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Preference Model Assisted Activity Recognition Learning in a Smart Home Environment

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Abstract*—Reliable recognition of activities from cluttered sensory data is challenging and important for a smart home to enable various activity-aware applications. In addition, understanding a user's preferences and then providing corresponding services is substantial in a smart home environment. Traditionally, activity recognition and preference learning were dealt with separately. In this work, we aim to develop a hybrid system which is the first trial to model the relationship between an activity model and a preference model so that the resultant hybrid model enables a preference model to assist in recovering performance of activity recognition in a dynamic environment. More specifically, on-going activity which a user performs in this work is regarded as high level contexts to assist in building a user's preference model. Based on the learned preference model, the smart home system provides more appropriate services to a user so that the hybrid system can better interact with the user and, more importantly, gain his/her feedback. The feedback is used to detect if there is any change in human behavior or sensor deployment such that the system can adjust the preference model and the activity model in response to the change. Finally, the experimental results confirm the effectiveness of the proposed approach.

I. INTRODUCTION

In a smart environment, it is important to provide various context-aware applications to make inhabitants feel more comfortable. For achieving this goal, ubiquitous computing is brought into our living space. By collecting lots of sensory data and extracting specific information from datasets we can develop many kinds of context-aware applications which would improve quality of life. For instance, developing satisfactory healthcare is a key issue for elderly people. By monitoring and collecting the statistics of their daily behaviors, their health states can be acquired and doctors can provide professional suggestions remotely based on the collected information. Similar applications such as security and surveillance, home automation, etc. can be better achieved by recognizing users' current activities and then providing corresponding services based on their prior preferences. In other words, activity recognition and preference learning are among two key techniques for developing satisfactory context-aware applications in the smart home environment.

Research on recognizing activities have become an appealing trend in the area of ubiquitous computing. For constructing a reliable activity recognition system, there are several challenges we have to address. For example, it is difficult to correctly detect starting time and ending time of an activity; concurrent and interleaved activities are hard to recognize due to their fuzzy starting time and ending time; furthermore, the environment itself is dynamic. In addition, these challenges become even more difficult in an environment involving multiple users [1].

In the literature survey, several researches have been done to address most of the above-noted challenges. For correctly detecting the starting/ending time of an activity, Oliver et al. [2] propose a Layer Hidden Markov Model (LHMM), which can be regarded as a cascade of Hidden Markov Models (HMMs), to deal with different time scales in different layers. Therefore, it can identify more complex patterns in human behavior, which lasts for longer periods of time. In addition, activity duration varies with different activities. Tapia et al. [3] use time windows of different sizes to detect activities of interest by applying Naïve Bayes classifiers. In [4], they annotate raw data as "one" when a sensor is triggered and "zero" otherwise. After the preprocessing procedure, the preprocessed data are used to recognized activities by applying HMM and Conditional Random Field (CRF).

For taking concurrent and interleaved activities into account, Tapia et al. [3] make use of several Naïve Bayes classifiers to recognize different activities at the same time. Furthermore, skip-chain CRF is applied to recognize multiple goals in [5] because the authors observe multiple concurrent and interleaved activities in the MIT PlaceLab dataset. Modayil et al. [6] propose Interleaved HMM (IHMM) focusing on improving the performance in the recognition of interleaved activities where the observations come from a wrist-worn Radio Frequency Identification (RFID) reader and tags.

In fact, there usually are several members living together in a home environment; therefore, interactions among activities should be taken into consideration for accurately recognizing activities of interest. Some prior results in [7-10] deal with the problems that may appear in a multi-user environment, but all of them try to recognize activities in computer vision context where observations are obtained from cameras. However, there is a major concern of using cameras to in-

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vestigate the underlying problem, possible offense of users' privacy.

Most of the researches on activity recognition so far focus on constructing and building their activity models in a static environment, but relatively few endeavor to address how to deal with the problems that may occur in a dynamic environment. Therefore, the primary focus in this work is to recognize activities of interest in a dynamic environment.

