A Probabilistic Framework for Base Level Context Awareness of a Mobile or Wearable Device User

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***Abstract*—A framework for determining probabilistic context awareness of a mobile or wearable device user with single or multiple sensors is presented. The functionality of this module or subsystem consists of acquisition of raw data from single or multiple, homogeneous or heterogeneous sensors and processing it to derive contextual information for the device user. The framework takes into consideration the base level context of continuous motion and voice activities of the device user and spatial environment surrounding the user along with other deterministic input. The output of that framework is posteriorgram i.e. a posteriori probabilities of each class of each descriptor of context. The framework has several advantages of being expressive, simple, scalable and extendable along with providing output in probabilistic form. The usefulness of such a framework lies in the fact that providing base level context awareness as input gives flexibility to develop various types of application programming interfaces (APIs) and its adaptability to increase or decrease the descriptors of context to be inferred, without change in the base level framework of context awareness. The base level context awareness comprising of deterministic and probabilistic context can be used to derive meta level context awareness of various kinds.**

***Index Terms*—probabiloistic framework, context awareness**

I. Introduction

MEMS sensors such as accelerometer, gyroscope, magnetic compass, barometer, temperature sensor, camera etc., are widely embedded in mobile phones wearable devices due to their several utilities, small footprint and low cost. The inclusion of sensors in mobile and wearable devices has made it feasible to make the device context aware.

With increase in understanding of context awareness and its usefulness in different domains there has been a growth of context aware systems. Yurur *et al.* [1] did a survey on emerging concepts to applications of context-awareness in mobile platforms. Bettini *et al.* [2] provide a survey of context modelling and reasoning. Various research efforts such as Context Toolkit, CARISMA, CoBRA, GAIA, QoS DREAM, PACE, SOCAM, COSMOS, etc., were also developed that use middleware solutions such as GSN, ASPIRE, Hydra, etc. These research approaches have the disadvantage that the context is tied to a particular application and thus it is difficult to update the context information so as to be used for other context aware applications. The disadvantages can be overcome by another approach, in which the retrieval of context and development of applications utilizing it are separate activities. Thus, the context of the device user can be used for heterogeneous domains of applications having different frameworks, that may have different ways of handling context and may be based on dissimilar principles.

The paper presents a probabilistic framework for determining the base level information about classes of one or more descriptors of context being explicitly represented. The descriptors of context are (i) continuous motion activity of the device user, (ii) continuous voice activity of and around the device user and (iii) spatial environment of the device user. These descriptors provide the fundamental context of the device user having semantic interpretation that may be derived directly or indirectly from sensor inputs, hence we call it as base level context awareness (BLCA). A probabilistic output for each class within the three descriptors can be used to obtain the uncertainty of any hard decision or inferences. The information theoretic evaluation of confidence measures about context inferences can also be made. Meta level context awareness (MLCA) can also be derived from BLCA.

MLCA is the composite information that is derived from base level context information. Hence, MLCA requires knowledge of occurrence of one or more classes of a descriptor or/and descriptors of BLCA. For example, suppose the device user is driving a car, then halts and finally gets out of the car. This sequence has several classes of descriptors in BLCA. Initially the device user is in a car, i.e., the user is in the spatial environment of a car and is performing the motion activity of driving, then comes to halt, i.e., the motion activity becomes stationary and finally, the motion activity consists of getting out of the car with spatial environment of parking area or garage etc.

II. Modelling of Probabilistic BLCA

The descriptors of context awareness, i.e., motion activities, human voice activities and spatial environment around the device are defined as three separate random processes (RP). The random process for continuous motion activity descriptor of context is defined as,

$$\left\{M[\alpha, l]: \ \alpha \in \Omega_M, \ l \in \tau_M\right\} \tag{1}$$

This work was done at Indian Institute of Technology, Delhi under research project from, and in collaboration with STMicroelectronics Inc.

978-1-7281-3575-5/19/$31.00 ©2019 IEEE

where, τ_M are discrete time index. The continuous time signal is sampled uniformly at $t = l(T_{sx})$ where l is integer and T_{sx} is sampling time period of $M[\alpha, l]$. Similarly, $V[\beta, m]$ and $S[\gamma, n]$ is also defined as RP for continuous voice activity and spatial environment descriptor of context respectively.

