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Context Representation and Maximize Power Efficiency in Mobile Sensing

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Abstract:

Context representation and maximize power efficiency in mobile sensing applications require continuous data achievement and construal on more mobile sensor application level Existing model framework and inhomogeneous decreasing device battery lifetimes and it's operations put a heavy workload on the smart phone processor and sensor. Overcome from existing system in proposed using Fuzzy logic is an approach to novel context-inferring algorithms and generic framework designs that can help readers enhance existing between quality and price in mobile sensing applications, especially accuracy and power consumption. Proposed Focusing on a specific sensor to discover possible target applications in order to exploit contextual data. Proposed system providing an accurate user state framework model and more maximize power efficiency while the model operates on mobile sensor applications. Proposing developed the future of context-aware mobile sensing applications intends to generate and simplify a generic framework structure for user states.

Keywords: - **Mobile sensing, Energy efficiency, Context-awareness, Machine learning**

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I. INTRODUCTION

Today's, mobile phones are powerful devices since they are not only used for their fundamental purposes like calling or texting but also used for browsing the Internet, taking instant snapshots, tracking any geo-location etc. Increasing the feature set is mostly achieved by integrating complex sensing capabilities on mobile devices. These mobile devices manage to perform these kinds of rich features using their on-board sensors like the accelerometer, Bluetooth, camera, GPS, microphone, audio, video, Wi-Fi, light sensors and etc. Therefore, they are introduced to electronics consumers as smart phones.

Specifically smart phones could provide a large number of applications within the defined research area. Human beings involve in a vast variety of activities within a very diverse context. A specific context can be extracted by a smart phone application, which acquires relevant data through built-in sensors. A desired activity within the context is then inferred by successful algorithmic implementations.

Even major challenge standing up to sensor rich devices is resource-limitation and continuously capturing user context through sensors imposes heavy workloads both physically and computationally during the operation of mobile devices, thereby drains the battery power rapidly.

By utilizing sensors, some meaningful information about user locations, routines and surroundings can be extracted in real-time, allowing some applications to adapt to constantly changing environmental conditions and user preferences. As an example of the user activity sensors, an online application can be used for socializing platforms to update current user locations so that user followers can track the user.

However, some mobile application fields like social networking applications such as Facebook (see[1])and MySpace(see[2]) could use mobile devices as measurement devices. Consequently, context-aware applications are becoming essential in our day to day life which in return implies a greater power consumption required by Smartphone. In this sense, a framework is required to create a control mechanism for sensor utilizations and to help context aware applications work their functionalities properly.

In this paper, focus on using fuzzy logic is an approach to novel context inferring algorithms and generic framework designs that can represent user states. user state as an important way to represent the context. User state may contain a combination of feature such as motion, location and background condition that together describe user's current context. The framework also applies different sensory sampling operations in order to examine the device battery lifetime. We define duration as the length of the time a sensor is turned ON for active data collection. We define sensor sleeping sensor sampling duration as the time a sensor stays idle. The sensing and sleeping durations are generally referred to as sensor parameters. Reducing power consumption for the system operation perspective does not mean that recognition of user state transitions is not concise. There is a challenging tradeoff between power consumption and accurate user context extraction. The system also has to be sure that these missing user state transitions are estimated.

This paper addresses novel approaches to solve the way to balance the complexity of the trade-off, and represents the user states in detail. Proposed methods are summarized as follows: First, the fuzzy logic algorithm proposed in this paper is a flexible way to add and update user states and their relationship to the sensors, after each sensor reading before recognition of user states, the second a sensor-specific user feedback classifier is employed. For some sensors like the accelerometer or GPS etc, for finding out any change of current user state. Lastly to achieve power efficiency, the sensor management scheme assigns the minimum set of sensors and heuristically determines sampling length and intervals for these set of sensors to detect user's states.

