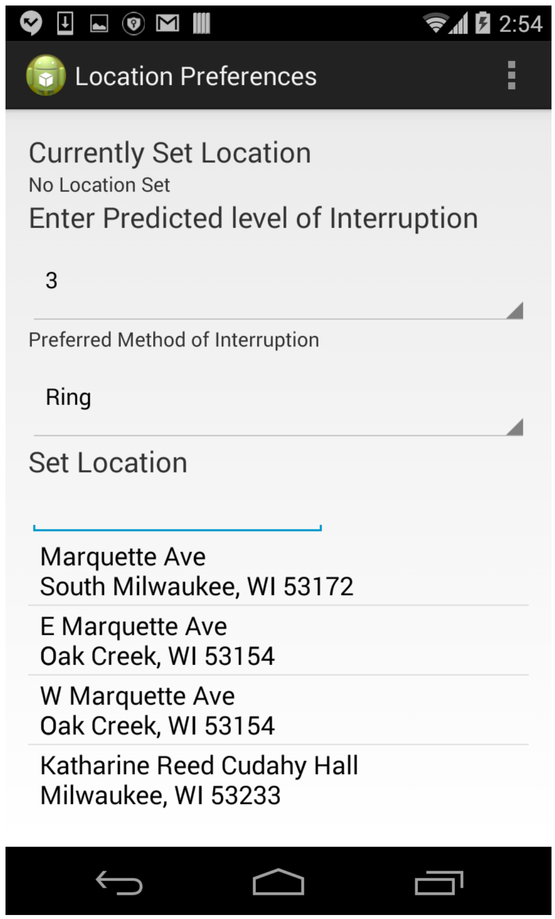

Figure 2: Location Preferences

The user's location is determined by location services provided by Google Play Services. The location services API from Google Play Services tracks the device location and updates it automatically.

As soon as the application detects an incoming call from the android broadcast receiver it obtains the last known location from location services. The POI

Calculation class then compares the last obtained location against the locations previously entered in location preferences. Even though GPS technology has been improving each year, current GPS chips used in cellphones are still not hundred percent accurate. The last obtained position provided by location service is compared with locations in location preferences and if they are off by less than the radius of accuracy the user's location preferences are used in the calculation. If the distance from the last obtained coordinates and the locations saved in location preferences is further than radius of accuracy the situation is considered non measurable and the default values are used.

4.4.2 Schedule Preferences

Schedule preferences uses the native application calendar of user's device. There are 3 cases to consider while evaluating the calendar context. One is the user has nothing scheduled at the time of an incoming call or text. Another case is the user has entered PLI and preferred method of interruption in the calendar. And the last case is user has scheduled an event but has not entered PLI and PMI. In the first case if the user does not have anything scheduled the value of PLI is set to 1 since this context is non-measurable and we do not want a non-measurable context impact our final PLI calculation. If the user has an event but the PLI and PMI have not been entered the default values supplied by the user will be used. In order to enter PLI and PMI the user has to enter PLI followed by PMI between $ sign. The $ sign is used as a delimiter to fetch PLI and PMI from calendar entry. The value of PMI is either R or V where R stands for ring and V stands

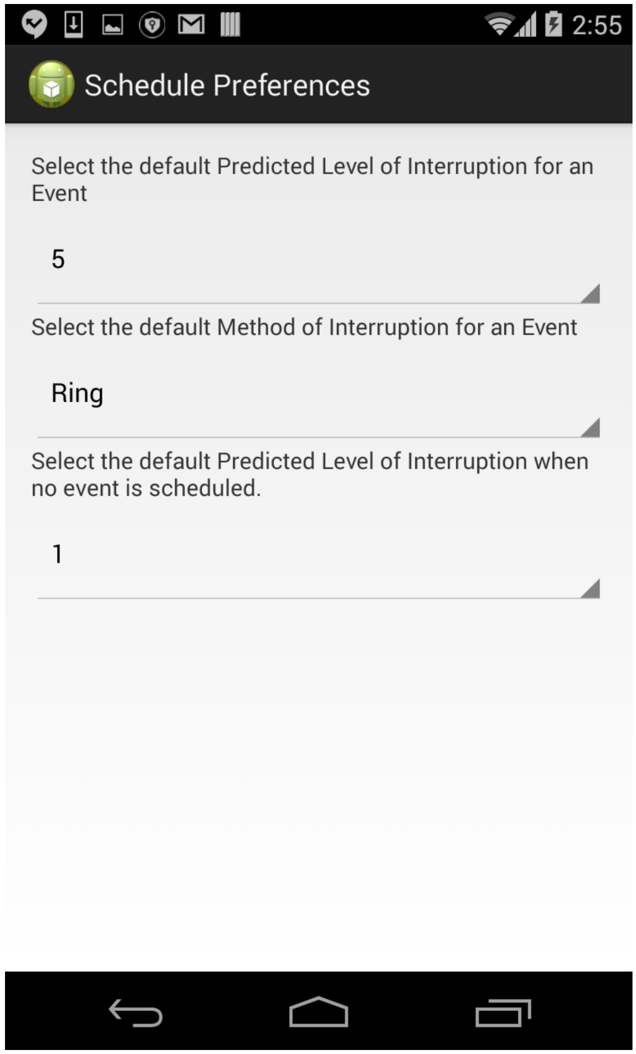

Figure 3: Schedule Preferences

for vibrate. Upon an incoming call the application uses current device time to detect an event and evaluate scheduled preferences according.

4.4.3 Contact Preferences

The contact preferences UI allows the user to create contact group profiles and add existing contacts to a particular contact group. The user can also specify predicted level of interruption and preferred method of interruption for each group.

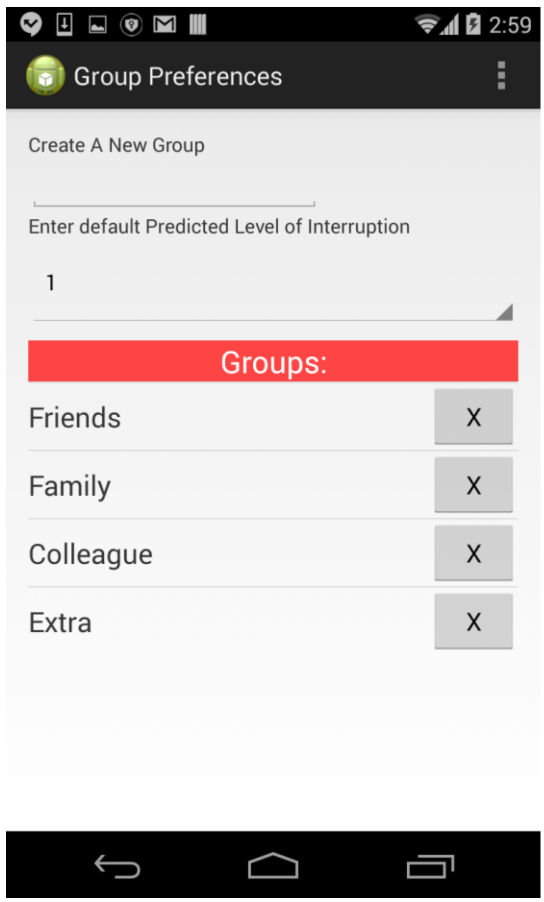

Figure 4: Group Preferences

A contact cannot belong to more than one group at a time. The contact's name, phone number, group name all are stored in the internal SQLite database. Whenever a call comes in the calculation module fetches data using the incoming phone number to run calculations. If the phone number already exists in the contact list and has been assigned to a group the PLI value is obtained from the matrix. If the caller does not belong to any group nothing is returned by the query and the default PLI is used in calculation.