Our goal is to prove that a user's preference model can assist his/her activity model in a dynamic environment. Everyone has his/her unique habits, which makes the patterns of a person's activities highly different from others. However, knowing a user's preference is helpful for recognizing his/her on-going activities since the activity model can get a user's instant feedback from the interactions initiated by the services provided based on a preference model. That is, once the preference model is established, the activity model will be empowered with the ability to receive the information fed back from users by a preference model. The authors in work [11] has mentioned the explicit feedback; however, we exploit the implicit feedback in this paper. Based on the assistance from a preference model, an activity model has information about changes from users' behavior or from their surrounding dynamic environments.

On the other hand, a user's preference model can also benefit from his/her activity model. To be more specific, the output of an activity model can be regarded as high level contexts, which are parts of the input to a preference model. With the high level contexts, a preference model gains more high-level knowledge about things happening in the environment rather than just low level sensor data. In this way, a preference model can be enhanced to provide more appropriate and attentive services to inhabitants whenever necessary. We will address and verify this benefit in our future work.

The rest of the paper is organized as follows: Section II provides an overview of the proposed system. Section III presents the construction of the activity model. In Section IV, how to establish a preference model is described. The hybrid system combining an activity model and a preference model is shown in Section V. Section VI states our experimental results and the performance of the system. Finally, Section VII draws the conclusions of our work.

II. SYSTEM OVERVIEW

The proposed hybrid system (See Fig. 1) comprises two main components: an activity model and a preference model. The hybrid system not only has the ability to recognize the activities but also provides services to an inhabitant according to his/her habit. Moreover, the relation between these two models is also taken into account. The activity model classifies current activities which a user performs based on the information collected from various multi-modal sensors deployed in the home environment. Features are extracted after sensor data are preprocessed. By calculating the mutual information between each activity and feature, informative features in particular are selected whereby the activity model is learned.

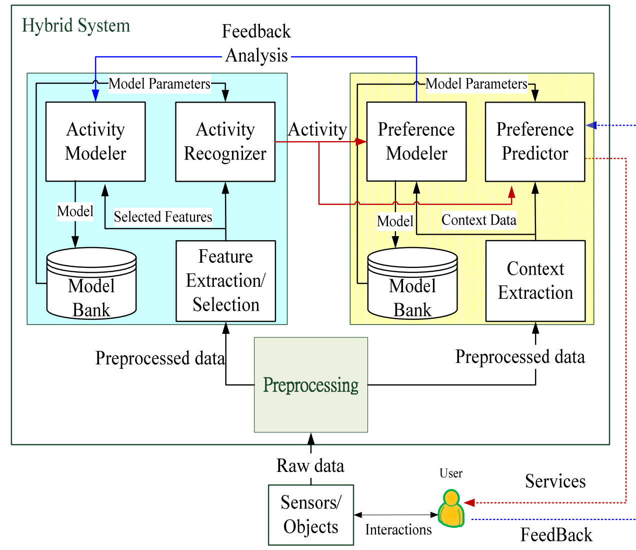

Fig. 1. System Overview of the hybrid system

The preference model perceives a user's interactions, including the information of different contexts, and then appropriate services are inferred and delivered to the user automatically. Note that the way we use contexts, consisting of aggregated features, rather than an individual feature as the input to the preference model is just similar to that by which we take to select features as for an activity model. After constructing these two models, we propose an approach to model cooperation between the two models in the hybrid system. Just as said before, the hybrid system observes each interaction from users and then tries to provide its best- estimated service automatically. Given the service, the users will feedback acceptance/rejection of the service to the system. In turn, the system, after analyzing the feedback, then infers the most probable labels for updating the original models involved. In the following sections, we will describe the details of each component.