The remainder of this paper is organized as follows. In Section 2, we present relevant prior works and their relations to our study. In Section 3, we describe the system design scheme which is the core component. In Section 4, proposed strategies for energy efficiency. In Section 5, we list the empirical results of different sensor power consumptions as one of the motivations of our system design and discuss where we evaluate our system in terms of state recognition accuracy, state transition discovery latency and device lifetime. Finally, we present the conclusion and our future work direction in Section.

II. RELATED WORK

There has been a fair amount of work investigating multisensory mobile applications and services in recent years. The proposed for mobile sensing to recognize user states accurately enough by trying to consume less power, however most of those works provide only partial answer to the tradeoff between data accuracy and less power consumption, and there has not been much work done for constructing a total framework.

Most of the studies rely on recognition of user activities and definition of common user behaviors. For instance, gesture recognition of users is well studied using video cameras. The applied methods in relevant studies are based on statistical models and fuzzy logic model, which this paper also intends to use. However, none of these studies engage themselves to model a common framework in order to construct a base structure for future context-aware mobile sensing applications. They would rather have canalized solutions to solve their own unique applications instead of a generalized approach. Therefore, this paper mostly focuses on a specific sensor user feedback classifier to discover possible target applications in order to exploit contextual data. It's mainly reducing the power consumption while being intended to continuously receive accurate sensor contextual data.

The author Yi Wang [3] proposes a sensor management System, which is called Energy Efficient Mobile SensingSystem (EEMSS). This system improves device battery life by powering a minimum set of sensors and applying duty cycles this system models user states as a discrete time Markov chain and they are have fixed duty cycles when they are active, and they are not adjustable to different user behaviors. Another study which analyzes energy efficient sensor management strategies in mobile sensing introduced with name of Ozgur [4].This system achieves which attempt to control mobile phone sensors in such a way that correct user state recognitions are still obtained while reducing energy consumption. This paper includes important information on how the system framework should be constructed and modeled.

The hierarchical sensor management system is also studied by introducing “SeeMon” system in [5] which achieves energy efficiency and less computational complexity by only performing a continuous detection of context recognition when changes occur during the context monitoring. Gellersen et al. [6] pointed out the idea that combining a diverse set of sensors that individually captures just a small aspect of an environment may result in a total picture that better characterizes a situation than location or vision based context. The concept of sensor fusion is well-known in pervasive computing.

Moreover , Zappi et al [7] pointed accuracy-power trade-off by dynamic sensor selection scheme for user state recognition. Rachuri et al. [8] also uses different sampling period schemes for querying sensory data in continuous sensing methods in mobile systems to evaluate power-accuracy trade-offs. S.Gaonkar et al. [9] studies energy efficiency in mobile device based localization, and the authors show that humans can be profiled based on their mobility patterns and thus location can be predicted. The proposed “EnLoc” system achieves good localization accuracy with a realistic energy budget. A common low cost sensor used for detecting motion is the accelerometer. These as the main sensing source activity recognition are usually formulated as a classification problem where the training data is collected with experimenters wearing one or more accelerometer sensors in a certain period. Different kinds of classifiers can be trained and compared in terms of the accuracy of classification [9, 10, 11, 12]. Other methods used for activity detection benefit from signal processing and pattern recognition techniques. Relevant studies such as [13]–[19] construct a framework which is designed to control the acquisition and interpretation of data from one or more sensing’s. This inference framework is implemented for a range of context workloads by using diverse algorithmic primitives.

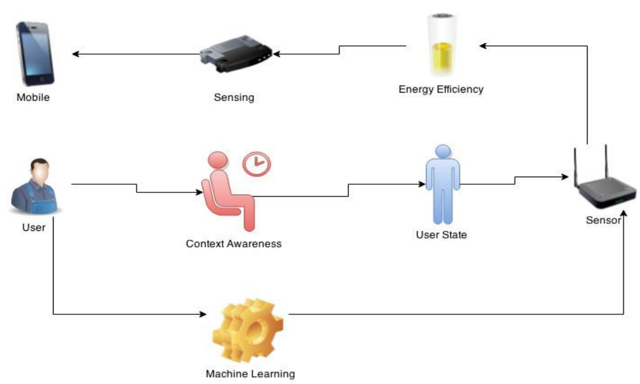
In our system design, we build on many of these past ideas and integrate them in the context of effective power management for sensors on mobile devices. In order to achieve human state recognition in an energy efficient manner, In this proposed a fuzzy logic approach for managing sensors, and do so in such a way that still maintains accuracy in sensing the user’s state.