4.4.4 Time of Day Preferences

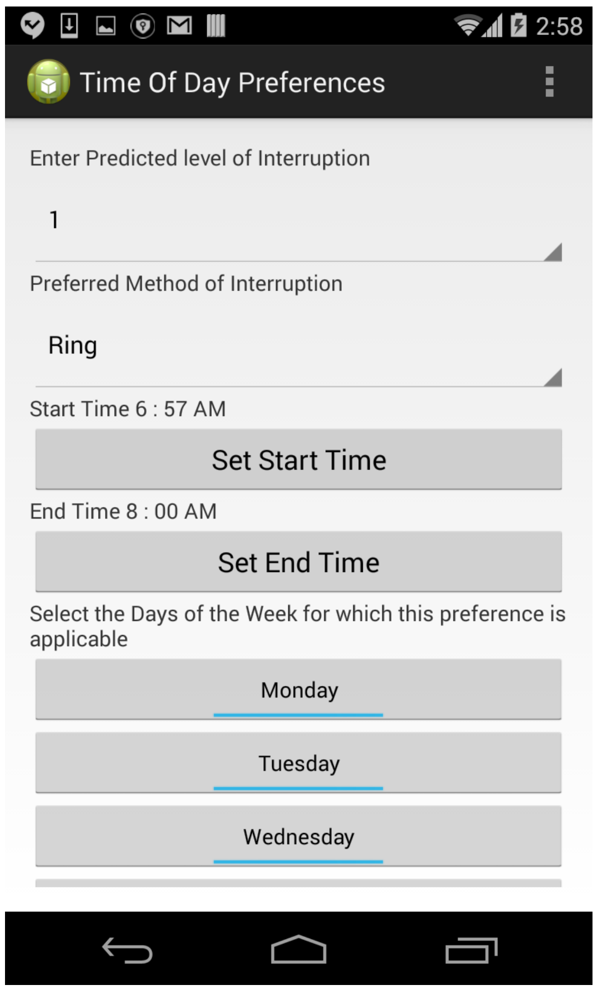

Figure 5: Time of Day Preference

Time of day preferences screen allows users to create profiles for time intervals of days. The first screen allows a user to create profiles of time intervals of day.

After creation of profile it provides users a screen to select a start time, end time and preferred method of interruption for that particular profile.

4.4.5 Driving Preference

Google Play Services has an Activity Recognition API that allows the android operating system to be aware of user's current activity. Even though constantly updating this information can be helpful in identifying whether the user is driving or not It is still not practical to do so since the gps is one of the most power hungry sensors of a handheld device. The ideal case would be to detect whether the user is driving or not upon an incoming call but unfortunately that is not possible since in worst case it can take even an hour to get gps coordinates. Which is why this service runs in the background receives

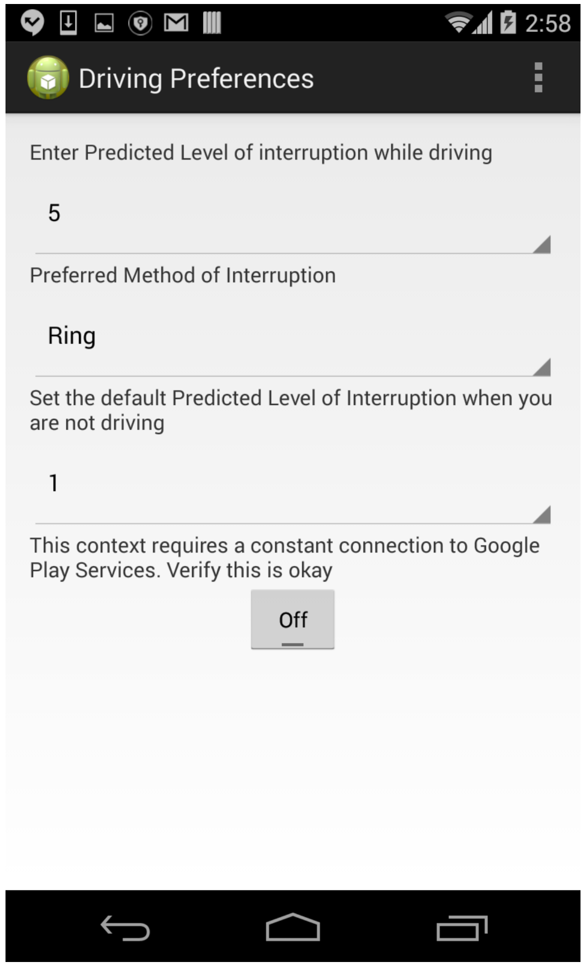

Figure 6: Driving Preferences

location updates every 30 seconds from google play services and stores the last 5 activity updates.

4.4.6. Bluetooth Device Preference

Bluetooth device preference screen provides an interface for users to add Bluetooth devices by Bluetooth device name and allows the user to enter PLI for that particular device and Preferred Method of Interruption. The application runs a Bluetooth discovery service every 2 minutes to scan discoverable Bluetooth devices in proximity. If the Bluetooth discovery service detects a Bluetooth device in proximity that has already been added using Bluetooth device preference screen it writes the last seen time of Bluetooth device to the SQLite database. Upon an incoming call the last seen time of Bluetooth devices is checked and if it less than 2 minutes from incoming call time the PLI for that Bluetooth device is used in calculation.

