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A Pervasive Multi-Distribution Perceptron and Hidden Markov Model for Context Aware Systems

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Abstract.
Fueled by the recent advancements in pervasive environment, affluent context aware systems is among the rousing in computing today, including embedded environment, different wireless network technology, electronic communication and so on. Context-Aware Collaborative Filtering using Genetic Algorithm approach resulted in an improved mobile business model by determining optimal similarities between contexts. In this work, we plan to devise a hybrid framework called Multi-distribution Perceptron and Hidden Markov Model to smoothen the mobile networks with different degrees of context- confidence. Initially, Multi-distribution Layer Perceptron Model is designed aiming at improving the precision rate with the aid of Multi-distribution Bayesian Posterior measure. Experimental analysis shows that the M-PHMM framework is able to reduce the computational complexity for obtaining user patterns by 26.05% and improve the precision rate by 18.90% compared to the state-of-the- art works.

Keywords. Context Aware, Collaborative Filtering, Genetic Algorithm Approach, Multi-distribution Perceptron, Hidden Markov Model.

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INTRODUCTION

An increase in the technology development has caused an increase in the mobile devices, including laptops, mobile phones, and so on. This has resulted in an increase surge in their uses. Context Aware Collaborative Filtering using Genetic Algorithm (Dao, Jeong and Ahn, 2012) was introduced based on user interest and context similarity resulting in the improvement in precision rate. Context Aware using Fuzzy Linguistic approach (Zhou, et al., 2012) determined the user activity resulting in accuracy of context being detected. Model driven planning and optimization algorithms was applied in (Harrington and Cahill, 2011) to reduce the uncertainty related to the context by applying model driven approach. In (Santos, et al., 2010), the results achieved from user context were applied in mobile and social network applications with the objective of improving the feature extraction runtime. In (Raychoudhury, et al., 2013), survey related to middleware for pervasive computing was introduced. However, the above said methods lack the rate at which precision can be addressed, which is solved in the proposed M-PHMM framework using Multi-distribution Bayesian posterior algorithm.

One of the most challenging issues in constructing pervasive and smart spaces is to measure and identify the human activities of daily living (ADLs). In (Duong, et al., 2009), Coxian Hidden Semi Markov. Model was designed with the objective of providing reliability with respect to significant reduction to computation. Dynamic sensor configuration (Kurz, Hölzl and Ferscha, 2013) aiming at improving the recognition accuracy was designed using cooperative sensor ensembles. In (Bacciu, 2015) unsupervised feature selection was introduced in pervasive applications that reduced time-series redundancy.

In (Bacciua, Micheli and Sperduti, 2013), Hidden Markov Model was applied for tree structured data with the object of capturing discriminative structural information in pervasive environment. Estimation of user activity was performed in an efficient manner using distributed scheme (Ning, et al., 2013) resulting in reduced mean square error. QoS provisioning for context aware systems was addressed in (Mohammady, Naderi and Chowdhury, 2014). Though reliability and accuracy was addressed, the computational complexity involved in the design remained unaddressed, which the proposed framework addresses through MHMM algorithm.

In (Bacciu, Micheli and Sperduti, 2013), a generative tree structure mapping was introduced with the objective of improving the accuracy with which the mapping was performed. Mutual information test was used in (Bacciu, et al., 2013) to improve estimation accuracy and reduce the computational speed using false negative and false positive control. In (Sarkar, 2014), hidden markov model based activity recognition was introduced with the objective of improving object usage information. Goal oriented recognition was designed in (Hoelzl, Kurz and Ferscha, 2014) to detect composed and time sequence activities using Hidden Markov Model.

In (Okwechime, Ong and Bowden, 2011), multimodal motion controller was designed to provide real time interactive control using context aware non verbal responses. Spatial and temporal extents were learnt in an

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extensive manner for action detection using split and merge algorithm (Zhou, Shi and Wu, 2015) that resulted in improve detection accuracy. In (Hassan, et al., 2014), sensor cloud technology was applied in pervasive environment with the objective of reducing the complexity related to cost. Fall detection algorithm with hidden markov model was introduced in (Lim, et al., 2014) to reduce computational complexity and at the same time to improve the rate of accuracy. In (Tao and Liu, 2013), multi-layer hidden markov model was introduced for human robot detection that resulted in the improved accuracy.

