

Dynamic User Activity Prediction using Contextual Service Matching Mechanism

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Abstract—The significance of context-based services is significantly increasing with the advancement of integrated technologies of sensors and ubiquitous technologies. The existing approaches are reviewed to find out that identification of user's activity has more scope of improvement. After reviewing the current literature towards context-based methodologies, it is found that existing methods are devoid of considering dynamic context; while the modelling perspective is mainly towards considering predefined and static contextual information. Further, existing models doesn't have any inclusion of potential belief system nor any incorporation of service matching. Further, practical world case-studies is characterized by complex activity of user while it is quite challenging to extract the accurate contextual information associated with complex user activity. From the practical deployment scenario, the existing system offers less supportability toward collaborative network, which is highly essential to be considered for constraint modelling for user activity detection. Therefore, the proposed manuscript contributes a solution towards existing research problems by introducing a Dynamic User Activity Prediction using Contextual Service Matching Mechanism. A mixed research methodology is used to prove how service matching mechanism is important in contextual service discovery using multimodal activity data. The first contributory solution towards addressing the research problem is by introducing a novel and simplified belief system that considers both static contextual parameters as well as dynamic activity-based contextual parameter. The second contributory solution towards existing problem is to develop a novel service matching module that takes the input from service reposit, user calendar events, and collaborative units for assisting in similarity-based recommendation system. The model considers Hidden Markov Model for activity determination considering states of activity. With a combined usage of user activity context, feature management, and collaborative model, the proposed system offers better granularity in investigating user activity. The experimental and simulation analysis of the proposed outcome shows the enhanced accuracy performance of proposed system under different test environment. The study also investigates the impact of the service matching mechanism as well as relevance feedback on the accuracy to find that the proposed system excels better accuracy.

Keywords—Contextual information; service discovery; prediction; ubiquitous computing; user activity

I. INTRODUCTION

With the significant advancement in Information and Communication Technology (ICT) in various fields e.g. mobile network, cloud computing, Internet-of-Things (IoT), etc. there

is abundant information in multiple forms [1][2]. However, such raw information is never directly useful for anyone and hence this leads to the birth of contextual information [3]. The usage of contextual information is found in the human-centric application, community-based application, and opportunistic application. They are further found in various classified applications e.g. user tracking, identification of human activity, social network, environmental monitoring, healthcare sector, etc. The majority of the identification of the human-based activity is carried out using smartphones, wearable sensors, development boards, etc. A context can be defined as sensed data utilized for representing the specific state/circumstances of a defined entity [4]. Contextual information is closely associated with sensory data. It is quite evident that there are various sources of origination of contextual information where the major complexity is to represent the accurate context in presence of higher uncertainty [5]. Various forms of reasoning approach, as well as dynamic interpretation, is essential for modeling contextual information from abstraction process at high-level [6][7]. The robustness of the contextual modeling must be minimized to enhance their technology adoption as well as to ensure better compatibility with the upcoming application of ubiquitous computing. Effective modeling of contextual-based services also calls for the inclusion of heterogeneity as well as comparability, which is highly essential in framing up the application of user activity detection. At present, there have been various research work being carried out towards context-based application, where different methodologies and environment has been considered [8]-[12].

However, irrespective of such research work, various challenges still exist in the area of contextual modeling. Various researchers have reported various levels of difficulties as well as technical challenges associated with contextual information [13]-[17]. Out of various challenges, some of the challenges associated with contextual information modeling are the complicated relationship among the context along with ambiguity in the dependencies of various internal factors [18]. If the model suffers from inaccurate reasoning then it fails to offer a significant conclusive interpretation of the queried context. To improve the accuracy of user activity detection from contextual information, existing research approaches are found to adopt supervised learning techniques (e.g. k-nearest neighbor, Support Vector Machine, etc.), fuzzy logic, naïve Bayesian, Decision tree, and stochastic approach. The prime issues in such algorithms are i) hardcoded thresholding, ii) no

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preference to quality, iii) problematic validation scheme, iv) less computationally efficient, v) accuracy depends on the size of the dataset, etc. All these issues have not yet been solved in the present state of research work and only some of them have been addressed concerning user activity. From the viewpoint of user-activity detection, one of the most challenging aspects is to perform prediction of upcoming user activity as well as intention. This research problem is less emphasized in the existing system and hence this manuscript introduces context-based solution to address this problem.

The proposed system also implements a novel mechanism of Markov modeling for enhancing the predictive operation of dynamic user activity using contextual service mechanism. Section II discusses the existing research approaches towards using contextual information followed by outlining problem identification in Section III. The adopted research methodology is briefed in Section IV followed by a discussion of the analytical model in Section V. The discussion of the predictive approach is illustrated in Section VI. The simulation approach is discussed in Section VII while the discussion of obtained results is discussed in Section VIII. Finally, Section IX summarizes the finding as well as the contribution of the proposed study.

II. RELATED WORK

Usage of context has always been proven to be an essential factor for extracting certain latent traits when the information is quite bulky and unorganized. Existing research work has a different mechanism to use the service factor for catering to the demands of the developed design.

Most recently, the formulation of the context factor is implemented by Ehatisham-UI-Haw [19] towards an activity recognition system. In this approach, the granularity of the context is obtained from the behavioral aspects of the user where a classification modeling is carried out to identify fine and course-grained activity. Yachir et al. [20] have introduced a framework for service discovery followed by service selection in IoT applications. However, less evidence is shown to prove that the selection process offers higher reliability. Other authors e.g. Guo and Ma [21] and Yao [22] offer to construct a ubiquitous system with an aid of context. The uniqueness in the study of Guo and Ma [21] is that a scheduler system is designed for context-awareness based on activity data obtained from wearables. This system makes use of a smartphone that acts as a gateway for data aggregation from multiple wearables as well as it also carries out scheduling operations to implement a context-aware engine.