III. ACTIVITY MODEL CONSTRUCTION

For constructing an activity model, several issues need to be addressed. The first issue is how to preprocess sensor data such that the preprocessed sensory data can be utilized to extract informative features. The second issue is how to choose among these informative features to represent an activity model effectively. The last issue is how to train the parameters of an activity model from the selected informative features so that activities of interest can be successfully classified.

A. Data Preprocessing and Feature Extraction

We have deployed a wireless sensor network which contains sensors to measure light intensity, temperature, humidity, pressure, acceleration, current-flow, etc. Some of the deployed sensors are installed on objects to detect interactions from users. Moreover, readings of the sensor are analog and sampling rates based on sensor's characteristic and activities of interest we want to recognize in this work.

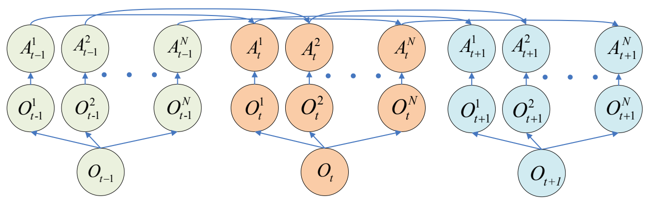

Fig. 2. The DBN structure of the activity model in our hybrid system

After receiving the sensory data, the Preprocessing unit (as shown in Fig. 1) discretizes the sensor readings, resulting in several sensor states for each sensor type, and we define the change from a state to another as an "interaction". In addition, sensors deployed in the sensed environment will send interaction information to the smart system only in the event of state change, and the Feature Extraction unit will then process the information of each sensor and obtain various features afterwards. Here, interaction is treated as a basic feature in our work.

One kind of feature of interest in this work is the sequential-interaction feature, which is to characterize the temporal relations among all interactions whenever the state of an object has changed. A bi-gram feature is a pair of two sequential interactions. For instance, brushing teeth should follow squeezing of toothpaste and starting to brush. Such an activity consists of sequential actions; hence, the sequential-interaction features are suitable for representing interactions with a specific sequence in this activity.

Another kind of feature of interest in our work is a concurrent-interaction feature which captures the relationship among simultaneous interactions associated with different sensors. For example, a user can read a book while listening to the music at the same time. Similar to the sequential- interaction feature, a pair of two interactions within the same detecting time window will be regarded as a concurrent-interaction feature.

B. Feature Selection

All available features can be represented as a feature vector $F = \left\langle F^1, F^2, ..., F^M \right\rangle$, and each element in the vector stands for one of the three kinds of features, *i.e.*, interaction, sequential-interaction, and concurrent-interaction). In addition, there are several states for each feature, and the states of the *i*-th feature can be denoted as $F^i \in \left\{ f^{i1}, ... f^{ik} \right\}$. For selecting more effective features from the overly rich feature set obtained from our widely deployed sensors so as to enable our learnt model to be more discriminative among various activities of interest, information gain is calculated for each pair of activity and feature. The activities of interest are formulated as $A = \{A^1, A^2, \dots, A^n\}$ and the information gain (or mutual information) is calculated by the following equation:

$$I(A^i;F^j) = H(A^i) - H(A^i \mid F^j) \tag{1}$$

where

$$H(A^i) = -\sum_{a \in A^i} P(A^i = a)\log(P(A^i = a)) \tag{2}$$

$$H(A^i \mid F^j) = -\sum_{f \in F^j} P(F^j = f) H(A^i \mid F^j = f) \tag{3}$$

After estimating the information gain of each pair of activity and feature, the Feature Selection unit chooses those features with higher mutual information. These selected features are more highly associated to their corresponding activities. Therefore, we can use such features to construct activity models, and treat the unselected features with lower mutual information as noises which may compromise the accuracy of activity recognition.