Based on the aforementioned methods and techniques, in this paper, a hybrid framework called Multi-distribution Perceptron and Hidden Markov Model (M- PHMM) is introduced with the objective of reducing the computational complexity and minimize the message overhead for context aware systems in pervasive environment.

DESIGN OF MULTI-DISTRIBUTION PERCEPTRON AND HIDDEN MARKOV MODEL

In this section, an efficient framework called Multi-distribution Perceptron and Hidden Markov Model (M-PHMM) in pervasive environment is designed with the objective of improving the precision rate and minimizing the message overhead at relatively lesser amount of time. The training procedure in M-PHMM follows multi-distribution that follows sequence of distribution instead of a single distribution to smoothen the mobile networks with different degrees of context- confidence. This multi-distribution model is followed in the proposed work to obtain a robust estimation of context- confidence probabilities on the data acquired during the service usage monitoring.

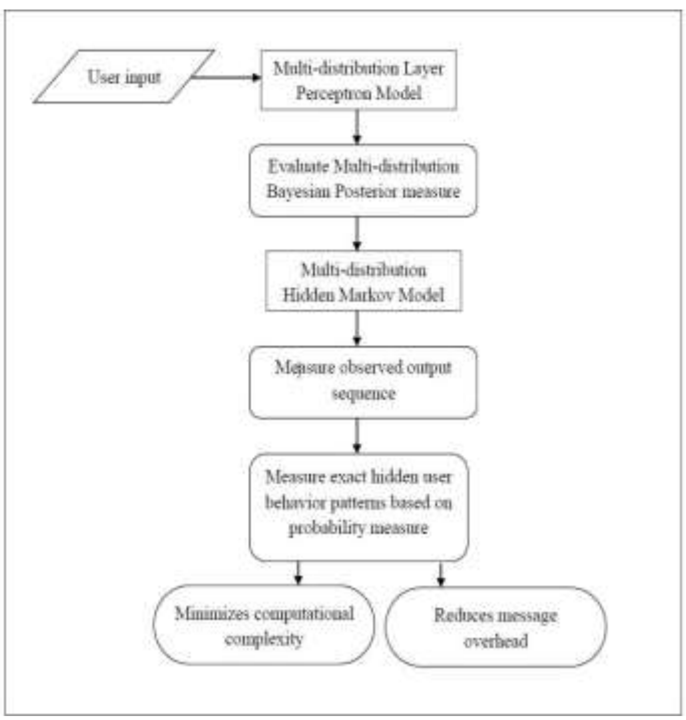

Figure 1. Block diagram of Multi-distribution Perceptron and Hidden Markov Model

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1) Design of Multi-distribution Layer Perceptron Model

The context aware systems using Multi-distribution Layer Perceptron using a Bayesian posterior measure with user behavior provided as input is shown in figure 1. The context aware systems using multi-distribution layer perceptron is viewed as a set of MLPs, one for each context aware system by integrated multi-distribution hidden markov model.

An HMM is a generative model in which the observable user behavior characteristics based on the user input is assumed to be generated using a Hidden Markov Model that transitions between 'n' states denoted by '$\alpha x= \alpha 1,\alpha 2,..,\alpha n$' with '$m$' outputs denoted by '$\beta x= \beta 1,\beta 2,..,\beta m$' for each class context '$cx= c1,c2,..,cn$'. Figure 2 shows the block diagram of Multi-distribution Layer Perceptron Model.