The work carried out by Klimek [23] has developed an intelligent mechanism for context-awareness associated with a use case of mountain hikers. The data is obtained from various sensors as well as mobile networks followed by data processing and analysis of human activity. The work carried out by Shen et al. [24] have developed a model where activities of human are assessed for understanding its gesture. The data is captured from the wristband followed by applying classification technique to determine the activity context. The performance of such monitoring-based applications could be further enhanced using ontology as seen in the work of Ni et al. [25]. Pahlevan et al. [26] have harnessed the potential of

contextual information for developing a dynamic algorithm using financial data captured from web services. Although such an approach assists in the identification of activity to some extent there was no inclusion of a classification approach for further enhancing the performance of detection of user activity. There are various studies to prove that the process of identification of various activities can be further enhanced using the clustering approach. Existing studies have witnessed the usage of extreme learning mechanisms for activity recognition systems as seen in the work of Chen et al. [27]. The study has used a neural network for identifying the activity of humans based on sensory data. Study on classifier design for a similar purpose is also seen in the work of Wang et al. [28].

Various studies are being explored towards user activity prediction. The work carried out by Alam et al. [29] has presented an algorithm that can predict user activity using the Markov model of finite order to ensure the prediction accuracy of 88%. The sensor-based contextual data can be also used for developing an application for identifying user activity. The work carried out by Pham et al. [30] has used a sophisticated machine learning scheme for recognition of human activity motivated by Long Short Term Memory and Convolution Neural Network. The activity data used in the study bears the characteristic of spatial and temporal aspects using capsule networks. A study towards a prediction-based approach was also presented by Huang et al. [31] that takes the contextual information for forecasting the most probable mobile application using time and location information as the context. The study outcome is benchmarked with linear and Bayesian network models. However, the limitation of this model is its higher dependency on manual setting of threshold that is not feasible in many of the smart applications. The work carried out by Kim et al. [32] has used a Bayesian network for predicting using historical contextual data showing 90% of accuracy performance. Lawal and Bano [33] have used a convolution neural network with two streams to localize human activity.

Elmalaki et al. [34] presented a framework that can significantly discretize between decision-making and application logic. The authors have presented a system to configure sensitivity using a java package for discovering the level of upcoming sensitivity. Implemented using the prototype, the study outcome has proven reduced overhead and reduced processing time. However, the model significantly misses analysis of any significant behavior as it is too dynamic. Xu et al. [35] have used q-networks to localize the human activity from the video sequence using Spatio-temporal aspects. At present context-based research work is also studied concerning ubiquitous and pervasive computing for better compatibility with upcoming wearable devices. A learning approach with a higher degree of activeness can superiorly assist in exploiting the power of context factors as shown in the study of Hsu et al. [36]. A development environment is designed for building navigation systems with better efficiency in learning. However, the model misses various essential functional tracks important in ubiquitous learning as well as it doesn't discuss any form of synchronization/communication among multiple devices for sharing context. Most recently, Kamberov et al. [37] have performed an investigation about the

significance of device integration for contextual sharing. However, the idea presented is without any numerical proof despite its potential thought. Popescu et al. [38] have developed an automated machine learning system for human activity recognition systems.

Xu [39] has also presented a study towards context-based services towards mobile data associated with activity detection. According to Khalid et al. [40], a better optimization principle can upgrade the performance of predictive accuracy that can be used for recommendation systems as well. Hence, the author applied swarm intelligence on the contextual information aggregated from the social network to perform recommendations. The recommender also maps various cloud-based services for the users to offer better precision. A similar form of study has also been carried out by Kim and Yoon [41] by additionally using probabilistic-based graphical structure. Study towards recommendation system is also carried out by Neto and Sales [42] in the context of the education system. Therefore, this section offers evidence that there has been considerable work being carried out towards using context-based information for curving activity detection by multiple means. Apart from these, there are some recent studies that has been carried out towards similar direction viz. classification system of activity (Singh et al. [43]), activity modelling using behavioral context (Asim et al. [44]), adaptive model of intervention using user-centric approach (Bilal et al. [45]), recognition of human activity (Siddiqi et al. [46]).

Therefore, various studies have evolved out to address the problems in activity detection and analysis characterized by benefits as well as issues. The next section outlines the research problems extracted from existing studies.

III. RESEARCH PROBLEM

The previous section has briefed that various research-based approaches do exist to offer to the model of the user activity. However, there are following open-end issues that are required to be addressed for further improving context-based user activity identification-based services. The open end problems captured after reviewing the existing literature in the prior section are as follows:

- **Lack of Considering Dynamic Context:** Existing studies mainly consider the static context where the information is either from a dataset or from a synthetic approach without the inclusion of any time-based properties in it. Hence, modeling of user activity detection based on static context is less reliable when exposed to the real-time environment of deployment.
- **Doesn't include Robust Belief System:** A robust belief system is always dependent on the deciding factor as well as dynamic observation. Normally, information related to belief is considered to be stored in an information server that is used for matching the queried user identity. Hence, the normal (or static) belief system is not in a condition to offer stable specificity performance and very often its accuracy degrades exponentially.