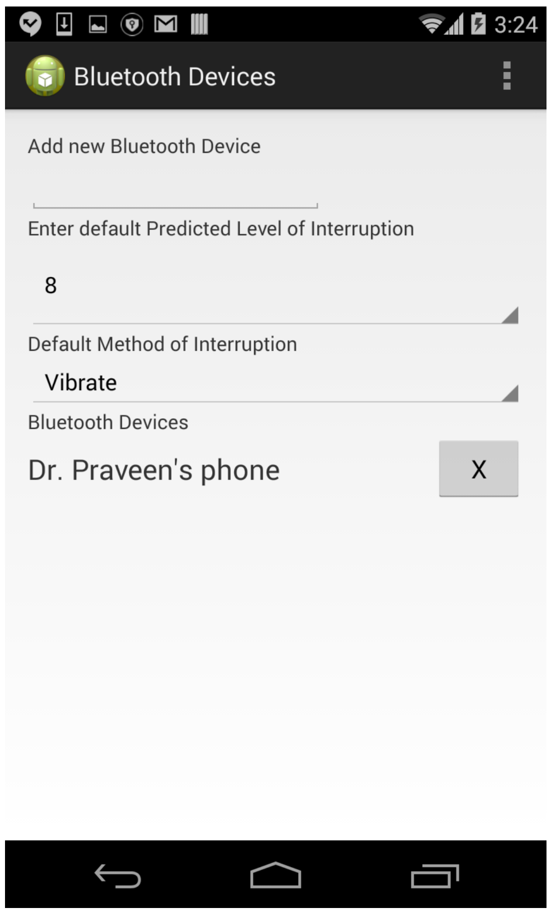

Figure 7: Bluetooth Devices

4.4.7. App Preference

The app preference screen allows the user to set PLI for Facebook and twitter app. The application runs a service in the background that continuously monitors the apps running on foreground and writes the last time the app was used on a shared preference file. The last running

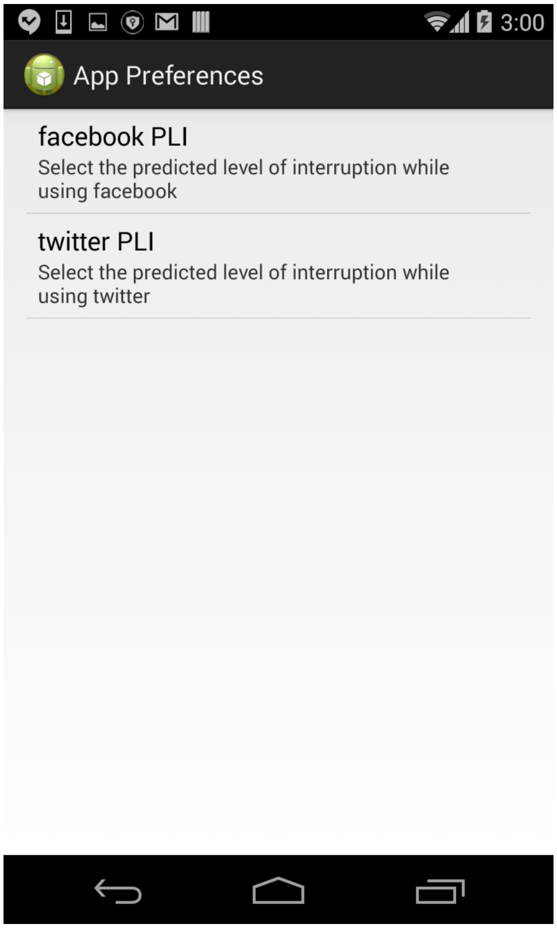

Figure 8: App Preference screen

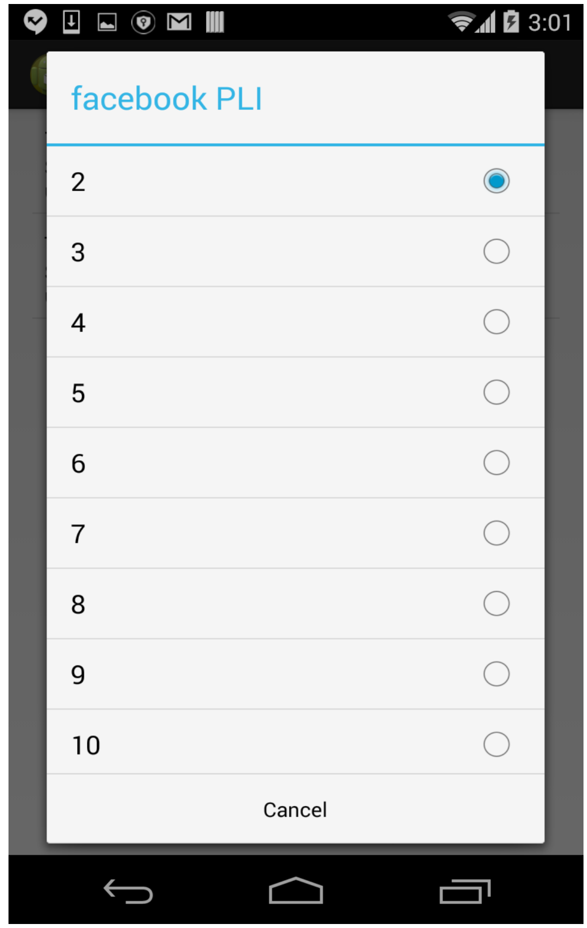

Figure 9: Setting PLI of Facebook

time of apps on foreground are checked as soon as the broadcast receiver detects an incoming call and calculation module checks whether Facebook or twitter app had been on foreground less than 2 minutes ago. If the last running time of Facebook and twitter is less than 2 minutes of the incoming call the PLI of the last app on foreground is used in calculation module.

CHAPTER 5

System Evaluation

5.1 Various Models

5.1.1 Weighted Sum with Adjusted Weights Model:

“The weights are adjusted by first checking whether or not the context is measurable. Any non-measurable context, regardless of the weight attributed by the user, cannot be allowed to have a higher weight than a measurable context. The weights are first readjusted so all the measurable contexts have a higher ranking than the non-measurable contexts. The exact ranks from here are then determined by the ranks set by the user. For further clarification, say the user has ordered the contexts in order of most important to least important as follows: driving, contact, location, schedule, time of day. A call comes in for which the measurable contexts are contact and time of day. The model is then readjusted so contact and time of day receive the greatest weights. As contact initially had a higher weight, it would receive the greatest weight. Time of day would then receive the next greatest weight. Finally, the remaining context, in order of importance, would be driving, location, and schedule.”[35]

5.1.2 Hidden Markov Model:

Hidden Markov Viterbi algorithm has been used to predict the Interruptions. We have 2 states in our problem one is good interruption the other is bad interruption. There is a probability of these states occurring for each time interval of day and caller group. The B matrix contains probability of the states for each event (which is caller group and time of day). In our survey we asked a series of questions from Q10-Q25. We have assumed that each subject received these 16 phone calls in the same sequence as the questions. From the sequence of answers the subjects provided we can obtain observation state sequence which is required to construct matrix A. In matrix A we have number of times the subject goes from the state of good interruption to good interruption, good interruption to bad interruption, bad interruption to good interruption and bad interruption to bad interruption. All of these entries are divided by the number of states in the observation which is 16.