Each of the descriptors of base level context have distinct classes that specify different attributes of contextual information. The sample space of the RP $M[\alpha, l]$ is Motion Activity Vector (MAV). MAV has elements signifying different motion activities performed by the device user in possession of the device. Similarly, Voice Activity Vector (VAV) has different elements of human voice activities of the device user as well as human voice around the device and Spatial Environment Vector (SEV) has elements denoting spatial environment around the device. Examples of MAV, VAV and SEV are given below:

$$\begin{aligned} MAV = [&stationary;\ walking;\ jogging;\ cycling;\\ &stairs\ up-down;\ elevators\ up-down;\\ &in-vehicle;\ none\ of\ these]^T \end{aligned} \tag{2}$$

$$\begin{aligned} VAV = [&silence; single\ person\ voice\ activity,\\ &group\ voice\ activity;\ none\ of\ these]^T \end{aligned} \tag{3}$$

$$\begin{aligned} SEV = [&street;\ nature;\ beach;\ stadium;\ office;\\ &mall;\ home;\ none\ of\ these]^T \end{aligned} \tag{4}$$

III. Probabilistic Framework for BLCA

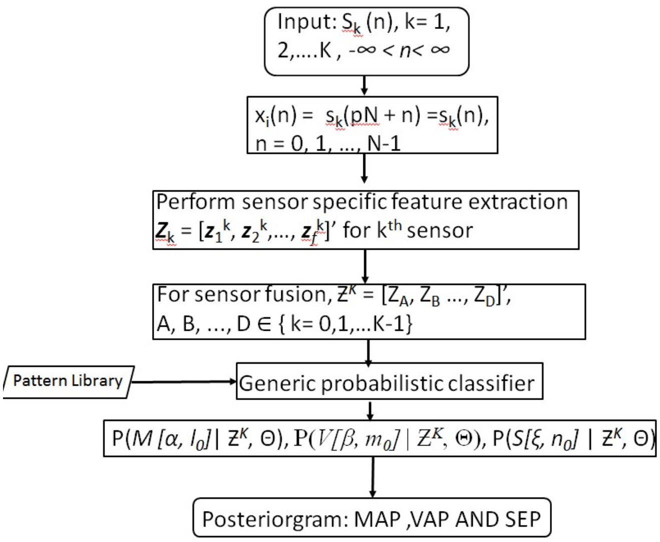

Fig. 1. Steps of algorithm for obtaining probabilistic output of BLCA.

Let $\mathbb{Z}^K$ be the composite feature vector for MAV derived from different sets of sensors. The composite feature vector extracted from the sensors is given as input to the supervised classifier, and the classifier Θ is trained. A posteriori probability is the probability of each class ma_i in the sample space Ω_M, given the composite feature vectors $\mathbb{Z}^K$ at a particular time instant with given parameters of training libraries Θ. The time sequence of a posteriori probability is given as Motion Activity Posteriorgram (MAP).

$$\begin{aligned} P(M[\alpha, l]|\mathbb{Z}^K, \Theta) = [&P(ma_1|\mathbb{Z}^K, \Theta), P(ma_2|\\ &\mathbb{Z}^K, \Theta), \ldots,\ \ P(ma_M|\mathbb{Z}^K, \Theta)] \end{aligned} \tag{5}$$

Similarly, posteriorgrams VAP $P(V[\beta, m]|\mathbb{Z}_V^K, \Theta_V)$ and SEP $P(S[\xi, n]|\mathbb{Z}_S^K, \Theta_S)$ can also be computed.

IV. Implementation of Framework and Results

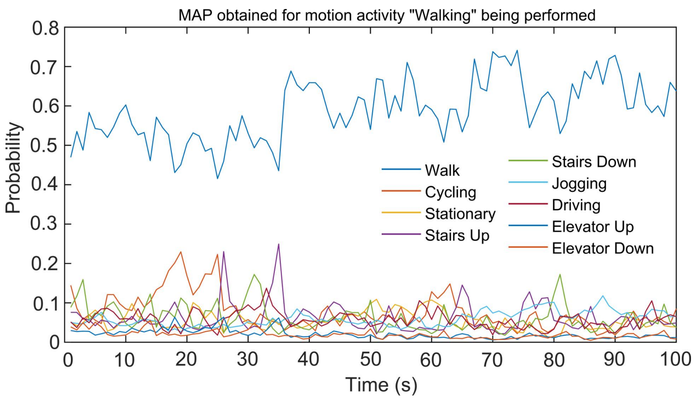

Fig. 2. MAP obtained for the motion activity of walking being performed using accelerometer, barometer and gyroscope.

Raw data for the motion activities being performed are obtained from accelerometer, barometer and gyroscope, providing 35 dimension composite feature vector. The feature vectors are used to train models of the classifier Θ to obtain parameters. To recognize 9 motion activity classes, modelling techniques such as HMM, ANN, SVM and CNN were implemented. The time sequence of posterior probability of each class in MAV, i.e., MAP is obtained from probabilistic multi-class SVM using DAG as shown in Fig. 2. Weighted average accuracy of 95.12% is obtained for MAV using accelerometer, barometer and gyroscope. VAV and SEV were similarly implemented for obtaining the composite BLCA. This was used to study MLCA for the application referred in last paragraph of Section 1.

V. Conclusion

The presented framework has the advantage of simple representation, along with the capability to extend to a number of classes for each descriptor of the context. The novelty of the framework lies in providing a framework with posteriorgram as the output for base level context awareness, that is independent of the specific applications to be built. The probabilistic output of BLCA is useful for deriving MLCA based on information available in BLCA.

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