III.SYSTEM DESIGN

We make some assumptions about the energy efficiency and the underlying the mobile sensing. These are the construction of the proposed frame work

- User state estimated method
- Mobile sensing
- Energy efficiency
- Context-awareness
- Machine learning

User state representation engine infers an instant user behavior in light of prior knowledge of a human behavior pattern and availability of sensory observation at decision time. If sensory observation exists, the method applied process is called recognition method; otherwise, estimation method, estimation is applied whenever power efficiency is taken into consideration Evaluation method relies on updating probability weights iteratively that decides which user state is selected to represent instant user activity.



. Figure 1.Context Awareness System

The system approach to gather aggregate sources of information from the open services through the network and integrate them after to form an analysis, validation of the problems in each entity. This early research could derive valuable high-level human behavior information planning, mobility and social interactions. Sensor management system, which is called Energy Efficient Mobile Sensing System (EEMSS). This system models user states as a discrete time Markov chain and improves a device battery life by powering a minimum set of sensors and also by applying duty cycling into sensor operation. However, sensors have fixed duty cycles when they are active, and they are not adjustable to different user behaviors. Also, given system is predetermined and not time-variant.

The system makes an observation after a predefined number of sensor samplings are acquired. Then, user state is recognized with the help of extracted context from samplings. Actual sampling time in sensor operation can be extended in order to prolong a mobile device battery lifetime. User states and interval waiting time for each user state, the expected waiting time for an upcoming sensor sampling is calculated time.

A specific context can be extracted by a smartphone application, which acquires relevant data through built-in sensors. A desired activity within the context is then inferred by successful algorithmic implementations. Unfortunately, all of these operations put a heavy workload on the Smartphone processor and sensors. Constantly running built-in sensors consume relatively much more power than a smartphone does for fundamental functions such as calling or text messaging. Mobile device batteries do not last a long time while operating sensors simultaneously. Context-aware applications are becoming essential in our day to day life which in return implies a greater power consumption required by Smartphone.

We address short text categorization as a hierarchical two level classification process. The first-level classifier performs a binary hard categorization that labels messages as Neutral and Non neutral. The second-level classifier performs a soft-partition of Non-neutral messages assigning a given message a gradual membership to each of the non-neutral classes. Among the variety of multiclass ML models well suited for text classification, we choose the model for the experimented competitive behavior with respect to other state-of-the-art classifiers.

IV.PROPOSED STRATEGIES FOR ENERGY EFFICIENCY

A Fuzzy logic models (Pedrycz, 1984) describe associations between linguistic terms defined in the input and output domains of the system .A fuzzy logic algorithm can be applied to a system which aim to recognize user state. The algorithm using fuzzy logic system can generalized the mobile sensing observations with certain accuracy. Therefore the model comprises a well-adapted approach more multisensory scenarios. It deals with inaccuracy and uncertainty it can be built based on the experts experience. The fuzzy logic approach is also characterized by low computational cost.

4.1 Basic Definitions:

Individual elements of the relation represent the strength of association between the fuzzy sets. Denote A a collection of M linguistic terms (fuzzy sets) defined on domain X, and B a collection of N fuzzy sets defined on, used to specify sensor readings which occur periodically in a system.
Fuzzy logic is characterized by the following elements,

Let X be some set of object, with elements noted as x,

$$X=\{x\}$$

A fuzzy set A in X is characterized by a group function mA(x) which maps each point in X onto the real interval [0.0, 1.0].As mA(x) approaches 1.0, the "grade of group" of x in A increases. The model is a table storing the rule base to obtain a crisp output, the resulting fuzzy set is defuzzified by the fuzzy-mean method applied to the centroids bj of the fuzzy sets Bj.