C. Training and Classification

To take into account temporal information and relationship between an activity and its corresponding informative features, we use Dynamic Bayesian Network (DBN), which models time information and predicts probability of an activity. Figure 2 shows the graphical structure of our proposed activity model. For each time slice *t*, the activity vector performed by the residents is formulated as $A_t = \left\langle A_t^1, A_t^2, ..., A_t^N \right\rangle$, and the feature vector extracted at time *t* (as our observation to the model) is denoted as $O_t = \left\langle F_t^1, F_t^2, ..., F_t^M \right\rangle$. Hence, the problem to predict activities given the previous activity estimates and the observation at *t* can be expressed as $P(A_t|A_{t-1},O_t)$. The parameters of an activity model are trained with Expectation Maximization (EM) algorithm. The Activity Modeler estimates parameters for the activity model by evaluating $\theta^* = argmax_\theta P(O_{1:t}|\theta)$ where θ is the set of parameters of the activity model and $O_{1:t}$ is the set of features collected so far, and then these estimated parameters are stored in the Model Bank. After training an activity model, the labels of the activities in the *t*-th time interval can be recognized by the Activity Recognizer, which evaluates $P(A_t|O_{1:t})$ based on a Bayes Filter. The inference of current on-going activities can be formulated as follows:

$$P(A_t = a_t \mid O_{1:t}) \propto$$
$$P(O_t \mid A_t = a_t) \sum_{a' \in A} P(A_t = a_t \mid A_{t-1} = a') P(A_{t-1} = a' \mid O_{1:t-1}) \tag{4}$$

IV. Preference Model Construction

The procedure of establishing a preference model is similar to that of constructing an activity model. There are also three main procedures, namely, preprocessing of raw data into contexts, context selection, and construction of a preference model to infer a service which a user prefers. The difference between these two models is that contexts are regarded as basic elements to represent a preference model, and the contexts are in the sense similar to what features represent in an activity model. In other words, a preference model for a user can be constructed by integration of contexts.

As for construction of a preference model, the underlying sensory data will be interpreted as lower level contexts via context interpreters in the Context Extraction unit based on domain knowledge. The meaning of a context refers to some information related to an object of interest and its status. For example, "TV is turned on", "sofa is occupied", and "the

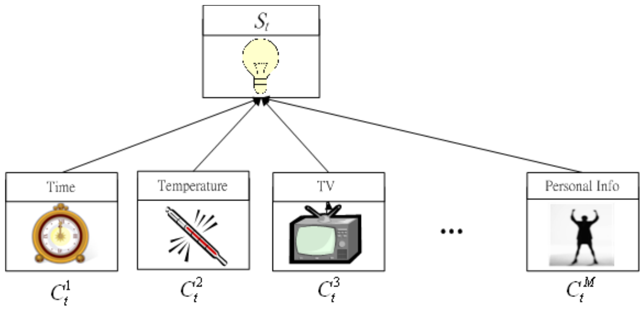

Fig. 3. The Bayesian preference structure modeling the relationship between contexts and a service

temperature is 27.5 degree". These contexts are formulated as a context vector $C = \left\langle C^1, C^2, \ldots, C^m \right\rangle$.

Like what we have done in constructing an activity model, after extracting contexts from sensory data, we select contexts to represent preference models by calculating information gain for each service and context pair. Let the services we want to provide be formulated as $S = \{S^1, S^2, \ldots, S^m\}$. Considering the temporal information and the services our system may provide, a service at time t is represented as $S_t \in \{S^1, S^2, \ldots, S^m\}$. Given the current observation $Z_t = \left\langle C_t^1, C_t^2, \ldots, C_t^m \right\rangle$ and the state of the previous service, the service at time t can be inferred from $P(S_t|S_{t-1},Z_t)$. The Preference Modeler also models the structure among services and context data by using DBN, and its parameters of preference model are trained with EM algorithm and stored in the Model Bank. The label of the services at time t can be predicted by Preference Predictor, and the posterior can be represented as $P(S_t|Z_{1:t})$ where $Z_{1:t}$ is the observation collected so far. The inference of the services provided at time t can also be achieved by applying Bayes Filter.