5.2 The Seven Scenarios:

There are 5 scenarios here that are used to compare between 3 models which are Weighted Sum with Adjustable Weights, Hidden Markov model and our Bayesian model. To compare the models we have used survey data provided by survey participants. The same participant's data has been used in scenario to compare the three models. We have reused some of the scenarios specified in Vilwock, Madiraju and Ahamed [35].

Scenario 1: Subject 1 is at school in the classroom. It is 1pm in the afternoon and subject 1's class is having a study session. Everyone is quiet, and that is the way they would like the room to stay. Right in the middle of class Subject1 receives a call from his mother.

Weighted Sum with Adjusted Weights: Following values have been calculated from survey data.

Table 7: Scenario 1

Context	Weight	P(I)
Location	3/15 = .2	.5
Schedule	2/15 = .13	.5
Contact	5/15 = .33	.95
Time Of Day	4/15 = .26	.75
Driving	1/15 = .06	.5

Final P(I) = (.2*.5)+(.13*.5)+(.33*.95)+(.26*.75)+(.06*.5) =.7035 > .5

Output: Interruption

Desired Output: No Interruption

Remarks: Assuming subject 1 has Contact group and time of day configured properly. If subject1 configures location and schedule properly then the results would have been a little better than this since P(I) of location, schedule and driving would have been lower. But however small the P(I) values are these unmeasurable contexts would have still contributed to increase the final P(I).

Our Model:

Table 8 Factors in Our Model

Context	Factor
Location	1
Schedule	1
Driving	1
App in Foreground	1
Bluetooth	1

Contact/Time Of Day PLI: .5

Calculation: Threshold is 1*1*1*1*1*.5 = .5 which is not greater than the threshold .5

Output: No Interruption

Desired output: No Interruption

Remarks: Even though our output is equal to the threshold our model performed better than the weighted sum with adjustable weights model. If subject 1 had configured any of the other contexts such as Bluetooth, Location or schedule subject could have had even better result.

Table 9: Hidden Markov Model: The A Matrix

	Bad Interruption	**Good Interruption**
Bad Interruption	**2**	**4**
Good Interruption	**5**	**4**

Table 10: Hidden Markov Model: The B Matrix

	Friends Before Office	Colleagues Before Office	Family Before Office	Extra Before Office	Friends During Office	Colleagues During Office	Family During Office	Extra During Office
Bad Interruption	**5%**	**0%**	**0%**	**75%**	**50%**	**0%**	**50%**	**90%**
Good Interruption	**95%**	**100%**	**100%**	**25%**	**50%**	**100%**	**50%**	**10%**

	Friends during Evening	Colleagues during Evening	Family during Evening	Extra in Evening	Friends at Night	Colleagues at Night	Family at Night	Extra at Night
Bad Interruption	**0%**	**50%**	**0%**	**25%**	**75%**	**100%**	**0%**	**100%**
Good Interruption	**100%**	**50%**	**100%**	**75%**	**25%**	**0%**	**100%**	**0%**

Value Of PI: 16 as there are 16 states

Predicted Value: Good Interruption

Desired Value: Bad Interruption

Accuracy: We have observed 93.75% accuracy according to the responses we have got from the survey.

Scenario 2: Subject 2 is driving along the highway headed office in morning, unless the caller is important prefers not to be disturbed while driving. An unknown caller calls.

Table 11: Weighted sum with adjusted weights Model (Scenario 2)

Context	Weight	P(I)
Location	1/15 = .066	.5
Schedule	2/15 = .133	.5
Contact	3/15 = .2	.3
Time Of Day	5/15 = .333	.6
Driving	4/15 = .266	.2

Final P(I) = (.066*.5)+(.133*.5)+(.2*.3)+(.333*.6)+(.266*.2) =0.4125 < .5

Output: No Interruption

Desired Output: No Interruption

Table 12: Factors of Our Model

Context	Factor
Location	1
Schedule	1
Driving	.8
App in Foreground	1
Bluetooth	1

Contact/Time Of Day PLI: .7

Calculation: .5*.8=.4 Threshold; PLI .7 is greater than .4

Output: No Interruption

Desired output: No Interruption

Remarks: Our model is giving desired output and has performed better since it has a greater difference with the threshold than the weighted sum with adjustable weights model.

Table 13: Hidden Markov Model: The A Matrix (Scenario 2)

	Bad Interruption	Good Interruption
Bad Interruption	2	5
Good Interruption	5	3

Table 14: Hidden Markov Model: The B Matrix (Scenario 2)

	Friends Before Office	Colleagues Before Office	Family Before Office	Extra Before Office	Friends During Office	Colleagues During Office	Family During Office	Extra During Office
Bad Interruption	20%	20%	10%	10%	40%	10%	10%	10%
Good Interruption	80%	80%	90%	90%	60%	90%	90%	90%

	Friends during Evening	Colleagues during Evening	Family during Evening	Extra in Evening	Friends at Night	Colleagues at Night	Family at Night	Extra at Night
Bad Interruption	10%	70%	10%	5%	40%	70%	10%	50%
Good Interruption	90%	30%	90%	95%	60%	30%	90%	50%

Accuracy: We have observed 75% accuracy according to the responses we have got from the survey from subject 2. We are not comparing Hidden Markov model with the other models since the Hidden Markov Model is not taking the driving context into consideration for lack of observations.

Scenario 3: Subject 3 gets a call at 5 a.m. from a co-worker, explaining to him that the boss is in a bad mood and to please bring the report information that was not thought to be needed until Friday.

Table 15: Weighted sum with adjusted weights Model (Scenario 3)

Context	Weight	P(I)
Location	2/15 = .133	.5
Schedule	1/15 = .066	.5
Contact	5/15 = .333	.85
Time Of Day	4/15 = .266	.75
Driving	3/15 = .2	.5

Final P(I) = (.133*.5)+(.066*.5)+(.333*.85)+(.266*.75)+(.2*.5) = 0.68205 > .5

Output: Interruption

Desired Output: Interruption

Table 16: Factors of Our Model (Scenario 3)

Context	Factor
Location	1
Schedule	1
Driving	1
App in Foreground	1
Bluetooth	1

PLI is .2

Calculation: Threshold is 1*1*1*1*1*.5 = .5, .2 which is less than the threshold .5

Output: Interruption

Desired output: Interruption

Remarks: Our model seems to be performing better since it has a greater difference with the threshold than the weighted sum adjustable weight model.

Hidden Markov Model:

Accuracy: 56.25%

Predicted value: Interruption

Desired output: Interruption

Scenario 4: Subject 4 is in the gym in the evening and does not prefer to take calls while lifting. A friend of his calls in the middle of a strength training session. He has created a location profile for gym since he goes to the gym 3-4 times a week.