- *Initial State Probability*: An irreducible and aperiodic that begins with its periodic distribution:

$$\pi i = Pr(S0 = i), \{\forall i \in \{1, . . . ,N\},$$

$$\pi i \geq 0, \sum Ni=1 \ \pi i = 1.$$

• *State Transition Probability*: a is described as {N × N} state transition matrix where each element a_{ij} of a is equal to a transition probability from state i to state j,

$$a_{ij} = \Pr(S_t = j \mid S_{t-1} = i),$$

$$\forall i,\ j \in \{1, \ldots, N\},\ a_{ij} \geq 0,$$

$$\sum_{i=1}^{N} a_{ij} = 1.$$

There is no requirement that transition probabilities
Must be symmetric ($a_{ij} \neq a_{ji}$) or a specific state might
Remain the same in succession of time (a_{ii} =0).

• *Visible Process*: A set of observations is defined as a
Discrete time process with a finite space of K,

$$\vartheta[1:T] = \{\vartheta_1 = k, \vartheta_2, \ldots, \vartheta_T\}, \forall k \in \{1, \ldots, K\}.$$

• Observation Emission Probability: b is described as {N× K} observation emission matrix where each element b_{jk} of b is equal to a cross probability between hidden
State and emitted observation,

$$b_{jk} = \Pr(\vartheta_t = k \mid S_t = j),$$

$$\forall k \in \{1, \ldots, K\}, b_{jk} \geq 0,$$

Parameters are usually denoted as a triplet $\lambda = \{a_{ij},\ b_{jk},\ \pi_i\}$.

4.2 System Adaptability:

The most important feature of context-aware applications is being capable of adapting themselves to user behaviors. User context differs in time and the corresponding user state also does. Since user behavior shows various patterns from one user to another, a sequence of user states for each user will be arranged in a different formation with respect to variant user state transitions occurring throughout time. For instance; one user might remain in same user state for a long time; whereas, others might be more active by changing their user states frequently. Therefore, it cannot be expected from relevant user state transition matrix to remain stationary. User state transition matrix evolves in time and must adapt itself to user choices.

4.3 Entropy Rate

Entropy is a measure of uncertainty in stochastic process. It quantifies the expected value of information contained in a specific realization of any random variable; hence, the value of entropy rate shows predictability of a random distribution. In this study, entropy rate is used to track changes in user state transition matrix. Since the transition matrix is initially set the default setting for all users, the framework has to adapt itself toward unique user behaviors in time by tracking changes in transition matrix. In this regard, when entropy rate converges into a stable value, it points out that the framework could manage to update the transition matrix into the current user behavior.Thereby, it is accepted that a required adjustment on user adaptation is set accurately.
Entropy rate for a Fuzzy is given by

$$F(S_t) = \lim_{t\to\infty} F(S_t \mid S[1:t-1]) = \lim_{t\to\infty} F(S_t \mid S_{t-1}),$$

$$= \sum F(S_t \mid S_{t-1} = i) \Pr(S_{t-1} = i),$$

$$= \sum_i (\sum_j a_{ij} \log a_{ij})\ \pi_i = \sum_i a_{ij} \log a_{ij}.$$

With time-variant property, let $ep(s,\ t)$ denote an average value of a sequence of entropy rates in time range of s up to t by