- **Non-Inclusion of Service Matching:** Existing system has less potential contributions towards an effective service discovery for assisting multiple numbers of users with heterogeneous context. Developing a service matching system is yet a computationally challenging problem in the case of the availability of dynamic context. At present, there is no such research work that has proven cost-effective service matching based on dynamic contexts.
- **Complex User Activity Detection:** At present, there are large numbers of studies in the last decade corresponding to user activity detection. But the major pitfalls are i) considering less number of features (or context), ii) less change of environmental parameters during the collection of context, and iii) usage of available optimization techniques that use an iterative process. It should be known that such a model of user activity detection is not in support of low-powered devices in mobile networks.
- **Less Supportability of Collaborative Network:** The absence of a collaborative network is another significant loophole that doesn't support the application to support ubiquitous computing. Although there are many research works claiming to support ubiquitous computing, none of the research work at present is reported to offer the supportability of a collaborative network that is an essential backbone of any ubiquitous application.

Apart from the above highlighted research problem, an essential observation is that there is a potential research gap where the core limitation of an existing literatures that considers static context. However, the practical applications of user activity determination demands inclusion of dynamic context. Hence, the prime motivation is to develop a scheme which can be practically validated where dynamic context modelling can be carried out with a potential and simplified belief system. With an upcoming smart and intelligence applications, services, and robots [47]-[49], there is a need to include the dynamic context as well as service modelling to make it properly functional. Hence, this acts a prime motivation factor to carry out development of proposed system. The proposed system considers the adoption of dynamic context, includes a comprehensive belief processing system using the CIOB model [50], develops a novel service matching mechanism with higher supportability of a collaborative network, and offers cost-effective user activity detection. The above-mentioned points of research problems are addressed in the proposed system as discussed in the next section.

IV. PROPOSED METHODOLOGY

The present work is an extension of the prior contextual model named CCSS [51] that uses a Context Collection and Request analysis Unit (CCRU) for refining the user request at the first level using beliefs and further refines the request using Collaboration Unit (CU) to match the service requirement of the user. The use of user activity as a context in Ubiquitous computing has been shown in many studies, by using inefficient service matching in the service discovery model.

This motivated us to address the use of user activities as one of the important contexts in the service matching process of the service delivery model.

The main aim of the proposed model DUAP is to incorporate the additional context of multiple user activities along with user profile and another context into the CIOB model [50] to get the best possible match of the desired service for the user in the ubiquitous application.

The idea is also to extract significant features from the activity context to generate dynamic belief and predict the most appropriate service. Referring to Fig. 1, the Service Matching Mechanism (SMM) exploits both static and dynamic context as multi-modal context along with recommendations and relevance feedback mechanism. The mechanism functionality is as described. The basic CIOB model takes multi-modal static context parameters such as user profile, location context, environmental context, etc. There is the inclusion of additional context information in the CIOB model namely activity context. The activity is dynamic as well every activity context holds certain hidden intentions. Getting the context as an intention from users' activity may assist SMM, service discovery, and customization of service. If the accurate activity and their respective features of the user are known then it is possible to determine the multi-modal user activities such as the status of different gestures like walking, sitting, running, etc. This is feasible by computing from linear and angular acceleration in x, y, and z planes given by accelerometer and gyro meter fixed with the portable mobile devices. These gestures along with their other context can be mapped to their probable intentions by behavioral pattern analysis. For example, if a person is running from the past one hour from one location to another in the early morning then the system predicts his behavior or intention as the user is jogging. This user may look for some health drinks, so that the health drink service discovery may notify and collaborate both the user and the service content. If the past pattern of the user is captured and the system has a continuous learning mechanism then the ultimate goal of the context-based service tailoring may be achieved.

The research methodology adopted for the study is a mixed-mode where experimental, analytical, and simulation have been carried out. Fig. 2 shows the flow adopted in designing the research methodology. The contribution of the proposed system are as follow:

- Capturing Data from Wearable Device Module: A prototype is developed for a wearable device using a microcontroller and Smartphone. It can capture the sensory signals and split the signals into two forms of features i.e. time domain and frequency domain feature. This offers better granularity in numerical analysis resulting in enhanced accuracy.
- Context Formulation: A significant mathematical modeling is carried out for formulating the context of the user activity. The prior CCSS model is used as well as the CIOB model where the context parameters are directly fed to the belief model to formulate a belief system regarding the queried activity tracked from wearable devices.

- Similarity Matching Mechanism: This block mainly takes the input of belief and along with service deposits, user event calendar, and the collaborative unit, it performs matching of the queried user activity to understand its intention. The term intention could be also related to any emergent action undertaken by the user owing to certain critical conditions in either positive or negative aspects. It performs further operations:
 - User Activity Modeling: This block is responsible for allocating mathematical variables for defining user activity concerning time instances and contextual information.
 - Model Fitness: This block maintains a check on the goodness of the proposed model in presence of uncertainties. This is mainly used for ensuring prediction of the next level of activity also.
 - Anticipation Function: As the proposed system performs predictive analysis hence this function is used for retaining the anticipated outcomes for analysis of the correctness of the identified user's intention.
 - HMM Incorporation: Hidden Markov Model (HMM) is mainly used for modeling the proposed analytical model and it is explicitly used for determining the upcoming user activity based on the higher probability value of the user context.

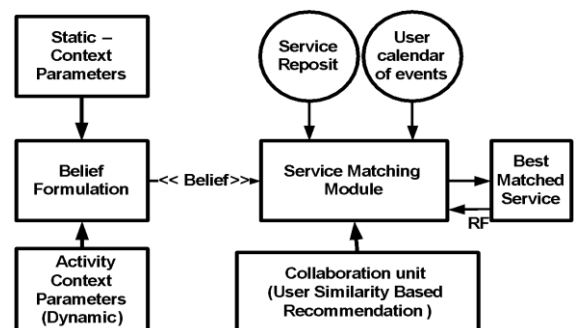


Fig. 1. Schema of Proposed System of DUAP.