V. Hybrid System

As in Fig. 1, the hybrid system consists of an activity model and a preference model. Hence, the observation at time t can be reformulated as $X_t = \{O_t, Z_t\}$. In other words, the sensory data observed at time t could be preprocessed with the different viewpoints so that features and context data are used to construct a hybrid system at the same time. Moreover, the label we want to predict can be denoted as $Y_t = \{A_t, S_t\}$. The problem can also be reformulated as $P(Y_t|X_{1:t})$. After reformulating our problem, we will discuss the influence of activity model to a preference model and the inverse later.

A. Relationship among activities and services

The preference model is constructed with the information of context. With the different level of the expression power of the context, we can regard the current activities, which are recognized by an activity model, as high level context data and utilize them as the input of a preference model. To model the relation of each service-activity pair, the mutual-information-like weight function is calculated, and the equation is formulated as below.

$$W(S^i, A^j) = \sum_{a' \in A^j} P(S = S^i, A^j = a') \left(\log \frac{P(S = S^i, A^j = a')}{P(S = S^i) P(A^j = a')} \right) \quad (5)$$

To model the relation between services and activities, there is a rank table constructed for each preference model which contains the information of weight function of activities. The weight vector of service S_i can be denoted as $R^i = \{r_1^i, \ldots, r_n^i\}$ where $r_j^i = W(S^i, A^j)$. The activity whose weight function value is higher is more related to this service, and all these activities are regarded as the context data which may help to discriminate different services the user desired. Then, the preference model is represented with the high level context and other low level contexts interpreted from sensory data.

B. Simultaneously activity recognition and services providing

Based on the structure of an activity model and a preference model, the hybrid system can be thought as a two layer network. The lower layer consists of the activity model whereas the higher layer is the preference model which is built with the context of activity and other low level context data. According to the original problem we want to solve, $P(Y_t|X_{1:t})$ can be reformulated as $P(S_t,A_t|X_{1:t})$ = $P(S_t|A_t,X_{1:t})P(A_t|X_{1:t})$. With the property of conditional independence, the equation can be reduced to $P(S_t|A_t,Z_{1:t})P(A_t|O_{1:t})$. The prediction of the activities and the services the users desired at time t can be solved with Bayes Filter. The parameters of the hybrid system are estimated using EM algorithm.

C. Adaptation of preference model

After the modified preference model is retrained, there are two cases in classifying services: first, the preference model successfully predicts the service the user needs. In this situation, the result of activity recognition is validated by user's response and the activity model is considered suitable to user. Second, the preference model incorrectly predicts the service and delivers it to the user automatically. In the second situation, it suggests that, whenever a wrong service is provided automatically to the user, he/she will terminate the wrong service and then actively start another service which the user really desires. The action of making correction of the originally assigned service symbolizes that the user rejects the label which is predicted by system, and provides a correct label for this context data afterwards. However, the preference model we built is only to detect when the right time to provide services is, and the model will not know whether the users has terminated the services or not. Hence, we directly monitor the state of the sensor attached to the electric appliance. For example, if the system detects that the user wants to watch TV, then the TV will be turned on by the system after prediction is made through the preference model. Now, the current sensor mounted on the TV set will be used to observe whether the user accepts the service or not. If the user doesn't have the intention to watch TV, he/she will turn off the TV naturally. Therefore, we can monitor the situation

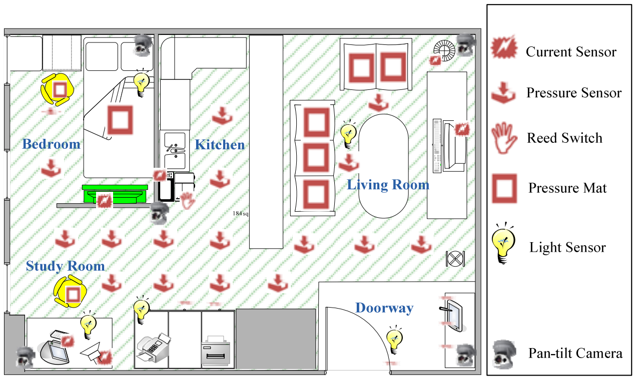

Fig. 4. Overview of the experiment environment in our Attentive Home Lab at National Taiwan University