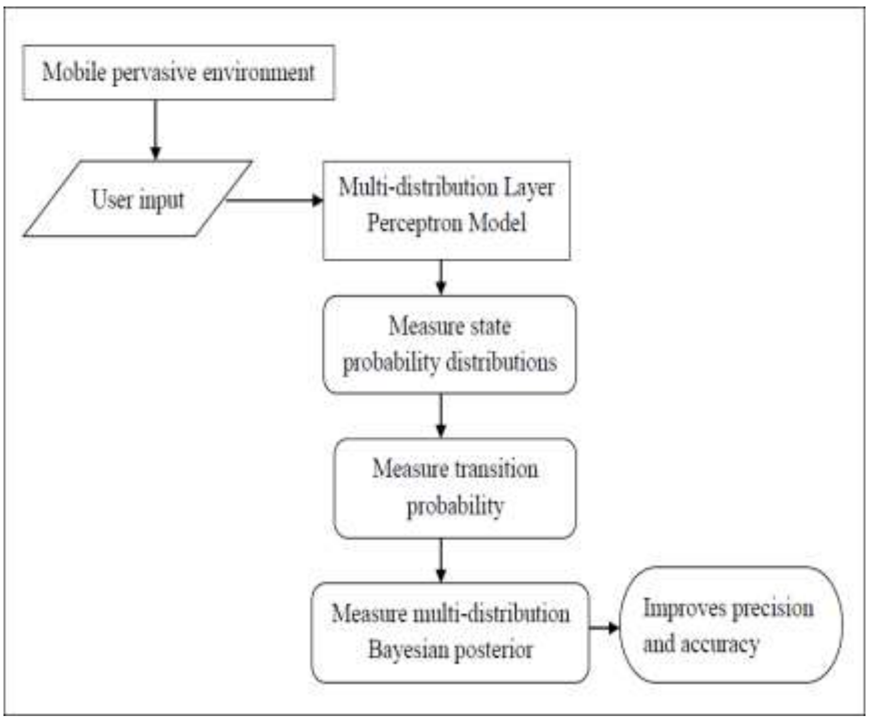

Figure 2. Block diagram of Multi-distribution Layer Perceptron Model

As shown in figure 2, with the objective of improving the precision and accuracy using Multi-distribution Bayesian Posterior measure. The key parameters in the M- PHMM framework include the inceptive state probability distributions and transition probability that are mathematically formulated as given below

'$\gamma=\{prob(pd0= \alpha i)\}\ where\ pd0\ is\ the\ state\ at\ time\ '0'$ ' (1)

'$P=pab=prob(pd0= \alpha b)|(pd0-1= \alpha a)$ ' (2)

Let us consider two different processes to obtain the relationships between a fixed state set and outputs using M-PHMM framework and is formulated as given below.

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$$\omega=(P,\gamma) \tag{3}$$

Using (3), the first process in M-PHMM framework denotes the transition between states, whose parameters are obtained through the transition probability matrix '$pab=(pd0= \alpha b)|(pd0-1= \alpha a)$'. The second process describes the relationship between state and all the possible outputs, whose parameters are obtained through state probability distribution '$\gamma=\{prob(pd0= \alpha i)\}$'. In the M-PHMM framework, only the outputs are visible whereas the states and transitions between the states are not observable, and are therefore said to be as Hidden Markov Model.

In the M-PHMM framework, every state is related with a distinct user behavior and context. In order to improve the precision rate during the training procedure, the following function is mathematically formulated while measuring user behavior for each state.

$$F= Prob\ (Ui\ |\alpha x,) \tag{4}$$

From (4), 'Ui' refers to the user behavior patterns with respect to each state 'αx' for each class 'cx' respectively. With Multi-distribution Layer Perceptron model, the M- PHMM framework evaluates the Bayesian posterior probabilities with the objective of improving the precision rate and is formulated as given below.

$$Prob\ (U_i\ |\alpha_x, c_x) = \left(\frac{Prob(\alpha_x\ |U_i, c_x) * Prob\ (U_i\ |c_x)}{Prob\ (\alpha_x, c_x)}\right) \tag{5}$$

Input: states '$\alpha_x = \alpha_1, \alpha_2, .., \alpha_n$', outputs '$\beta_x = \beta_1, \beta_2, .., \beta_m$', class context '$c_x = c_1, c_2, .., c_n$', user behavior patterns '$U_i = U_1, U_2, \ldots, U_n$'
Output:
Step 1: Begin Step 2: For each input states α_x and user behavior patterns U_i Step 3: Measure state probability distribution using (1) Step 4: Measure transition probability using (2) Step 5: Obtain the relationships between state probability distribution and transition probability using (4) Step 6: Measure Bayesian posterior probabilities using (5) Step 7: End for Step 8: End

Figure 3. Multi – distribution Bayesian posterior algorithm

Where 'αx' is the posterior probability for a specific user behavior 'Ui' with context 'cx' respectively. In a similar manner, using Layer Perceptron model, the user behavior patterns for different class context is evaluated with sequence of distributions called the multi-distribution, aiming at improving the accuracy of the user patterns being detected at an earlier stage.