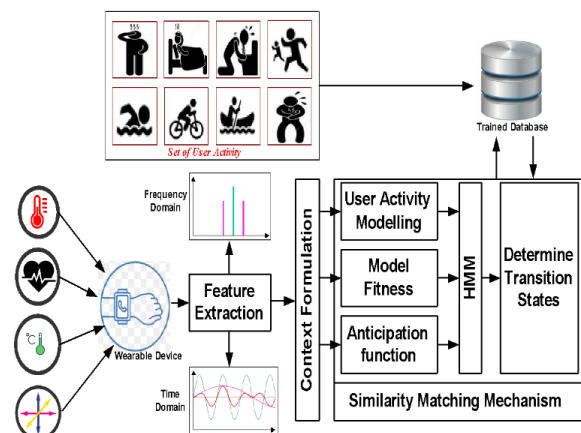


Fig. 2. Top Level Architecture DUAP.

The complete modeling is carried out in two stages i.e. training stage and the validation stage. The training stage consists of capturing the real-time multiple dynamic activities from multiple users to build a trained dataset using the main block of SMM. In the validation stage, the inputs are taken from different users to formulate a query for testing the effective predictive capability of DUAP. The contribution of the proposed methodology is that it offers discrete set of information that assists in analyzing the model more effectively. For this purpose, the experimental approach is used for aggregating data while the analytical approach is used for the complete implementation of the predictive approach based on contextual user activity. Finally, the simulation method is used for assessing the final trends of research outcomes. The next section illustrates the analytical modeling of DUAP. Hence, adoption of all the three research methodologies, unlike any existing system reported in Section II, assists to accomplish the target aim of proposed model.

V. ANALYTICAL MODELING

This section presents an elaborated discussion of the proposed analytical modeling meant for signifying the importance of the service matching mechanism towards contextual service discovery. For effective analytical modeling, the study consider a situation where heterogeneous sensors were deployed in the embedded form to extract dynamic user activity-based information. Consider that variable I to represent set of information captured from the wearable device where the study considers different sets of user activity as u_1, u_2, u_3, u_4 , and u_5 . Consider that a variable S represents problem space where different contextual information about the features resides corresponding to all the instances of sensory data collected. Empirically, it can be expressed in Equation (1) as,

$$S = \alpha_1 + \alpha_2 + \alpha_3 + \dots + \alpha_N \quad (1)$$

The study considers that $A: S \times I$ is an analytical model that is responsible for mapping all the test order o such that $o \in I$ as well as $S \times I \rightarrow \beta$, where the variable β may consider as service decision in terms of problem space. To check the significance of user activity in proposed model, a function ϕ is deployed to check the mode fitness. It can be expressed in the form of Equation (2):

$$\phi(x): y \times \beta \quad (2)$$

In the above equation, the argument x of the function ϕ represents $[o, A(\psi_o, o)] \subseteq x$ while the variable y should represent $m.I$ and the variable m represents times of information being relayed from the sensor. Therefore, it can say that service decision β is nearly equivalent to the problem space of the information instance. The model fitness of the work initiates by considering instances of the test say δ ; hence, δ will be a subset of $m.I$ consider that $\gamma(o)$ be the probability factor where the order o is a part of δ itself. The anticipation of the assessment function $\phi(x)$ is represented mathematically as,

$$\vartheta \rightarrow \sum_{o \in I} (\gamma(o) \cdot \phi(x)) \quad (3)$$

In above Equation (3), the numerical outcome of ϑ is required to be emphasized for enhancing the service discovery as well as service matching mechanism to obtain best-matched

services. Therefore, considering that A_{op} is the optimized analytical model representing best-matched service, the above expression (3) is reformulated as follows:

$$A_{op} \cdot \text{Max}_i [\vartheta(\delta, A)] \quad (4)$$

Although, there are various forms of context-based information associated with belief formation. Different forms of user activity will also have different forms of context and hence, it is not possible to give a shape of every discrete morphology of all contexts. Therefore, the study considers that there are two cases of context say α_a and α_p that corresponds to the active context and passive context respectively. The proposed model will also consider that these two forms of context (active/passive) will be evaluated based on the corresponding analytical model's A_a and A_p respectively for formulating a better predictive model. The inclusion of probability is considered in this i.e. $\gamma(\alpha_a)$ and $\gamma(\alpha_p)$ corresponding to type α_a and α_p respectively. Lemma-1 illustrates this operation as follows:

Lemma-1: Consider that A_{op} is the best service model on instance δ i.e. $A_{op} = A_{op}(a) + A_{op}(p)$, which will mean that $A_{op}(a)$ is the best-matched service for δ_a and $A_{op}(p)$ is the best-matched service for δ_p .

Proof: It is obvious that despite the presence of different forms of context viz. $\alpha_1, \alpha_2, \alpha_3, \dots, \alpha_n$, which will mean that there are n -number of context information about the user activity, then,

$$\alpha = \alpha_1 + \alpha_2 + \alpha_3 + \dots + \alpha_n \quad (5)$$

Consider that $\alpha_a = \{ \alpha_1, \alpha_7, \alpha_9, \dots \}$ and $\alpha_p = \{ \alpha_2, \alpha_4, \alpha_{10}, \dots \}$ than it can be said that,

$$\alpha = \alpha_a + \alpha_p \quad (6)$$

where, $(\alpha_a + \alpha_p) \leq n$. Similar fact discussed above is also applicable to the time instance δ with respect to δ_a and δ_p . Hence, it can also be written as,

