Battery Optimization of Android Phones by Sensing the Phone Using Hidden Markov Model

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Abstract- The paper presents a novel framework that includes an inhomogeneous (time-variant) Hidden Markov Model(HMM) and learning from data concepts. The framework either recognizes or estimates user contextual inferences called 'user states' within the concept of Human Activity Recognition (HAR) for future context-aware applications. Context-aware applications require continuous data acquisition and interpretation from one or more sensor reading(s). Therefore, device battery lifetimes need to be extended due to the fact that constantly running built-in sensors deplete device batteries rapidly. In this sense, a framework is constructed to fulfill requirements needed by applications and to prolong device battery lifetimes. The ultimate goal of this paper is to present an accurate user state representation model, and to maximize power efficiency while the model operates. Most importantly, this research intends to create and clarify a generic framework to guide the development of future context-aware applications. Moreover, topics such as user profile adaptability and variant sensory sampling operations are examined. The proposed framework is validated by simulations and implemented in a HAR-based application by the smart phone accelerometer.

Index Terms- accelerometer sensor, entropy rate , HAR based application, Hidden Markov Model.

I. INTRODUCTION

The understanding of human activity is based on discovery of the activity pattern and accurate recognition of the activity itself. Therefore, researchers have focused on implementing pervasive systems in order to create high level conceptual models to infer activities and low-level sensory models to extract context from unknown activity patterns. In this sense, a successful research has been conducted in the area of human-centric ubiquitous sensing. 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. Unfortunately, all of these operations put a heavy workload on the smart phone processor and sensors. Constantly running built-in sensors consume relatively much more power than a smart phone does for fundamental functions such as calling or text messaging.

Consequently, context-aware applications are becoming essential in our day to day life which in return implies a greater power consumption required by smart phones. 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. This paper proposes an inhomogeneous (time-variant) Hidden Markov Model (HMM) based framework in order to represent user states by defining them as an outcome of either the recognition or estimation model. Thereby, a statistical model is required to track *time-variant* user activity profiles in order to predict the best likely user state that fits into instant user behavior. As a result, user states are either recognized as an inference of actual sensor readings or as an estimation of the missing inference.

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II. METHODOLOGY

The Hidden Markov Model (HMM) can be applied to a system which aims to recognize user states. In this system, sensor readings (i.e., extracted user contexts through mobile device based sensors) are seen as inputs. These readings undergo a series of signal processing operations and eventually end up with a classification algorithm in order to provide desirable inferences about user behaviors/profiles for context-aware applications. A required classification algorithm differs in terms of explanation of extracted user context through a specific sensor.

Classification algorithms produce observations (i.e., **visible states**), ϑ, of HMM. Among observations, only one observation is expected to provide the most likely differentiation in selection of instant user state representation. This observation is marked as instant observation, which also indicates the most recent element of observation sequence of HMM. On the other hand, user states are defined as **hidden states**, *S*, of HMM since they are not directly observable but only reachable over visible states. Therefore, each observation has cross probabilities to point any user state. These cross probabilities build an emission matrix, *bjk*, which basically defines decision probabilities of picking user states from available observations. In addition, a user state might not be stationary since a general user behaviour changes in time. Thus, it is expected from a user state either to transit into another user state or to remain same. These occurrences build a time-variant user state transition matrix, *aij*, which defines transition probabilities among the user states.

The wireless network is made with different algorithms for Sensor to access the different process that may leased too many disadvantages. We propose an **HMM** scheme, which fulfills the battery lifetime of user mobility while using the multiple sensor at a time. We propose to increase the battery efficiency of 75% with the accuracy value of human activity recognition. This research intends to create and clarify a generic framework to guide the development of context aware applications. The proposed framework is validated by simulations are implemented by HAR-based application in the smart phone.

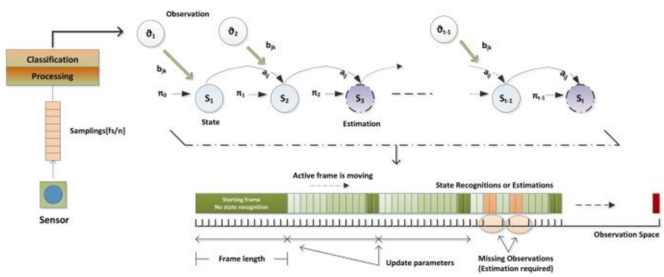

Fig. 1. Operation of the proposed framework.

III. STUDIES AND FINDINGS

ALGORITHM, BODY PARAGRAPHS , FIGURES &TABLES AND REFERENCES

A. Algorithm

The Hidden Markov Model (HMM) is a popular statistical tool for modeling a wide range of time series data. In the context of natural language processing (NLP), HMMs have been applied with great success to problems such as part-of-speech tagging and noun-phrase chunking. Hidden Markov models have close connection with mixture models. A mixture model generates data as follows. For sequence or spatial data, the assumption of independent samples is too constrained. The statistical dependence among samples may bear criticism Information. The Hidden Markov Model (HMM) is a powerful statistical tool for modeling generative sequences that can be characterized by an underlying process generating an observation sequence.

