A Context-aware Cost of Interruption Model for Mobile Devices

Sina Zulkernain, Praveen Madiraju and Sheikh Iqbal Ahamed
Department of Mathematics, Statistics and Computer Science
Marquette University
Milwaukee, Wisconsin, USA
{sina.zulkernain, praveen.madiraju, sheikh.ahamed}@marquette.edu

***Abstract*—Unwanted and untimely interruptions have been a major cause in the loss of productivity in recent years as 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 interruption. The cost of interruption (COI) gives as a measure the probabilistic value of harmfulness of an inopportune interruption. Bayesian Inference stands atop among the models that have been applied to calculate this COI. However Bayesian inference based models suffer from not being able to model context accurately in situations where priori, conditional probabilities and uncertainties exist while utilizing context information. Hence, this paper introduces Dempster-Shafer Theory of Evidence to model COI. Along the way, we also identify different contexts necessary for interruption management applications. We also show an illustrative example of a mobile interruption management application where the Dempster-Shafer theory is used to get a better measurement of whether to interrupt or not.**

Keywords- Context; Cost of Interruption (COI); Dempster-Shafer; Uncertainty;

I. INTRODUCTION

Personalization of communication media has brought forth huge popularity among users. But the astonishing on-going growth of handheld devices, especially with almost everyone owning a cell phone, has put up the problem of interruption. A user can be thrown out of the comfort zone just because of a simple but untimely and misplaced disruption. The implication of the situation has grown serious concerns in various domains from psychology, health doctrine to pervasive and mobile computing. A survey 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 [25]. It results in a loss of 700 billion dollars per year, considering an average labour rate of $25 per hour for information workers [30]. 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 [31]. Hence a large body of research in ubiquitous and context-aware computing has been conducted to nullify or at least minimize the effects of interruption.

Whether an interruption is beneficial or harmful depends on the surroundings of the user i.e. the context. The cost of interruption (COI) is a function of immediate task and the user's state of mind, which can also be seen as a function of the task at hand [1, 3, 17]. A proper ubiquitous computing system can theoretically understand the task at hand and infer the user's state of mind and therein get a measure of cost of interruption (COI). But 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 [14, 15, 26]. But measuring COI is a problem dependent on user's contexts where it is unrealistic to calculate the 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 Dempster-Shafer's Theory of Evidence and Rule of Combination [7, 23] 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 us to optimize the number of contexts to consider which will be used as the input parameters in the model.

In our earlier works, we proposed a system solution for managing the unwanted interruptions [28]. In order to achieve this, we first looked at desirable characteristics of the system and then proposed a system architecture which takes as input user preferences, relevant context information and then produces as output if an incoming call should be allowed to ring [29]. Here, we propose a mathematical model for calculating COI based on Dempster-Shafer theory taking into account uncertainty of context information. More specifically, in this paper we provide following contributions:

i) We identified the most important contexts to be considered in a mobile interruption management system by conducting a survey for a set of users.

ii) We incorporated "uncertainty" factor and proposed a mathematical model for measuring cost of interruption (COI) based on Dempster-Shafer theory. The limitation of Bayesian Inference is also shown in this regard

iii) We applied the developed COI model into an illustrative interruption management application to get a better measurement whether to interrupt or not

The rest of the paper is organized as follows. Section II concentrates on how and what contexts we pick as the prime ones and also shows how to calculate the COI. Section III provides a survey of related researches. Section IV covers the background on Dempster-Shafer theory, comparison of it with Bayesian approach and applicability in our problem area. In Section V we illustrate with a case study of an interruption management application where we apply the Dempster-Shafer theory for the measurement of COI. The last section concludes our results and paves the way for future work.

II. Preliminaries

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 as 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 a scale of 1 to 10 and the 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.

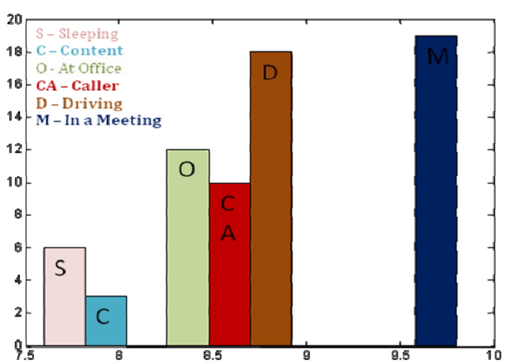

Figure 1. Histogram of users's survey

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 $C_S(t)$ and 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 follows:

A. Context-Location (C_L)

Location can be classified into two major divisions: i) In-Motion Location (C_L^M) and 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}).