$$A_{op}(a) = \text{Max}_{A(a)} \vartheta[\delta_a, A_a] \quad (7)$$

$$A_{op}(p) = \text{Max}_{A(p)} \vartheta[\delta_p, A_p] \quad (8)$$

The above expression also assists to offer the conditions e.g. $\gamma(\alpha_a) \cdot \vartheta[\delta_a, A_{op}(a)]$ is greater than $\gamma(\alpha_a) \cdot \vartheta[\delta_a, A_{op}]$. Similarly, the next condition will be $\gamma(\alpha_p) \cdot \vartheta[\delta_p, A_{op}(p)]$ is greater than $\gamma(\alpha_p) \cdot \vartheta[\delta_p, A_{op}]$. The concatenation of these will yield,

$$\gamma(\alpha_a) \cdot \vartheta[\delta_a, A_{op}(a)] + \gamma(\alpha_p) \cdot \vartheta[\delta_p, A_{op}(p)] \quad (9)$$

and the above expression (9) is always greater than $\vartheta[\delta, A_{op}]$. However, logically, as $A_{op} = \text{Max}_A \gamma[\delta, A]$. Therefore, from Equation (9), it can be mathematically presented that,

$$\vartheta[\delta, A_{op}] = \gamma(\alpha_a) \cdot \vartheta[\delta_a, A_{op}(a)] + \gamma(\alpha_p) \cdot \vartheta[\delta_p, A_{op}(p)] \quad (10)$$

However, in simpler meaning, it can be said that $A_{op} = A_{op}(a) + A_{op}(p)$.

The advantage of using the Lemma-1 is that the proposed system can apply its process of service matching mechanism for all the time instances of context data by exploring the optimized composition of the time instances itself within the scope of contextual forms. Hence, the inference of the term active and passive is highly flexible and extensible too and can be fine-tuned as per any application-level deployment. However, still, it is quite a challenging task for exploring the best service associated with the obtained belief from dynamic data of user activity. Hence, Hidden Markov Model (HMM) is applied over the various instances of information I . Once the system develops the belief factor considering both static as well as dynamic context (user activity context parameters), the service matching model will be responsible for predicting the form of the context based on the input of user activity. Hence, HMM can be significantly used for determining the consecutive probable activities and it can potentially assist in user activity prediction based on its corresponding contextual information. Therefore, the variable I is considered as training data that will be used for computing the HMM parameters and hence it splits the variable I in such a way that $I=[I_1 I_2]$, where a subset of information I_1 is used for training purposes for implementing the predictive operation of HMM while I_2 could be used for enhancing the contextual performance during comparative analysis with the trained data. Hence, better training using HMM could be used for contextual prediction of user intention.

VI. HMM-BASED ACTIVITY DETERMINATION

This section presents the mechanism of determination of consecutive probable activity with the help of HMM. The concept of the analytical model is presented in the prior section to develop a similar HMM-based model for user activity determination. For this purpose, a matrix mU is considered to denote all feasible dynamic activity of user such that consists of elements as u_1, u_2, \dots, u_N . The algorithm takes an input of user activity (Line-1) and performs extraction of the features f concerning time (f_t) and frequency (f_f) domain (Line-2). For all the values of service reposit and user calendar events (Line-3) to assess the user activity u , Markov model A , transition state, and anticipated outcome of the prediction. Further elaboration is as follows: Here, the variable A is considered to be a Markov chain for assisting in determining the transition state in the form of probability $\gamma(u_j | u_i)$. This denotes the transition of user activity u_i to u_j . The algorithmic steps for this purpose is shown as following:

Algorithm for User Activity Determination

Input: u (user activity)

Output: ϑ (expected outcome), $trans_state$ (transition state)

Start

1. *get* $U(t) = \{u_1, u_2, \dots, u_N\}$

2. $f \rightarrow [f_t, f_f]$

3. **For** $i=1:p$

4. Obtain $\alpha = \{\alpha_a, \alpha_p\}$ & $A = \{A_a, A_p\}$

5. $trans_state = [\gamma_a(u_j | u_i), \gamma_p(u_j | u_i)]$

6. $\vartheta[\delta, A_a, A_p] = \gamma(\alpha_a) \cdot \vartheta[\delta_a, A_a] + \gamma(\alpha_p) \cdot \vartheta[\delta_p, A_p]$

7. **End**

8. **End**

End

Hence, it can be said that $u \subseteq mU$. Hence, the maximum probability of transition associated with user activity can be denoted as $a(u)$ corresponding to the user activity u . Mathematically, it can be represented as,

$$a(u) \rightarrow \text{Max}_{v \in M} \gamma(v|u) \quad (11)$$

According to the principle of HMM, the Markovian characteristics can be depicted for $a(u)$ that is considered to be an elite forecast for the consecutive activity of the user. This condition is only valid if u is considered to be the present form of activity (or state). Therefore, a better form of user intention can be formulated from multiple dynamic activities where a selection of the most elite transition state is carried out for the consecutive state in the predictor design. Considering arbitrary samples from the δ instances of the HMM, the model can easily compute the accuracy of the HMM prediction as following:

$$\vartheta_{\delta, A} \rightarrow \sum_{u \subset mU} \gamma \quad (12)$$

As the presented model is all about probability for computing the next transition state, hence, the right-hand side of Equation (12) will signify probability γ as $\gamma(u)$. $\gamma(a(u)|u)$. The model uses similar contextual parameter $\alpha = \alpha_a + \alpha_p$ where A_a and A_p is considered as similar chain parameters for HMM corresponding to context form of α_a and α_p respectively. It will also mean that the system implements A_a and A_p Markov chains for determining the contextual form of u_a and u_p respectively. Therefore,

Transition state of $A_a = \gamma_a(u_j | u_i)$

Transition state of $A_p = \gamma_p(u_j | u_i) \quad (13)$

Therefore, equation (10) in Lemma-1 can be now remodeled concerning A_a and A_p HMMs corresponding to instances of δ_a and δ_p respectively as follows,

$$\vartheta[\delta, A_a, A_p] = \gamma(\alpha_a) \cdot \vartheta[\delta_a, A_a] + \gamma(\alpha_p) \cdot \vartheta[\delta_p, A_p] \quad (14)$$