Table 17: Weighted sum with adjusted weights Model (Scenario 4)

Context	Weight	P(I)
Location	3/15 = .2	.1
Schedule	2/15 = .133	.5
Contact	4/15 = .266	.9
Time Of Day	5/15 = .333	.75
Driving	1/15 = .066	.5

Final P(I) = (.1*.2)+(.133*.5)+(.266*.9)+(.333*.75)+(.066*.5) = 0.60865 > .5

Output: Interruption

Desired Output:No Interruption

Table 18: Factors of Our Model (Scenario 4)

Context	Factor
Location	.1
Schedule	1
Driving	1
App in Foreground	1
Bluetooth	1

Contact/Time Of Day PLI = .1

Calculation: Threshold Is .1*1*1*1*1*.5 = .05 PLI .1 which is greater than the calculated threshold .05

Output: No Interruption

Desired output: No Interruption

Remarks: In this case even though weighted sum with adjustable weights is close to threshold it still does not give the desired output. Our model excels in this scenario and has a value that is much greater than the calculated threshold.

Scenario 5: Subject 5 is in a meeting with her supervisor at 2 o'clock. Her husband calls her. She prefers not to be disturbed during the meeting.

Table 19: Weighted Sum with Adjusted Weights Model (Scenario 5)

Context	Weight	P(I)
Location	4/15 = .266	.5
Schedule	2/15 = .133	.1
Contact	3/15 = .2	.95
Time Of Day	5/15 = .333	.5
Driving	1/15 = .066	.75

Final P(I) = (.266*.5)+(.133*.1)+(.2*.95)+(.333*.5)+(.066*.75) = 0.5523 > .5

Output: Interruption

Desired Output: No Interruption

Table 20: Factors of Our Model (Scenario 5)

Context	Factor
Location	1
Schedule	.1
Driving	1
App in Foreground	1
Bluetooth	1

Contact/Time of Day PLI is .5

Calculation: Threshold is 1*.1*1*1*1*.5 = .05, PLI is .5 which is greater than the calculated threshold .05

Output: No Interruption

Desired output: No Interruption

Remarks: Our model provided a much better output than the weighted sum with adjustable weights model even in a case where she takes 95% calls from her husband.

Scenario 6: Subject 6 is attending meeting with Dr. Xavier that was thought not to be held before Friday. Dr. Xavier hates when someone's phone rings during a meeting. Fortunately subject 6 knew Dr. Xavier's Bluetooth device name. So he had the device name added in Bluetooth device preferences where he set PLI to .8. Subject 6's 5 year old daughter calls him at 2 o'clock to tell him to buy some chocolate for her on his way home.

Weighted sum with adjusted weights Model:

Table 21: Weighted Sum with Adjusted Weights Model (Scenario 6)

Context	Weight	P(I)
Location	1/28 = .035	.5
Schedule	5/28 = .178	.5
Contact	7/28 = .25	.9
Time Of Day	6/28 = .214	.6
Driving	2/28 = .071	.5
Bluetooth	4/28 = .142	.2
App in foreground	3/28= .107	.5

Final P(I) = (.035*.5)+(.178*.5)+(.25*.9)+(.214*.6)+(.071*.5)+(.142*.2)+(.107*.5) = 0.577 > .5

Output: Interruption

Desired Output: No Interruption

Our Model:

Table 22: Factors of Our Model (Scenario 6)

Context	Factor
Location	1
Schedule	1
Driving	1
App in Foreground	1
Bluetooth	.2

Contact/Time of Day PLI = .1

Calculation: Threshold is 1*1*1*1*.2*.5 = .1 PLI is .1 which is not greater than the calculated threshold .1

Output: No Interruption

Desired output: No Interruption

Remarks: In this case weighted sum with adjustable weights is close to threshold but does not give the desired output. Our model gives here the desired output even though the previous model fails.

Scenario 7: Subject 7 is at home Facebooking in the morning. He does not mind taking a call as long as it is important. He suddenly gets a phone call from his colleague who requests him to bring a thumb drive for a project they are both working on.

Weighted Sum with Adjusted Weights Model:

Table 23: Weighted Sum with Adjusted Weights Model (Scenario 6)

Context	Weight	P(I)
Location	4/28 = .142	.75
Schedule	5/28 = .178	.5
Contact	7/28 = .25	.9
Time Of Day	6/28 = .214	.7
Driving	2/28 = .071	.5
Bluetooth	1/28 = .035	.5
App in foreground	3/28= .107	.95

Final P(I) = (.142*.75)+(.178*.5)+(.25*.9)+(.214*.7)+(.071*.5)+(.035*.5)+(.107*.95)

= 0.724 > .5

Output: Interruption

Desired Output: Interruption

Our Model:

Table 24: Factors of Our Model (Scenario 7)

Context	Factor
Location	1
Schedule	1
Driving	1
App in Foreground	.95
Bluetooth	1

Contact/Time of Day PLI = .3

Calculation: Threshold is 1*1*1*.95*1*.5 = .475, PLI is .3 which is less than the calculated threshold .475