Figure 3 given above shows the algorithmic steps involved in the design of Multi- distribution Bayesian posterior algorithm. The Multi-distribution Bayesian Posterior (MBP) algorithm includes four steps. For each input state and user behavior patterns for each state, the MBP algorithm evaluates state probability distribution. Followed by this, transition probability is evaluated and the relationship between these two state probability distribution and transition probability is evaluated. Finally, the Bayesian posterior probabilities are measured for different class contexts for multi-distribution factor aiming at improving the accuracy rate of the patterns being derived.

2) Design of Multi-distribution Hidden Markov Model

The main objective behind the design of Multi-distribution Hidden Markov Model is to measure the hidden state sequence 'pi= $p1,2,\ldots,pn$' (i.e. hidden user behavior patterns) that corresponds to the observed output sequence 'oi=,$o2$,..,on'. Figure given below shows the block diagram of a graphical representation of Multi-distribution Hidden Markov Model. It comprises of five hidden user behavior patterns and 4 observable output sequence.

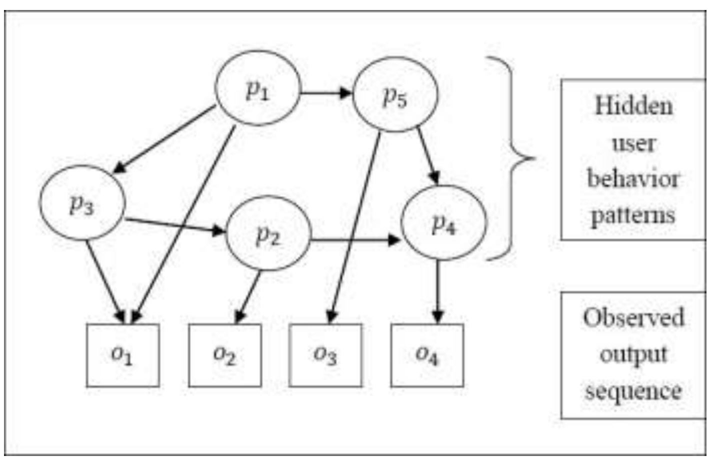

Figure 4. Block diagram of Multi-distribution Hidden Markov Model

Figure 4 shows the block diagram of Multi-distribution Hidden Markov Model that includes five hidden state sequence (i.e. hidden user behavior patterns) '$p1$,$p2$,$p3$,$p4$,$p5$' and four observed output sequence '$o1$,$o2$,$o3$,$o4$' respectively.

With the objective of reducing the computational complexity and minimizing the message overhead while obtaining the hidden user behavior patterns in order to arrive at the result, the Multi-distribution HMM has to satisfy two assumptions and is mathematically formulated as given below.

$$Prob\ (p_i |\ p_1, p_2, p_3, \dots, p_{i-1}) = \ Prob\ (p_i | p_{i-1}) \quad (6)$$

From (6), it is clear that the future user behavior pattern depends only on the current behavior pattern and not on the past behavioral patterns. As a result, the hidden behavior pattern at time interval 'i,' depends only on the previous behavior patterns '$pi-1$'. Therefore, if the hidden behavior patterns are once retrieved, it will be easy to obtain the behavior patterns relatively in a significant manner, reducing the message overhead.

On the other hand, the observed output sequence at time interval 'i, oi' depends only on the current hidden user behavior pattern 'pi' and is mathematically formulated as given below.

$$Prob\ (o_i\ | p_i = \ o_1, o_2, \dots, p_{i-1}, p_1, p_2, \dots, p_{i-1})$$

$$= Prob\ ((o_i\ |\ p_i) \quad (7)\&(8)$$

From (7) and (8) the hidden user behavior patterns and observed output sequence are obtained in an efficient manner using the probability measure that helps in recognizing the human activities in an intermittent manner. This probability measure for affluent context aware systems therefore minimizes the computational complexity in pervasive environment. To identify the exact probable hidden user behavior pattern from an observed output sequence, the Multi-distribution HMM measures the sequence which widens the state probability distribution and transition probability. This is mathematically formulated as given below.

$$Prob\ (p, o) = \ \sum_{i=1}^{n} Prob\ (o_i\ |\ o_{i-1}) | * Prob\ (p_i\ | o_i) \quad (9)$$

From (9), the new sequence obtained widens the affluent context aware systems in pervasive environment that model the training phase with time entity and monitor service usage in an efficient manner. In a similar manner, the training procedure follows multi with different degrees of context- confidence on the data acquired during the service usage monitoring. Figure shows the algorithmic description of MHMM.