The above-mentioned formulation is only valid if a selection of δ_a and δ_p is carried out based on arbitrary order to A_a and A_p . In the above Equation (14), the variable $\gamma(\alpha_a)$ and $\gamma(\alpha_p)$ represent test order in terms of probability whose scope resides within the two contextual categories. It will eventually mean that $\vartheta[\delta_a, A_a]$ and $\vartheta[\delta_p, A_p]$ is empirically equivalent to $\gamma_a(u)$. $\gamma_a(a_a(u) | u)$ and $\gamma_p(u)$. $\gamma_p(a_p(u) | u)$ respectively. One interesting fact about this model is that it suits very well with the CIOB model [43] in the decision generation module which consistently interacts with the belief processing module, where both update the information server. Therefore, the suitability of this predictive model is better justified using HMM approach over the contextual user's activity data.

The Lemma-2 discussed above exhibits the significance of retaining HMM features only in the cases when the information includes the inherent characteristics of the Markov principle. Therefore, this provides the evidence that incorporating HMM significantly assists in the prediction of user activity as a next probable states. However, the complete accuracy is directly depending on the size of the data. The significant *contribution* of this model of HMM is that it splits the data (to be trained or already trained) into multiple smaller parts to extract the

context of the user's intention, unlike any existing approaches reported in literature. The next section discusses the outcome accomplished from the proposed study.

Lemma-2: The significance of user activity and service matching mechanism for a model A is developed on the basis of on trained information I where A_a and A_p and designed depending upon I_a and I_p respectively. Therefore, the significance of service matching is maximum only when $\vartheta[\delta_a, A_a]$ is found greater than $\vartheta[\delta_a, A]$. Similarly, it is also valid for $\vartheta[\delta_a, A_a]$ is found greater than $\vartheta[\delta_a, A]$

Proof: In this case, the model considers that the initial contextual form α_a has the probability of $\gamma(a(u), u|\alpha_a)$ representing its present user activity being u and consecutive user activity being $a(u)$. Hence, it can be stated that updated anticipation function $\vartheta[\delta_a, A]$ is equivalent to the summation of $\gamma(a(u), u|\alpha_a)$, where $u \subseteq mU$. The overall sum is also said to be equivalent to the summation of $\gamma(a(u)|u, \alpha_a)$. $\gamma(u|\alpha_a)$. The generalized structure of this summation then becomes the summation of $\gamma(a(u)|u, \alpha_a)$. $\gamma(u)$. Therefore, a closer look at this logic will show that the expression $\gamma(a(u)|u, \alpha_a)$. $\gamma(u)$ is very much lesser than $\gamma_a(a_a(u)|u, \alpha_a)$. $\gamma_a(u)$, which can be shortly written as $\vartheta[\delta_a, A_a]$. Hence, this will prove that $\vartheta[\delta_p, A]$ is significantly less than $\vartheta[\delta_p, A_p]$.

VII. EXPERIMENTAL ANALYSIS

The analysis is carried out by capturing real-time data with multiple forms of bio-signals to understand the significance of user activity. The purpose is to predict user intention based on the computed contextual data. This section outlines the application environmental parameters as well as the performance assessment process undertaken to discuss the simulation settings considered for the study.

A. Application Environment

The application considered for the proposed system is a pervasive context-awareness system exclusively generated for predicting the user's intention related to their health. The model assumes that a user is equipped with a wearable device that has 4 different forms of sensors e.g. i) ambient temperature sensor, ii) heartbeat sensor, iii) body temperature sensor, and iv) accelerometer. The analysis uses an ambient temperature sensor TF41 that is cost-effective and can perform tracking of temperature under all forms of environmental conditions. A readily available heartbeat sensor circuit is used that works quite well with the 8051 microcontrollers. The heartbeat sensor is integrated into the board using amplifier LM358 OP-AMP. MAX30205 is used as the body sensor that is found to be directly under the compliance of ASTE E1112 with 16-bit resolution in temperature reading. Finally, ADXL335 is used as the 3-axis accelerator that works on low-power devices. An android application is developed that is wirelessly integrated with the transceiver module. The data captured by the temperature sensor will be related to both room and body. The corresponding inference is coded to identify certain standard situations e.g. hot ($>40^\circ\text{C}$), cold ($<10^\circ\text{C}$), fire ($>100^\circ\text{C}$), normal ($10\text{-}30^\circ\text{C}$), etc. Similarly, an inference system is developed for heat beats i.e. normal (60-100 beats per minute), tachycardia

(>100 beats per minute), and bradycardia (< 60 beats per minute). Usage of the accelerometer can be used for identifying the states/gait patterns e.g. walking, sitting, running, climbing up/down, etc.

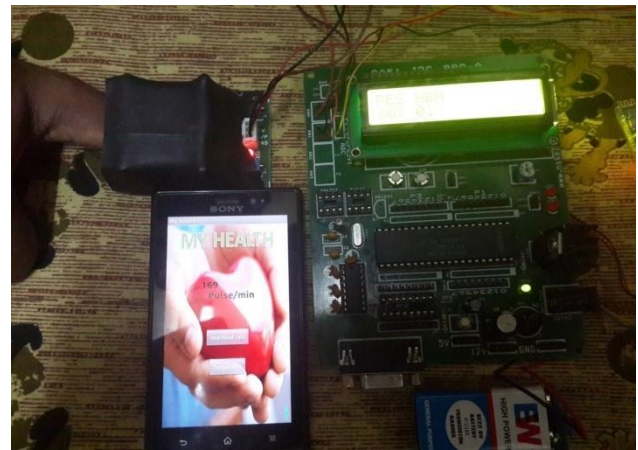


Fig. 3. Laboratory Prototype of DUAP.