Output: Interruption

Desired output: Interruption

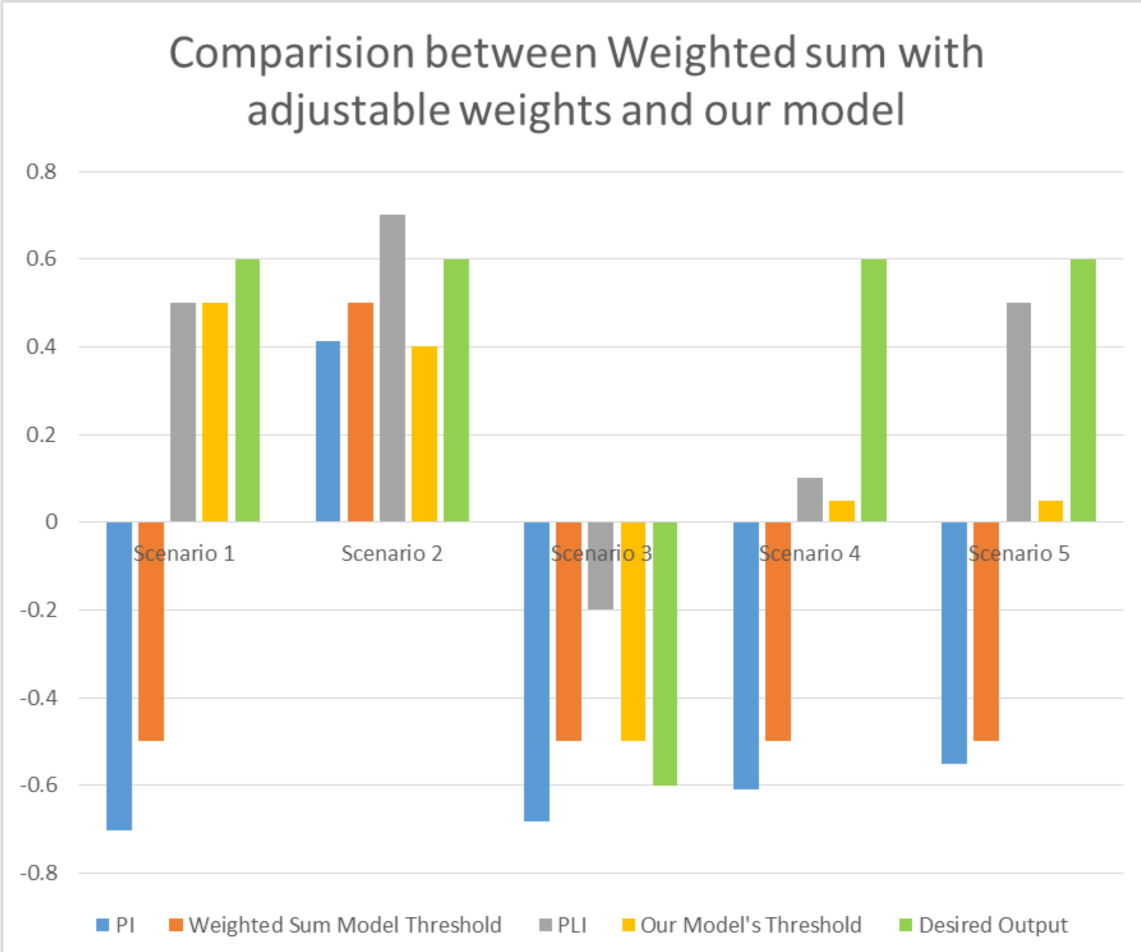

Chart 1: Weighted sum with adjustable weights and our model comparison

5.3 Justification of Addition of New Contexts and Default Values

Survey results:

We have conducted a survey on 20 participants.18 participants took the paper survey and only 2 took the online survey. In the survey questionnaire question 1, 2 was designed to find out most important caller groups, most important time intervals of day. Through question 4 we tried to understand how important the addition of Bluetooth can be to people. Question 3, 5,6,7,8 was included in the questionnaire to help us set default values for our application.

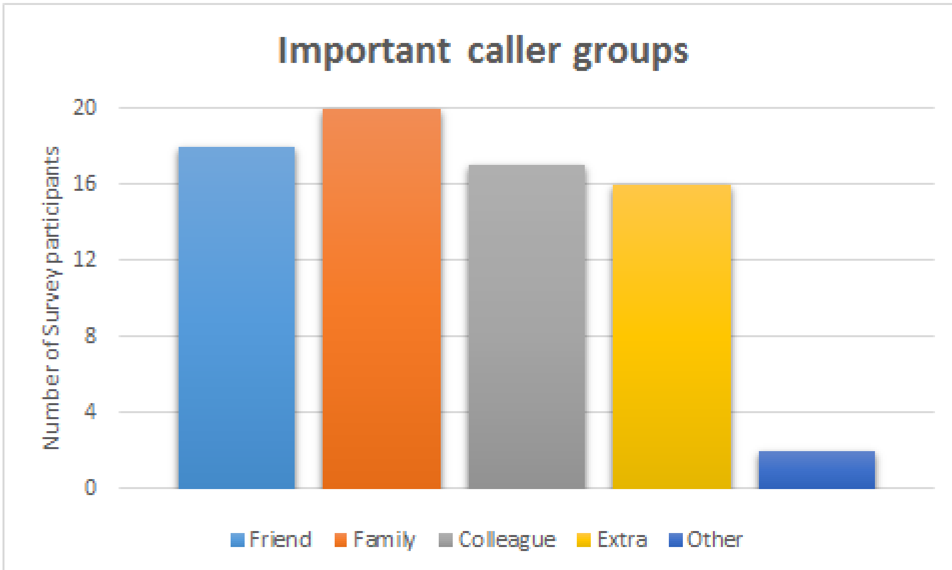

Chart 2: Important Caller Groups

Out of 20 participants 18 participants felt Friends caller group to be important to an MIMS. All of them thought Family must be included, 17 of them thought there should be a contact group for Colleagues, 16 of them thought there should be a caller group so that more importance could be given and only 4 participants felt that more contact groups like other business relations and close family members group is needed. However, our application allows the user to create as many contact groups the user requires.

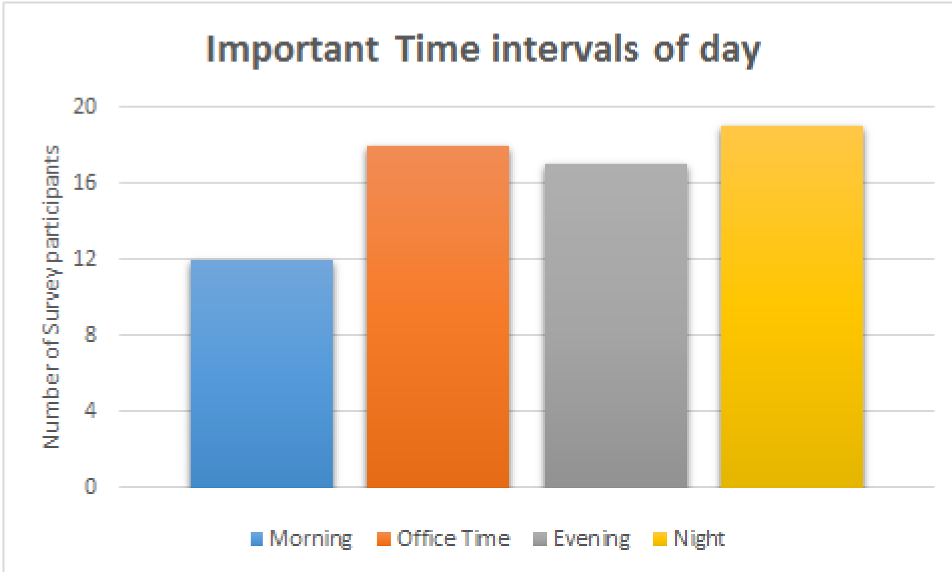

Chart 3: Important Time Intervals of Day

Out of 20 participants 12 thought they needed a Time of Day profile for morning, 18 participants felt they need one for Office time, 17 felt the need of a evening profile that represents the time after office and 19 of them thought they need a Night profile that represents sleeping time.