$$ep(s,\ t) = 1/(t - s + 1) \sum F(S_\tau).$$

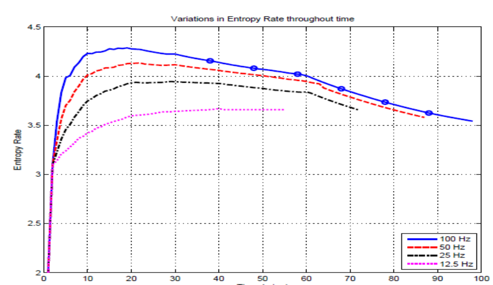


Figure 3.Entropy Rate Analysis

V.SIMULATIONS

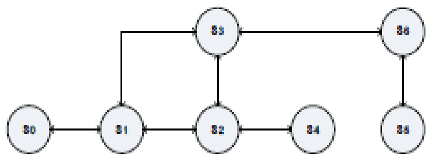


Figure 2. Example of User State Transition

Simulations are carried out in order to examine the defined trade-off between power consumption and accuracy in user state representations in light of the proposed framework for context-aware applications. Some case scenarios are created so as to indicate the framework is still valid under different system parameters. For the sake of simplicity, two-user state consisting fuzzy is considered. However, more complex models can be applied as well by using same system approach.

5.1 Power Consumption

The system makes an observation after a predefined number of sensor samplings are acquired. Then, user state is recognized with the help of extracted context from samplings. Actual sampling time in sensor operation can be extended in order to prolong a mobile device battery lifetime. Sampling intervals are modeled as Ii = n/fs where n and fs are an integer value and sampling frequency respectively. Ii defines a waiting time between two consecutive sensor samplings. During simulations, n = {1, 2, 4, 8} and fs = 100 Hz are taken. Given the probability of user states and interval waiting time for each user state, the expected waiting time for an upcoming sensor sampling is calculated by

$E[I_t] = \sum_i Pr(S_t = i)(I_t = i)$.

Since Ii is considered fixed for all user states throughout simulations, being at any user state does not change a relevant waiting duration to acquire a new sensor sampling. Reasonably speaking that the expected energy consumption at each sensor sampling is inversely proportional to waiting time,

$E[C_t] \propto 1/E[I_t]$

For instance; if $n = 1$ is taken for each user state, energy consumption turns out the highest since sensor sampling is being made at each available time slot. Otherwise, whenever $n > 1$, there comes time slots at which no sampling is made.

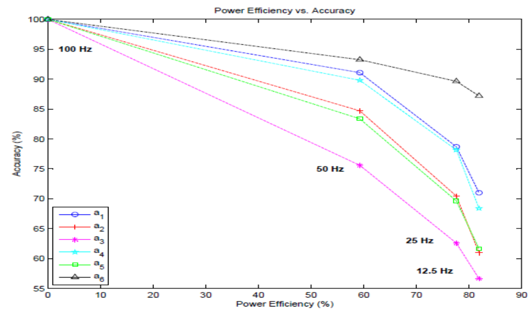


Figure 4. Power Consumption vs. Accuracy

5.2 Accuracy Model

The probability of error occurred during either recognition or estimation of user state is calculated by

$e_t = 1 - Pr(\hat{S}_t)$.

This information yields to find the expected recognition
error throughout observation space O with a number of
occurrences $\#O$

$E[e_{rec.}] = 1/\#O \sum_{t=1} e_{t}^{rec.}$

The expected estimation error uses arithmetic mean
method. However, assume that tf is where the first sampling is made. Then, the weight corresponding to an error occurred where the first estimation is made should have lower proportion than the weight corresponding to an error occurred where the last estimation is made because of the fact that while time goes by and an estimation is being made one after another, the accuracy of estimations are expected to degrade. Therefore, the relevant weight for any estimation point is reciprocal of the time distance to next available sampling time slot.

VI.CONCLUSION

Provided a generic system framework within the area of mobile device based context representation and maximize power efficiency in mobile sensing applications. Focuses on the fuzzy logic is an approach to novel context-inferring algorithms and generic framework designs that can help the user profile while examining the quality and price between accuracy in contextual inference from sensory data and required power consumption due to data acquisition and computational processing. Existing in homogeneity is characterized by time-variant system parameters, and the user profile adaptability challenge is modeled using the convergence of entropy rate in conjunction with the in homogeneity. During the proposed system a sufficient number of signals processing techniques using fuzzy logical model which is applied to find out an accurate user state representation model, and to maximize power efficiency while the model operates. Proposed system develop the future of context-aware mobile sensing applications intends to create and clarify a generic framework structure for user states.

VII. REFERENCE

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