The proposed prototype shown in Fig. 3 has been tested on 25 subjects to capture the data related to the user's activity. The raw data of user activity is then subjected to the proposed analytical model, where the prediction is carried out. Following are the steps to summarize the prototype implementation viz.

- Step-1: A hardware model is developed with 8051 microcontrollers and android application connected in the wireless medium.
- Step-2: The prototype of the wearable device is tested on 25 subjects to capture the raw data about user activity.
- Step-3: All the captured data of 25 subjects are subjected to training operation as discussed in HMM implementation in algorithm section. The captured trained data is exported to MATLAB for effective analysis, although any data analytic software can also be used.
- Step-4: The model considers new 10-15 subjects to captured the raw signal (untrained data).
- Step-4: The prediction algorithm is applied to understand the user's intention.

The final processing of the algorithm in MATLAB gives the predictive outcome to show the effectiveness of the proposed service matching mechanism. The next section discusses the performance assessment to validate the outcome.

B. Performance Assessment

The study outcome of the proposed system is assessed using standard parameters of True Positive (P_1), False Negative (P_2), False Positive (P_3), and True Negative (P_4). The model defines P_1 as the number of all the captured data of user activity that is precisely identified. P_2 is defined as several all the computed user activity that is captured with a higher degree of error. P_3 is the number of non-event-based data that has not been identified correctly, while P_4 represents several non-

event-based data that are precisely identified. The assessment of the proposed system is carried out using True Positive Rate (P_5), False Positive Rate (P_6), and Accuracy (P_7). Following are the expression for the same:

$$P_7 = \frac{(P_1 + P_4)}{\sum_{i=1}^4 P_i} \quad (14)$$

$$P_5 = \frac{P_1}{P_2 + P_1} \quad (15)$$

$$P_6 = \frac{P_3}{P_3 + P_4} \quad (16)$$

Equation (14), (15), and (16) represents the computation of True Positive Rate (P_5), False Positive Rate (P_6), and Accuracy (P_7). The proposed system also uses precision (P_8), recall (P_9), and accuracy (P_{10}) for finally assessing the outcome using the following expression:

$$P_8 = \frac{\sum_i P_i(i)}{\sum_i (P_1 + P_3)(i)} \quad (17)$$

$$P_9 = \frac{\sum_i P_i(i)}{\sum_i (P_1 + P_2)(i)} \quad (18)$$

$$P_{10} = \frac{\sum_i (P_1 + P_4)(i)}{\sum_i n(i)} \quad (19)$$

VIII. RESULTS ANALYSIS

The study outcome of the proposed system is initially assessed using Receiver Operating Characteristics (ROC) curve where P_5 and P_6 are the dependable characteristics' (Fig. 4). The trend for the empirical ROC is computed from the obtained numerical outcomes and the outcome that is further normalized using the binormal model. However, there are all the possibilities that there are certain levels of inaccuracies owing to the impartial or irregular distribution of data. Hence, for effective analysis of data, a smoother estimation of parametric ROC trend is applied by implementing a binormal model which shows dependencies on Gaussian distribution. It is also observed that the reliability of the ROC trend has higher dependencies on the threshold factor. If the threshold factor of P_3 is configured to 0.1 then the numerical value of P_5 will be approximately 80% in the trials. A closer look into the Area Under Curve (AUC) shows maximum coverage that directly interprets that the proposed system has the enhanced capability to perform efficient identification of the user's intention in the presence of the increasing value of the P_3 threshold.

The ROC performance in Fig. 4 highlighted the better performance of the proposed system while it is essential to understand various other parameters e.g. recall, precision, and accuracy. Table I highlights the numerical outcomes to shows that the proposed system offers approximately 89% of recall, 91.78% of precision, and 91.33% of accuracy for 10 different trials. By trials, it will mean that different subjects being used in the prototypes and tested for consistency in the outcomes at least 5-6 times. The observations against all the test cases are recorded as a single trial.

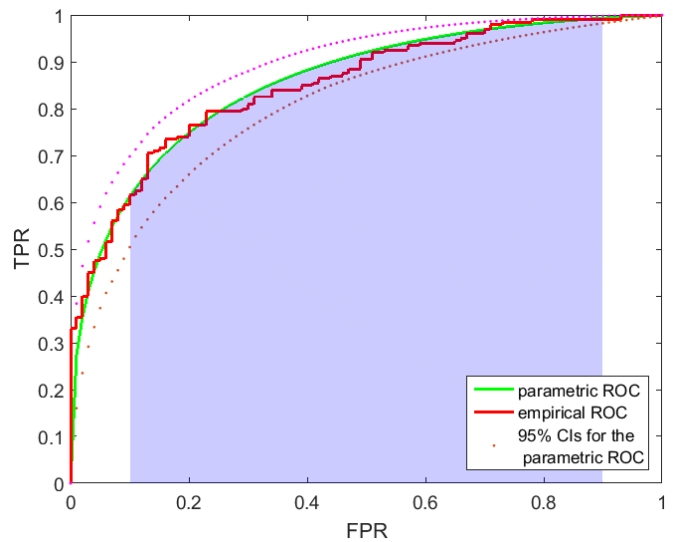


Fig. 4. Analysis of ROC Trend.