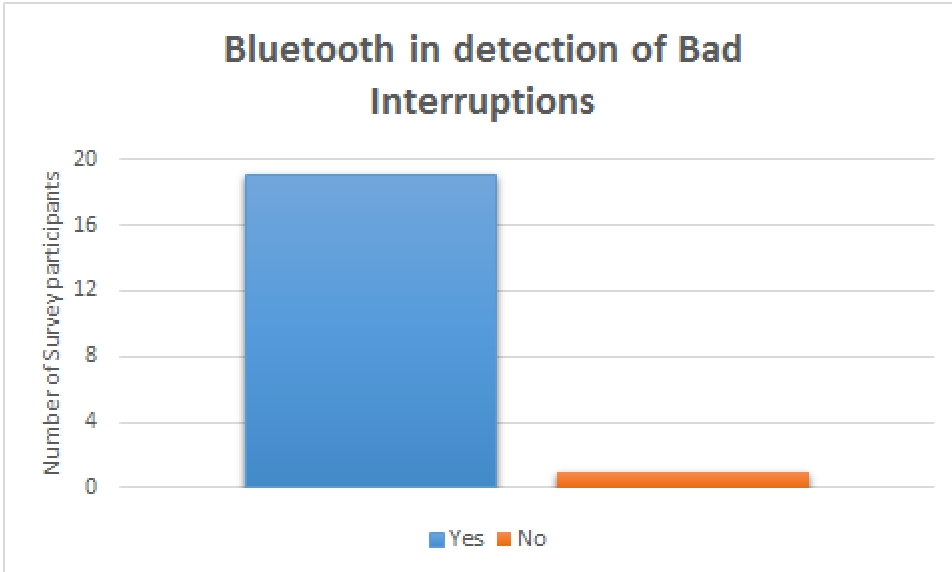

Chart 4: Bluetooth in Detection of Bad Interruptions

Out of 20 subjects 19 subjects thought that usage of Bluetooth can help a Mobile Interruption Management System detect bad interruption.

5.4 Application Performance Evaluation:

After development preliminary tests have been performed. Currently the size of the application is 6.21MB with the source code being 179 KB. The application services run constantly to be aware of location, driving, Bluetooth and app running in foreground contexts. We observed logging app in foreground on a shared preference file takes less than 3 milliseconds and battery consumption due to it should be negligible as this information is already available in the android operating system and it requires no additional computation to retrieve this information. Hence, in our application there are only 2 modules that may drain the battery of the device. One is the location module that uses google services to get location and driving information, the other one is the Bluetooth module that continuously monitors Bluetooth devices in proximity. The location module utilizes Google Play Services to retrieve location updates not only to detect location of the device but also driving context. We have used a Nexus 4 device and GSAM Battery monitor app to test the performance of our app. We have noticed google play services to consume 2%-4% and Bluetooth to consume 4%-6% battery. However, battery consumption can be further reduced by increasing the interval of location and Bluetooth discovery updates. These figures cannot be solely attributed to our app as the android operating system and other apps may be partially responsible for this consumption. CPU usage of the app is minimal since the app runs only upon incoming phone calls and users need less than 5 minutes to configure the application. Neither GSAM Battery Monitor app nor the android operating system was able to provide CPU and battery performance for the app since it is negligible.

CHAPTER 6

Conclusions and Recommendations

6.1 Conclusions

Considering the exponential rate of increase in number of mobile phones we must adequately address the issue of bad influences of it in the society including the enormous amount of man hours that might be lost through distraction of mobile calls. This has resulted in several applications of mobile interruption management with which mobile phones have been empowered to save the users from unnecessary distraction. With the revolutionary progress of digital technologies newer gadgets are coming and they must also be accommodated into systems including mobile interruption management systems. We have used caller group, time of day, calendar, driving, and location and introduced two new important contexts, Bluetooth devices and applications running in foreground that a mobile Interruption Management System may utilize. In fact nowadays mobile phones are in the neighborhood of Bluetooth devices of top management personnel, and applications like Facebook, twitter are being used extensibly in mobile devices. While presence of Bluetooth devices is a discouraging entity for mobile calls, mobile calls might be less detrimental to other applications mobile users may be harmlessly engaged in. In our thesis we have included these scenarios in deciding whether to allow the call to ring or not. Moreover, our dynamic model can help users redefine groups like family, friends or colleagues depending upon frequency of calls. In fact with time scenario changes, family, friend or colleague circles also get changed as the time intervals of the day. So the important parameters of groups of people and time intervals will get changed automatically making the application more realistic with the scenarios an individual will be facing throughout his life.

In this study we have designed an architectural model that any MIMS should be able to use. We have introduced an online call log/feedback database and an analysis module residing on a server that may help identifying complex usage patterns and communicate with the PLI calculation module and/or the matrix to overcome computational abilities of a smartphone.

We have also evaluated weighted sum with adjustable weights model, Hidden Markov Model and our model with configuration data extracted from survey participants. The use of real people data here is extremely important since it is impossible to truly evaluate the models without obtaining configuration data from end users. To evaluate models we randomly selected some scenarios that require cognizance of the contexts we used. In order to simulate the scenarios as realistic as possible subjects that have relevance to the scenarios were chosen. Our model performed exceedingly well in all of the scenarios. Out of 5 scenarios our model produced the desired output in all of them whereas the weighted sum with adjustable model failed in 3 of them. For the lack of observational data Hidden Markov Model could not be used to compare with the previously mentioned models in all of the scenarios however, it was used in scenario 1 and scenario 2 where HMM failed to produce desired output in one of them.

6.2 Future Works

For ease of development we have simplified the model by using the same driving factor for all groups connected through mobile phones. One may like to distinguish between very near relatives and distant ones while driving using a much small factor for distant relatives or friends to discourage receiving their call, while this may not be so for near relatives. We have used the same factor for Bluetooth devices, special days and locations. For example in the event of birthdays or marriage ceremony relatives and friends may get higher priority than other groups so different factors should be used for different groups. It is possible to improve the system by considering these factors with more generality. Another problem that has been being faced by common people is rush of mobile phones from different marketing companies for advertisement of their products. Most often it is disgusting for mobile users to receive so many mobile calls in which they have seldom any interest. It is possible to identify these mobile numbers, block them and relieve the users from call nuisance with the help of crowdsourcing. Features like letting the phone interrupt the user if more that 1 or 2 calls are made in a row from the same caller can also help block some unwanted calls and allow the user take calls that are possible good interruptions.

Knowing other people's location can also help decide whether a call should be let through or not. But there are privacy issues regarding knowing another person's location. Many might consider the idea of sharing their location with others as a violation of privacy. This can be avoided by sharing this information with a server that will know the location of people using the application. The server will just let the mobile application know whether the device is in proximity of another person in the presence of whom the call should not be let through.