B. 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.

C. 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) and 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 [9] measure the Predicted Interruption Value (PIV). 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.

III. Related Works

Different approaches have been explored when trying to tackle the problem of interruption management. The motivation came from the fact that interruptions, regardless of time, place or situation, are detrimental to both personal and socio-economic environment [3, 10, 11, 13, 19, 25, 28]. Whether an interruption is beneficial or harmful depends on the contexts the user is surrounded by. Numerous researchers, focused on modeling context, also paid attention on how they can specify the contexts that play significant role in understanding unwanted disruptions [4, 9, 13, 18, 20, 29, 27]. Further, a number of researchers also proposed models or systems that reduce the cost of interruption [2, 4, 6, 8, 16, 28].

Other researchers have built a mathematical model that can measure the cost of interruption. Most of these approaches use the Bayesian Probability model [14, 15, 16, 26, 27]. But a shortcoming of these works has been they have not taken into account that measuring cost of interruption (COI) or the decision to overrule interruption involves factoring 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 output that measure the COI, little or no information available about the system beforehand, etc. Hence, our research differentiates from the aforementioned works by exploring uncertainty factor for managing interruption and by introducing a new model based on Dampster-Shafer theory [7,23].

IV. OUR MODEL FOR COST OF INTERRUPTIONS

In our proposed model, we have explored the uncertainty factor for managing interruption and introduce the Dempster-Shafer theory in this domain to address uncertainity. In comparison with traditional probabilistic theory, Dempster-Shafer [7, 23] provides an alternative approach to the mathematical representation of uncertainty. In our model, uncertainty stems from the detection of the contexts we described in the previous section. Hence, the decision to accept or decline the interruption based on potentially uncertain context outputs will also be uncertain.

To our best of knowledge, in the research area of interruption management, none of the research works have considered the uncertainty factor nor used the Dempster-Shafer theory. Here we will first give the basics of Dempster-Shafer theory and also make comparison with Bayesian approach. Then, we will explain our model based on the theory.

In brief, Dempster-Shafer theory is a Theory of EVIDENCE born to tackle the problem of UNCERTAINTY. Obviously this gives rise to the question what it means by evidence and uncertainty.

UNCERTAINTY

Uncertainty applies to the prediction of future events or unknown [12]. Uncertainty can occur for two reasons: (i) random behavior expected from a system, or (ii) lack of knowledge about a system. Currently, traditional probability theory is used to deal with both kind of uncertainty. With frequentist approach it works fine considering random behavior of uncertainty. But in recent years, it has undergone some criticisms when it comes to dealing with uncertainty resulting from unknown.

For example [22], let us 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

Limitations of Bayesian Inference

The following are the limitations of Bayesian inference.

1. Bayesian approach requires the complete knowledge of the system with all the 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 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: (i) Basic Probability Assignment (*bpa* or *m*); (ii) Belief Function; and (iii) 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. bpa(A) or m(A) represents that a particular element of S belongs to the set A. So formally,

$$m: power(S) \rightarrow [0, 1]$$
$$m(\Phi) = 0$$
$$\sum m(A) = 1 \text{ where } A \text{ is a subset of the power set of } S$$

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

$$\text{If } B \subseteq A \text{ then}$$
$$Bel(A) = \sum m(B)$$

Plausibility Function: Plausibility of a set A is the sum of the bpa's of all the sets B that share some common elements with A.

$$\text{If } B \cap A \neq \Phi \text{ then,}$$
$$Pls(A) = \sum m(B)$$

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 [7, 23, 24] 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; and (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:

$$\text{If } A \neq \Phi \text{ and } B \cap C = A, \text{ then}$$

$$m_{12}(\Phi) = 0 \text{ and}$$

$$m_{12}(A) = (\textstyle\sum m_1(B)\, m_2(C))/(1 - K)$$

$$\text{where } K = \textstyle\sum m_1(B)\, m_2(C) \text{ when } B \cap C = \Phi$$

V. 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]*.

Recall from Section II where we talked about associating weights with contexts to find the outcome. 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.

VI. Conclusion

In this paper we have proposed a mathematical model for calculating cost of interruption by incorporating uncertainty and by applying Dempster-Shafer theory of evidence. We have also applied our cost of interruption model to a sample interruption management application.

We have already implemented a middleware on HTC G1 for the Android platform [29]. As a part of our goal to build better and accurate interruption management systems, we are now working on implementing the case study application described in this paper and apply the Dempster-Shafer Theory. Furthermore, we will undertake simulations to evaluate how this model performs in comparison with other models using Bayesian approach. We also like to explore possible applications of our system in 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.

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