TABLE I. SUMMARIZED NUMERICAL OUTCOMES

Trials	Recall	Precision	Accuracy
Trial-1	81.6%	83.8%	89.7%
Trial-2	87.8%	86.9%	91.6%
Trial-3	86.2%	91.7%	93.5%
Trial-4	82.8%	95.7%	87.9%
Trial-5	89.8%	98.6%	98.7%
Trial-6	90.6%	87.9%	91.6%
Trial-7	91.7%	89.2%	87.9%
Trial-8	97.6%	96.5%	91.4%
Trial-9	87.9%	89.7%	89.5%
Trial-10	95.9%	97.8%	91.5%
Average	89.19%	91.78%	91.33%

The effectiveness of the proposed model is assessed if the component block for Service Matching Module SMM is used or removed. Fig. 5 shows that the proposed study offers better accuracy on an increasing number of observations if the SMM block is considered. In absence of an SMM block, the accuracy drops, and thereby it shows the significance of the proposed SMM block in identifying the user's intention based on the HMM-based approach as well as contextual-based approach.

It is quite clear from Fig. 5 that the proposed system offers significantly better accuracy; however, a relevant feedback is applied to understand the self-sustainability towards accuracy performance. Relevance feedback is a mechanism where the outcome is once again cross-checked by the user. It is the cross to increase the probability of identification in presence of uncertainties. Fig. 6 showcases the impact of relevance feedback towards accuracy.

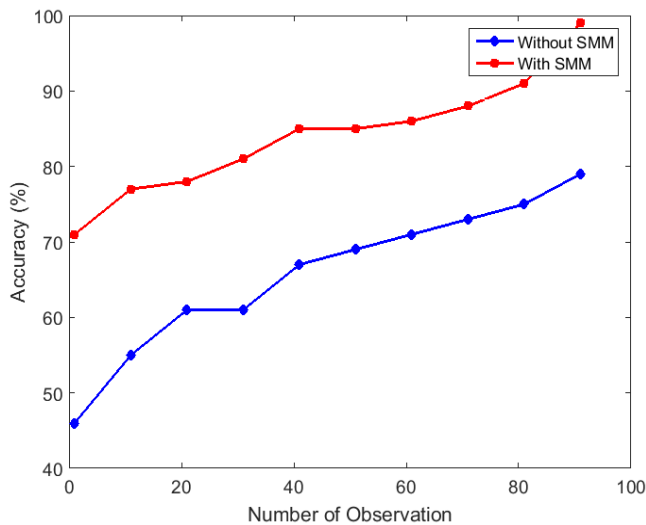


Fig. 5. Accuracy Observation.

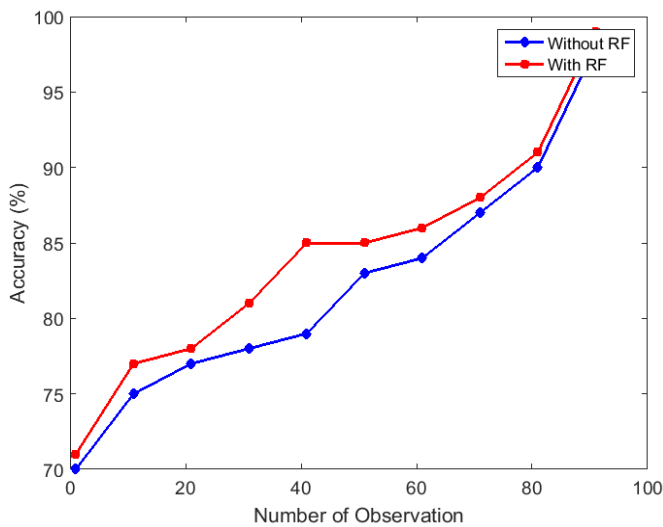


Fig. 6. Analysis with Relevance Feedback.

The graphical outcome in Fig. 6 shows that relevance feedback has the least significant impact on accuracy. Both the curve has a nearly similar performance of accuracy towards 100 observations. The prime reason behind this is the algorithm of the analytical modeling possesses the capability to perform uncertainty modeling while applying HMM for detecting the next state of transition. This phenomenon significantly reduces all the possible errors to a large extent in increasing time series analysis giving more stochastic characteristics to the accuracy curve. Hence, this states that the proposed system is highly reliable and requires lesser dependencies from a human user.

Discussion: From the outcome obtained in proposed study, it has been observed that the model offers better accuracy performance over increasing number of observation. The contribution as well as novelty of the proposed system, are as follows:

- With an aid of mathematical modeling, the proposed framework is highly capable of making a reliable prediction compared to existing approaches. The complete model is assessed for increasing number of trials to find the consistency of the prediction accuracy over multiple iterations.
- The proposed study adopts HMM in a very unique way, unlike existing system, that is reported to suit very well with any form of collaborative units. One of the essential contributory points observed from the numerical outcomes is that proposed system offers an efficient contextual learning operation, where sequence of raw data can be directly used for learning with potential statistical foundation. Adoption of HMM will permit consistency towards adding or deleting penalties while it offers more potential towards managing any form of inputs with variable length. Better flexibility in modelling the proposed scheme is therefore ensured.
- The overall runtime of the proposed system is approximately 0.56227 seconds in core i7 machine to make a prediction (or recommendation). The performance in this regards is nearly similar over other test environment too.
- The outcome of the study shows that proposed system can offer the clear establishment of a complex relationship with the complicated context captured from the wearable devices.

IX. CONCLUSION

The model presented in this manuscript is associated with the design of an activity-based context-awareness system where multimodal activity data is considered followed by feature extraction while the learning mechanism is applied further to develop to support an intelligent recommendation system. This paper discusses the significance of SMM in identifying the dynamic user activity using mixed-mode research analysis. The applicability of such an approach in the wearable device is designed keeping healthcare applications in mind due to its faster response time. At the same time, there is significant algorithm complexity of DUAP under several rounds of observation. This proves that the proposed algorithm offers cost-effective identification of user identity.

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