Input: states '$\alpha x = \alpha 1, \alpha 2, .., \alpha n$', outputs '$\beta x = \beta 1, \beta 2, .., \beta m$',
Output:
Step 1: Begin Step 2: For each states αx Step 3: Evaluate the probability measure for hidden user behavior patterns using (6) Step 4: Evaluate the probability measure for observed output sequence using (7) Step 5: Evaluate new sequence using (8) Step 6: End for Step 7: End

Figure 5. MHMM algorithm

As shown in the figure 4, the MHMM algorithm includes three steps. For each state, the probability measure for hidden user behavior patterns, the probability measure for observed output sequence and new sequence is evaluated. The new sequence obtained smoothen the mobile networks with different degrees of context- confidence and therefore minimizes the computational complexity involved in obtaining the exact hidden user behavior patterns.

EXPERIMENTAL SETTINGS

A hybrid framework called Multi-distribution Perceptron and Hidden Markov Model (M-PHMM). is implemented in JAVA platform with which the context training phase in mobile pervasive environment is performed. The experiment is conducted with the OPPORTUNITY Activity Recognition Data Set from UCI repository dataset and the results of the metrics are analyzed. OPPORTUNITY Activity Recognition Data Set results records the user daily activities for evaluating the proposed framework.

OPPORTUNITY Activity Recognition information dataset is used to compare the M-PHMM proposed framework with the existing Context-Aware Collaborative Filtering using GA approach (CACF-GA) (Dao, Jeong and Ahn, 2012) and Context Aware using Fuzzy Linguistic (CA-FL) (Zhou, et al., 2012). For experimental evaluation in M-PHMM 7 users are taken with the total of 242 attributes. Experiment is conducted on factors such as precision, accuracy, computational complexity and message overhead in pervasive environment.

The precision is the ratio of relevant information to the relevant information. The mathematical formulation of precision is given as below

$$P = \left[\frac{Ret\ Inf}{Rel\ Inf} * 100\right] \quad (10)$$

From (10), Precision 'P' is obtained using the relevant information '$Rel\ Inf$' and retrieved information '$Ret\ In$'. Higher the precision rate more efficient the method is said to be. Accuracy is measured based on the observations being made with respect to different user behavior patterns. The mathematical formulation of accuracy is as given below.

$$A = \frac{U_1, U_2, U_3 \ldots U_n}{n} \quad (11)$$

From (11), the accuracy 'A' is measured with respect to the number of observations 'n'. Higher the accuracy rate more efficient the method is said to be. The computational complexity is measured using the number of observations being made and the time taken to obtain the user behavior pattern. It is mathematically formulated as given below.

CC=n*Time (User Behavior Pattern) (12)

From (12), the computational complexity 'CC' is measured with respect to the observations being made 'n'.

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DISCUSSION

The result analysis of hybrid framework called Multi-distribution Perceptron and Hidden Markov Model (M-PHMM) is compared with the Context-Aware Collaborative Filtering using GA approach (CACF-GA) (Dao, Jeong and Ahn, 2012) and Context Aware using Fuzzy Linguistic (CA-FL) (Zhou, et al., 2012) for pervasive environment. Table `1 represents the precision rate obtained using JAVA and comparison is made with two other methods, namely CACF-GA (Dao, Jeong and Ahn, 2012) and CA-FL (Zhou, et al., 2012).

Table 1. Tabulation for precision

Relevant information (KB)	Precision (%)		
	M-PHMM	CACF-GA	CA-FL
20	83.45	69.15	52.18
40	85.14	73.11	67.06
60	89.37	77.34	71.29
80	81.15	69.12	63.07
100	84.32	72.29	66.24
120	86.26	74.23	68.18
140	90.33	78.30	72.25

Figure 6 shows the result of precision efficiency that measures the retrieved information in pervasive environment versus the varying number of relevant information in the range of 20 – 140 KB. To better perceive the efficacy of the proposed M-PHMM framework, substantial experimental results are illustrated in Figure 5 and compared against the existing CACF-GA (Dao, Jeong and Ahn, 2012) and CA-FL (Zhou, et al., 2012) respectively.