with the change of the state of the current sensor. To sum up, every time when a service is provided, there are corresponding sensors installed to detect the states of the electric appliances providing the mentioned service (abbrev. as "state of service" in the sequel). Once we know the state of the service, the prediction of the preference model can be modified after comparing it with the real state of service. The procedure of correcting the prediction of the preference model is listed in the following:

Step 1: Provide a service to the user according to the prediction of the preference model.

Step 2: Monitor the corresponding sensors related to the services which provided by the system.

Step 3: If the actual state of the service is different from the predicted service state at time t, the prediction of the preference model will be modified by the observation.

After getting the modified label, the preference model will be retrained with the sufficient modified dataset later, and the correction of the prediction not only can update the preference model but also can send feedback to activity model.

D. Preference model assisted activity learning

The idea for combining these two models is that the preference model can indirectly receive the information feedback from users by passively accepting services provided by the system or by actively starting some other services; hence, the model can be updated with this information whenever needed. However, the activity model only classifies the current activities with the information the sensor sensed, but it can't verify whether the user is performing the activity the system has recognized or not. With the assumption that some relation between a human's activity and his/her preference must exist, we combine these two models and use the information received from users by the preference model to verify the activities recognized by system or to correct the activity model. Moreover, after providing services, the system will monitor the reaction from users. Once users terminate the services immediately, the activity model of the hybrid system is adapted through the following procedure:

Step 1: Retrain the preference model with the modified dataset

Step 2: Based on the previous training data and the recognition of testing data, 10-fold-crossvaidation of activity A_i is executed to determine whether to update the activity model

Step 3: If the error rate of 10-fold-crossvalidation is higher than a threshold h, the activity model is updated with the data whose label is voted by the following equation:

$$j^* = \arg\max_j \frac{\sum_k r_i^k I[\tilde{A}^{i,k} = a^{i,j}]}{\sum_k r_i^k}, \; \hat{A}^i = a^{i,j^*} \qquad (6)$$

where $\tilde{A}^{i,k}$ is the candidate state of A^i which is voted by S^k, $a^{i,j}$ is the j-th state of A^i, $\hat{A}^i$ is the state of A^i voted by services, and I is an indicator.

In the third step, we compare the current activity states which are recognized by an activity model and the states of activities which are voted by the preference model with the feedback of users' to determine whether or not to modify the original activity model. The activity model will be updated if the predictions of the two models are different. However, if the predictions of these two models are the same, only the preference model will be retrained.

VI. Experiment

Figure 4 is the overview of our sensor deployment in our CoreLab at National Taiwan University. In this living lab, five kinds of sensors were deployed on different objects, and the location of each object is illustrated in the figure. To validate our approach, about twenty hours of sensory data were recorded. The activities of interest include working on PC, sleeping, waking up, going out, coming back, watching TV in the living room/bedroom, studying, preparing food, taking a drink, mopping, and brooming. In addition, the system will automatically control the lights, play a message, and turn on/off the TV based on the preference model learnt from the habits of inhabitants. The dataset was collected through several days by three volunteers, and the orders of performing activities could be arbitrary. However, to show the adaptive ability of our model to the change of users' habits and the environment, we change the deployment of environment or ask the volunteer to change his/her habit when he/she is performing activities, and all of activities have their corresponding changes except the activity "Waking up".