The future of mobile interruption management applications lie in machine learning. Users are not interested to enter countless inputs in order to allow their application to minimize interruption. Moreover, the number of combinations of contexts that need to be taken into consideration to allow a phone call is so big that it is not feasible for a user to enter data for all those combinations. Which is why the capability of learning user behavior in different contexts can help the system evolve and provide better service to the app users. In this thesis we have also shown how Hidden Markov model can be used even though we have shown it for only two contexts which are caller group and time intervals of day. The Hidden Markov model seemed quite promising in the scenarios we have evaluated but the problem with it is, HMM cannot be used unless there are enough observations. So after the system has been used for a while and enough observations are stored, the Hidden Markov Model can also be used to predict level of interruption. One can also think of incorporating complex context scenarios when people are engaged in demanding exercise like weightlifting or enjoying coffee to accommodate into MIMS.

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APPENDIX

Survey:

A survey has been conducted to compare three different models. Questions 1-4 were included in the questionnaire to justify the default values of number of groups and time intervals in app configuration. Moreover, **inclusion** of new contexts was justified by Question #4 so that the system could be more context aware. Questions 10-25 were used to specify matrices A, B and Pi. The rest of the questions were used to compare the weighted sum with adjustable weight and our model.

Survey Questionnaire

1. Tick the contact groups you feel people to be divided into in respect of importance of mobile calls? (Different contact groups need to be prioritized differently on various time intervals of a day. For example, Friends may get less priority while you are at work, whereas colleagues probably need to be given more priority)

a) Family b) friends c) colleagues d) other business relations, e) Extra, f) If you think you need more groups write their names here _______________

2. Tick the time intervals of day you feel to be distinguished in respect of mobile calls? (There are time intervals of a day that can be the causal factor for wanting to take a call or reject it. For example, one is less likely to be interested in answering a call at 3 o'clock in the morning another example would be one may not be interested to take a call from a colleague after office hours)

a) Before work b) Office time c) driving d) after work e) bed time f) special event time
g) Evening h) Night

3. How many calls is representative for deciding on how much priority should be given to each caller group? (The system tracks how many calls you considered as an interruption from each caller group. For example, if the number is 60 and out of last 60 calls from friends, you considered 30 calls as a bad interruption the predicted level of interruption for friends group will be set to 50%)

a) last 30 b) last 40 c) last 50 d) last 60

4. Do you think detection of certain Bluetooth devices in proximity can help a Mobile interruption management System in making the decision whether you would like to attend a call? (For example one may not be interested in answering calls while in proximity of a certain colleague or teacher, on the other hand, may not mind taking a call from anyone while hanging out with friends)

a) Yes, b) No

5. What percent of calls do you consider as bad interruption while you are driving?

a) 50% b) 33% c) 25% d) If none what percent of calls do you consider to be bad interruption?_______________

6. How likely are you to reject a phone call when you are in a location like your office (Workplace)

a) 50% b) 33% c) 25% d) If none what percent of calls do you consider to be a bad interruption?_______________

7. How likely are you to reject a phone call if you are around someone you prefer not to talk in front of like course instructor, boss or a colleague?

a) 50% of the time b)33% of the time c) 25% of the time d) If none what percent of calls do you consider to be a bad interruption? _______________

8. How likely are you to take a phone call if your phone rings while using the Facebook app?

a) 50% b) 33% c) 25% d) If none what percent of calls do you consider to be a bad interruption?_______________

9. Fill up the following table with likelihood of bad interruption in percentage from each caller group and times of day (For example in the morning I'll take calls from anybody but at office time my friends will get less priority, in the evening I like to answer calls from my friends)

	Morning	Office time	Evening	Night
Friends				
Colleagues				
Family				
Extra				

Answer the following questions

Instruction: Randomly select a person belonging to each group who called you in the last 30 days and think how you would feel if they call you today in the time intervals of day mentioned in each column below:

10. If someone from Caller group1(Friends) calls you in time of day1 (Before Office) how would you rate it?

a) A good interruption b) A bad interruption

11. If someone from Caller group2(Colleague) calls you in time of day 1 (Before Office) how would you rate it?

a)A good interruption b) A bad interruption

12. If someone from Caller group3(Family) calls you in time of day 1 (Before Office) how would you rate it?

a) A good interruption b) A bad interruption

13. If someone from Caller group4(Extra - The special group for that day) calls you in time of day1 (Before Office) how would you rate it?

a) A good interruption b) A bad interruption

14. If someone from Caller group1(Friends) calls you in time of day 2 (Office time) how would you rate it?

a) A good interruption b) A bad interruption

15. If someone from Caller group2(Colleague) calls you in time of day 2 (Office Time) how would you rate it?

a) A good interruption b) A bad interruption

16. If someone from Caller group3(Family) calls you in time of day 2 (Office Time) how would you rate it?

a) A good interruption b) A bad interruption

17. If someone from Caller group4(Extra - The special group for that day) calls you in time of day2 (Office Time) how would you rate it?

a) A good interruption b) A bad interruption

18. If someone from Caller group1(Friends) calls you in time of day 3 (Evening) how would you rate it?

a) A good interruption b) A bad interruption

19. If someone from Caller group2(Colleague) calls you in time of day 3 (Evening) how would you rate it?

   a) A good interruption b) A bad interruption

20. If someone from Caller group3(Family) calls you in time of day 3 (Evening) how would you rate it?

   a) A good interruption b) A bad interruption

21. If someone from Caller group4(Extra - The special group for that day) calls you in time of day3 (Evening) how would you rate it?

   a) A good interruption b) A bad interruption

22. If someone from Caller group1(Friends) calls you in time of day 4 (Night) how would you rate it?

   a) A good interruption b) A bad interruption

23. If someone from Caller group2(Colleague) calls you in time of day 4 (Night) how would you rate it?

   a) A good interruption b) A bad interruption

24. If someone from Caller group3(Family) calls you in time of day 4 (Night) how would you rate it?

   a) A good interruption b) A bad interruption

25. If someone from Caller group4(Extra - The special group for that day) calls you in time of day 4 (Night) how would you rate it?

   a) A good interruption b) A bad interruption

26. Please write below the number of calls you get per week

27. Please write below the number of bad interruptions you get per week

28. Fill up the following table with likelihood of bad interruption in percentage for each time intervals of day (For example if you consider 70% of phone calls as bad interruption in the morning then you should write 70% in Morning column)

Morning	Office time	Evening	Night

29. Fill up the following table with likelihood of bad interruption in percentage for each caller group (For example if you consider 50% of calls from friends as a bad interruption you should write 50% in Friends column)

Friends	Family	Colleague	Extra

30. Rank the following contexts by importance. Score the contexts with a value of 1 to 5 where 5 is the highest rank.

Context	Rank
Location	
Calendar	
Caller group	
Time of day	
Driving	

31. Do you think detection of app running on foreground can help a system make a decision whether or not a call should be taken?

a) Yes b) No

32. Please write down the percentage of bad interruptions you get during a meeting.

33. Write down the percentage of bad interruptions you get while you are at the gym.