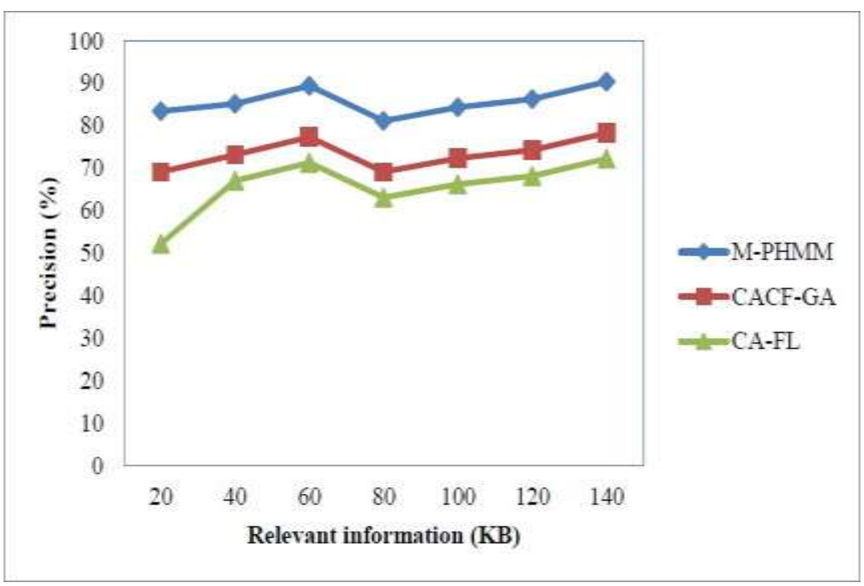

Figure 6. Measure of precision with respect to relevant information

The precision rate efficiency for different observations made by several users is performed at different time interval is shown above. Higher, the number of relevant information (i.e., based on the user behavior patterns), more successful the framework is. The results reported here confirm that with the increase in the number of relevant information, the precision rate efficiency also increases. The process is repeated with 7 different users.

As illustrated in Figure 6, the proposed M-PHMM framework performs relatively well when compared to two other methods CACF-GA (Dao, Jeong and Ahn, 2012) and CA-FL (Zhou, et al., 2012). The precision rate efficiency using M-PHMM framework is improved with the application of Multi-distribution Layer Perceptron where multi- distribution is performed using a Bayesian posterior measure. As a result, based on the state probability distribution and transition probability, the precision rate is significantly improved using M-PHMM framework by 14.44% compared to CACF-GA and 23.37% compared to CA-FL respectively. In table 2 we further compare the accuracy with different number of observations in pervasive environmental setting. The experiments were conducted with 21 observations and the accuracy obtained is measured in terms of percentage (%).

Table 2. Tabulation for accuracy

Number of observations (n)	Accuracy (%)		
	M- PHMM	CACF-GA	CA-FL
3	70.35	62.18	55.67
6	73.18	67.15	62.11
9	78.34	70.31	65.27
12	81.35	73.32	68.28
15	74.14	66.11	61.07
18	79.32	71.29	66.24
21	84.45	76.42	71.38

In order to improve the accuracy while obtaining the user behavior model with different degrees of context confidence, the user behavior patterns observed at various time intervals are measured. In the experimental setup, the number of observations ranges from 3 to 21 is illustrated in figure 7. The accuracy using the framework M- PHMM provides comparable values than the state-of-the-art methods.