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B. Body Paragraphs

The HMMs have found application in many areas interested in signal processing, and in particular speech processing, but have also been applied with success to low level NLP tasks such as part-of-speech tagging, phrase chunking, and extracting target information from documents. HMM is involved in the segment analysis along with the state transition. The main advantages of HMM are Higher Security, and Efficient in Battery life of mobile. When implementing a HMM, floating-point underflow is a significant problem. It is apparent that when applying the Viterbi or forward algorithms to long sequences the extremely small probability values that would result could underflow on most machines. Advantages in Hidden Markov chain Effective Can handle variations in record structure Optional fields, varying field ordering. Disadvantages are requiring training using an annotated data, Not completely automatic, May require manual markup, Size of training data may be an issue.

C. Figures

Like applied in simulations, only two user state scenario is taken. These are sitting and standing. The inferences related to walking and running are considered as standing since walking and running activities cause more variations over acceleration signal belonging to standing activity. To differentiate one activity to another, so many studies can be found in literature. Studies proposing online solutions mostly use decision tree based classifications with setting predefined fixed thresholds in order to cluster different states. On the other hand, some papers provide offline solutions after recording relevant observation data. These solutions propose a creation of high dimensional feature vectors at first by applying many signal processing techniques in order to extract signal characteristics such as energy, entropy, mean, rms, variance etc. in regardless of analyzing signal deeper in terms of what is really supposed to do so that a proper differentiation could be made.

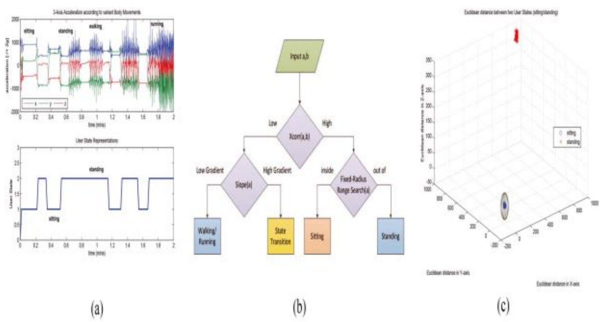

Figure 2: Observation analysis for the accelerometer sensor. (a) 3-Axis accelerometer signals.
(b) User state classification.
(c) Euclidean distance analysis.

D. Tables

Table 1: Filtering States While No Observation Received

Filter at $t-1$	$Pr(S_{t-1}=j \mid \vartheta_{t-1})$
	$\downarrow$
Prediction at t	$Pr(S_t = j \mid \vartheta_{t-1})$
	$\downarrow \ \vartheta_t$
Filter at t	$Pr(S_t = j \mid \vartheta^t)$

Table 2: Current Consumption vs. Data Rate in Accelerometer

($V_{DDI/O}$ = 1.8 V, V_S = 2.6 V)	
Data Rate (Hz)	$I_{DD}(\mu A)$
100	140
50	90
25	55
12.5	40
Autosleep Mode	23
Standby Mode	0.2

E. References

Wang *et al.* who proposes a 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.

Rachuri *et al.* uses different sampling period schemes for querying sensory data in continuous sensing mobile systems to evaluate accuracy-power trade-offs.

IV. EQUATIONS

First order HMM is proposed for creating a statistical tool to show dependencies of states at discrete time t that are influenced directly by a state at discrete time $t-1$[1]. Discrete time is used to specify sensor readings which occur periodically in a system.

- ***Hidden Process:***
  A set of hidden states is defined as a discrete time process with a finite space of N,
  $$S_{[1:T]} = \{S_1 = i, S_2, \ldots, S_T\}, \forall i \in \{1, \ldots, N\}.$$
- ***Initial Hidden State Probability***:
  An irreducible and a periodic Markov chain that begins with its ergodic distribution:

$$\pi_i = Pr(S_0 = i), \forall i \in \{1, \dots, N\},$$
$$\pi_i \geq 0, \sum_{i=1}^{N} \pi_i = 1.$$

- ***State Transition Probability***:

  a is described as $\{N \times N\}$ state transition matrix where each element a_{ij} of a is equal to a transition probability from state i to state j,

$$a_{ij} = Pr(S_t = j \mid S_{t-1} = i), \forall i, j \in \{1, \dots, N\},$$
$$a_{ij} \geq 0, \sum_{i=1}^{N} a_{ij} = 1.$$

- ***Visible Process***:

  A set of observations is defined as a discrete time process with a finite space of K,

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

V. CONCLUSION

The in homogeneity is characterized by time-variant system parameters, and the user profile adaptability challenge is modelled using the convergence of entropy rate in conjunction with the in homogeneity. Simulations are run and a smart phone application is implemented in order to demonstrate how entropy rate converges in response to distinctive time-variant user profiles under different sensory sampling operations. During the recognition process, a sufficient number of signal processing techniques is applied to find out the best context-exploiting methods on the sensory signal instead of applying computationally harsh pattern recognition methods.

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