In TABLE I, we list all of activities with their corresponding dynamic changes which are designed in our experimental environment. Based on these changes, there are three kinds of result in our experiment such as the performance of activity recognition before these changes occurring, the performance of activity recognition after these changes occurring, and the performance of activity recognition after adapting our original activity model to these changes. We use six-day data as our training data for constructing an activity model, and then use additional three-day data, which are collected before change occurs, as our testing data. The corresponding result is shown in the first bar of each activity type

TABLE I DYNAMIC CHANGE IN A HOME ENVIRONMENT

Activity	Dynamic change
Working on PC	Exchange the chair in the studying room and the one in the bedroom
Sleeping	Sleep on the chair
Going Out/ Coming Back	Put the shoes in the different shoe cabinet
Watching TV (living room)	Sit on the new sofa
Watching TV in the (bedroom)	Exchange the chair in the studying room and the one in the bedroom
Preparing Food	Prepare food without using microwave
Drinking	Drink with different cup
Studying	Sit on different place
Brooming/Mopping	Put the mop/broom in the different cabinet

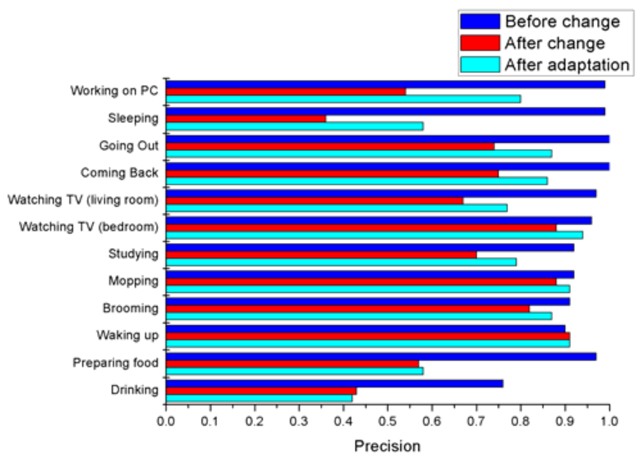

Fig. 5. Precision of activity recognition

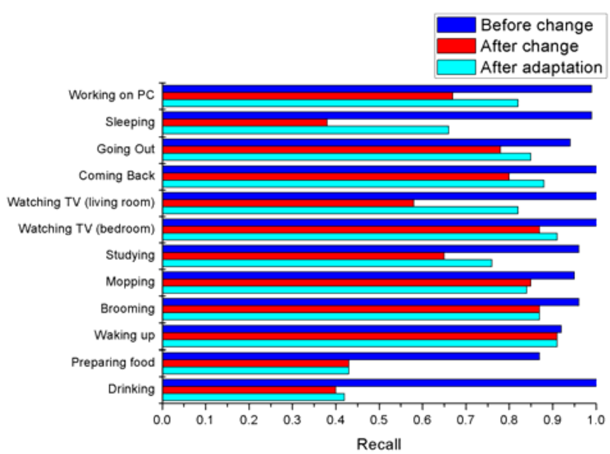

Fig. 6. Recall of activity recognition

in the fig. 5 and fig. 6. Additional three-day data, which are collected after occurrence of these changes, are used as another testing data, and the corresponding result is shown in the second bar of each activity in the fig. 5 and fig. 6. The last bar of each activity in the fig. 5 and fig 6 shows the result after the adaptation of our activity model with the testing data which are collected after occurrence of these changes.

The accuracy of activity recognition is mostly recovered after applying our approach, but some activities don't adapt to their corresponding changes because of some kinds of activities are service independent. Namely, users don't need any services when he/she is performing some activities due to his/her preferences. After analyzing the user's feedback, the hybrid system is leant with the information and will be adjusted to recognize activities more precisely.

VII. CONCLUSION

We have proposed a hybrid system, which modeled the relationship between an activity model and a preference model, to provide more appropriate services and better recognize activities. As been demonstrated in our experimental results, the cooperation between the two model enables information propagation between the two model so that the hybrid system can keep track of the changes from the environment and increase the system's practicality in a real world.

In the future work, more powerful models (such as CRF, HMM, etc) can be applied in the activity model and the preference model such that the hybrid system can model dependent features and become more discriminative to more complicated interactions between users and their surroundings.

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