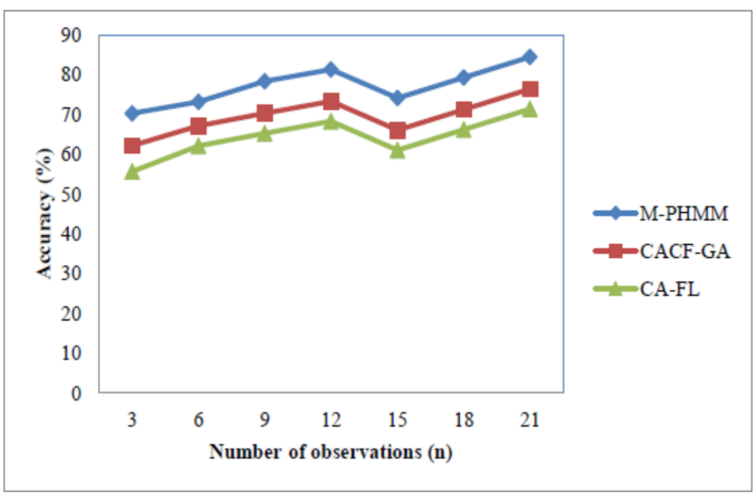

Figure 7. Measure of accuracy with respect to number of observations

The targeting results of number of observations to measure the accuracy using M- PHMM framework is compared with two state-of-the-art methods CACF-GA and CA- FL in figure 7 is presented. Our framework M-PHMM differs from the CACF-GA (Dao, Jeong and Ahn, 2012) and CA-FL (Zhou, et al., 2012) in that we have incorporated Multi-distribution Bayesian Posterior (MBP) algorithm where Bayesian posterior probabilities is used for measuring for different class contexts for multi- distribution factor. Based on the Bayesian posterior probabilities, the results are generated that helps in improving the accuracy rate of the patterns being derived using M-PHMM by 10.06% and 16.90% compared to CACF-GA and CA-FL respectively.

Table 3 shows the computational complexity for deriving exact user behavior models with respect to observations of size 21 in pervasive environment.

Table 3. Tabulation for computational complexity

Number of observations (n)	Computational complexity (ms)		
	M- PHMM	**CACF-GA**	**CA-FL**
3	1.98	2.52	2.92
6	3.25	4.30	4.60
9	4.45	5.50	5.80
12	5.82	6.87	7.17
15	4.33	5.38	5.68
18	6.82	7.87	8.07
21	7.55	8.60	8.90

Figure 8 given below shows the computational complexity involved in deriving the user behavior pattern for M-PHMM (Dao, Jeong and Ahn, 2012) framework, CACF- GA (Dao, Jeong and Ahn, 2012) and CA-FL (Zhou, et al., 2012) versus twenty one different observations. The computational complexity returned over M-PHMM framework increases gradually though not linear for different observations because of the rapid changes in the user behavior.

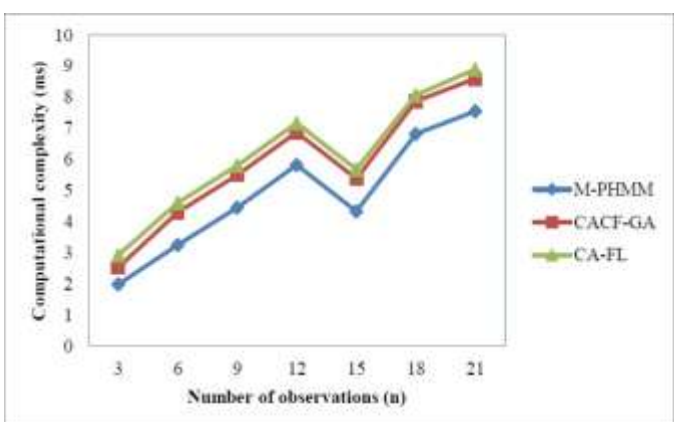

Figure 8. Measure of computational complexity

From figure 8, it is illustrative that the computational complexity is reduced using the proposed framework M-PHMM. For example with 12 observations, the computational complexity was 5.82 ms using M-PHMM, 6.87 ms using CACF-GA and 7.17 ms using CA-FL respectively. Though the computational complexity using all the three methods increase gradually, but using the proposed M-PHMM framework, it is comparatively less. This is because with the application of Multi-distribution Hidden Markov Model, the computational complexity is decreased.

With the help of Multi-distribution Hidden Markov Model, using probability measures, exact hidden user behavior patterns from observed output sequence are obtained at an early stage in an extensive manner. This in turn helps in reducing the computational complexity by 22.11% compared to CACF-GA and 29.99% compared to CA-FL respectively.

Table 4. Tabulation for message overhead

Methods	Message Overhead (%)
M-PHMM	62.35
CACF-GA	71.49
CA-FL	82.56

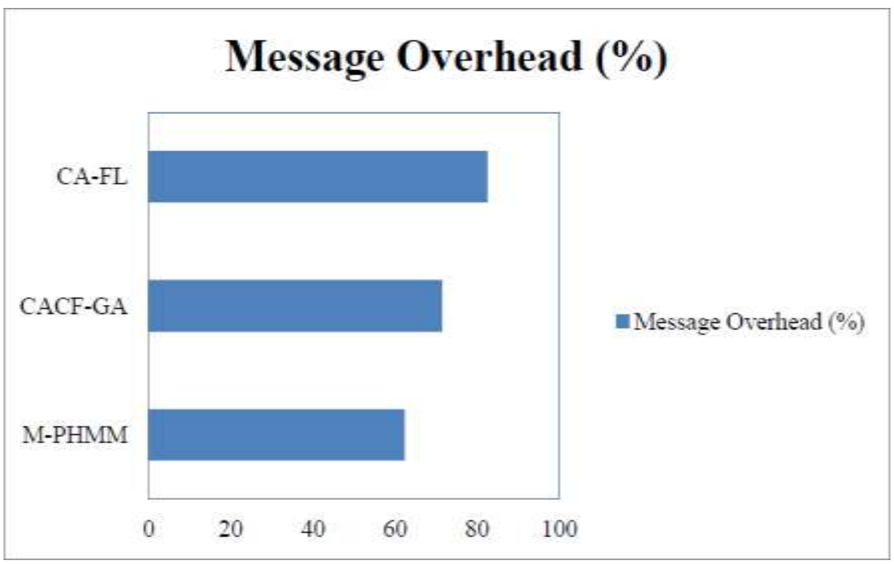

Figure 9. Measure of message overhead

Table 4 and figure 9 measures the message overhead with respect to seven different users with thirty five different observations measured at varied time period. From the figure it is illustrative that the message overhead using the M-PHMM framework is significantly reduced compared to the CACF-GA and CA-FL. This is because of the application of MHMM algorithm that obtains the exact robust estimation of the context- confidence probabilities on the data acquired during the service usage monitoring. Therefore message overhead is reduced in M-PHMM framework by 14.65% compared to CACF-GA and by 15.48% compared to CA-FL.

Pervasive computing identifies the user behavior with huge processing function that connects the users. It also cooperates in human ideas anticipating requirements that discussed for services performing and distributing the user information. Context awareness is developed in computing environment to classify the user behavior with certain conditions and interactions. However, it is not easy to allow an apparatus to identify and utilize the context of human individuals. In addition to that, Bayesian Posterior algorithm is required for extracting the user behavior pattern. The proposed M-PHMM framework with context aware service discovery forms the training phases with unit time to examine the service utilization by enhancing the prediction results. The enhanced user service behavior leads to the reduction of computational complexity. Theoretical analysis and experimental result shows that the proposed methods are designed for identifying the accurate prediction rate on the user behavior in mobile-pervasive computing environment. Initially, Affluent Context Aware Systems based on the User Behavior mechanism attains the decision from the similar users and also from the different user's profile. The proposed mechanism collect the information reported from the different users very easily by developing the Master-slave concept. Context information is used for constructing the user profile and then performs the similarity measure. Next, Active Context Source Discover Training Phase (ACSDTP) with Classifier Decision Tree Support (CDTS) mechanism is proposed to develop an effective modification (i.e., updating) of the pattern on training phase. CDTS mechanism is considered with weighted prediction for simple identification of context result on the training phase. Decision tree is performed with learning process to identify the inferred situations. Finally, Multi-distribution Perceptron and Hidden Markov Model framework is developed to reduce the computational complexity and message overhead in mobile networks with different degrees of context- confidence on dynamic observations. Therefore, MHMM algorithm effectively reduces the message overhead using exact user behavior patterns.

CONCLUSION

A hybrid framework called Multi-distribution Perceptron and Hidden Markov Model (M-PHMM) in pervasive environment to reduce the computational complexity and message overhead to smoothen the mobile networks with different degrees of context- confidence on dynamic observations is introduced. We then showed how this framework can be extended to incorporate Multi-distribution Layer Perceptron using a Bayesian posterior measure to improve the precision rate based on user behavior with different observations. The Multi-distribution Layer Perceptron model also provided efficient accuracy based on the Multi-distribution Bayesian Posterior (MBP) algorithm and hence improved the accuracy rate efficiency in pervasive environment. Next, the introduced Multi-distribution Hidden Markov Model reduces the computational complexity rate using hidden state sequence with respect to observed output sequence in pervasive environment. Finally, the MHMM algorithm effectively reduces the message overhead using exact user behavior patterns. In our experimental results the M-PHMM framework showed better performance than the CACF-GA and CA-FL over the parameters, precision rate, accuracy, computational complexity and message overhead in pervasive environment. The results show that M-PHMM framework offers better performance with an improvement of accuracy rate efficiency on exact patterns being mined in pervasive environment by 13.48% and reduced message overhead by 30.14% compared to CACF-GA and CA-FL respectively.

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