Mining Emerging Patterns for Recognizing Activities of Multiple Users in Pervasive Computing

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***Abstract*—Understanding and recognizing human activities from sensor readings is an important task in pervasive computing. In this paper, we investigate the fundamental problem of recognizing activities for multiple users from sensor readings in a home environment, and propose a novel pattern mining approach to recognize both single-user and multi-user activities in a unified solution. We exploit Emerging Pattern – a type of knowledge pattern that describes significant changes between classes of data – for constructing our activity models, and propose an Emerging Pattern based Multi-user Activity Recognizer (*epMAR*) to recognize both single-user and multi-user activities.**

I. Introduction

In recent years, sensor based human activity recognition has become an important research direction in pervasive computing. However, it is challenging because of noisy sensor data and complex pattern of human activities. To recognize various activities accurately and reliably, an appropriate activity model has to be deployed to relate low-level features to high-level concepts. Most existing work focuses on recognizing activities of a single user. However, in a living space (i.e., typically a home environment), there are usually multiple inhabitants. Recognizing activities of both a single user and multiple users has practical implications for many real-world applications.

A. Problem Analysis

We categorize the different cases of ADLs as follows.

1) Single-user sequential ADLs: In this category, a single user performs an activity in a sequential manner independently.

2) Single-user sequential ADLs with simultaneity: In this category, two or more users perform the same activity in a sequential manner both independently and simultaneously.

3) Multi-user ADLs with collaboration: The ADLs of this category involve two or more users working together to complete an activity in a cooperative manner, where each of them performs a partial step of the activity.

4) Multi-user ADLs with conflict: In this category, two or more users are involved in an activity in a conflicting manner, where users compete against each other for the activity.

B. Our Contributions

The paper makes the following contributions.

- *We propose a novel activity model based on Emerging Pattern for both single-user and multi-user, and especially, the multi-user model is capable of capturing user interaction.*
- *We propose a novel activity recognizer to recognize both single-user and multi-user activities in a unified framework. The feedback loop in the recognizer is novel in the way that it is able to adjust the boundary between two adjacent activities, resulting in more accurate recognition.*
- *We design our sensor platform for multiple users, conduct a real-world trace collection consisting of a variety of activity cases, and evaluate our recognizer through comprehensive experiments.*

II. Our Sensor Platform

We built our sensor platform from off-the-shelf sensors. It measures user motion (i.e., both hands' movements), user location, human-object interaction (i.e., objects touched and sound), and human-to-human interaction (i.e., voice).

III. Emerging Pattern

EP describes significant changes between two classes of data. An EP is a set of items whose frequency changes significantly from one dataset to another. An EP with high support in its target class and low support in the contrasting class can be seen as a strong signal indicating the class of a test instance containing it.

IV. Activity Model and Recognition Algorithm

A. Overview

We give an overview of the *epMAR* activity recognition system which is capable of recognizing both *Single-user ADLs* and *Multiple-user ADLs*, as illustrated in Fig. 1. There will be one or more observation sequences corresponding to a single user or multiple users input into the *epMAR* recognizer. The *epMAR* recognizer operates in two phases – model training and activity recognition. In the training phase, a training dataset for each of the users will be used to train our activity models. Our activity models consist of both a single-user model and a multi-user model. The single-user model is designed to recognize activities of a single user, whereas the multi-user model is capable of recognizing activities of multiple users. In the recognition phase, for each user's sequence, we first segment its sequence using a slide-window to obtain a test instance, and then apply our recognition algorithm to label this sequence segment. The above process will be performed

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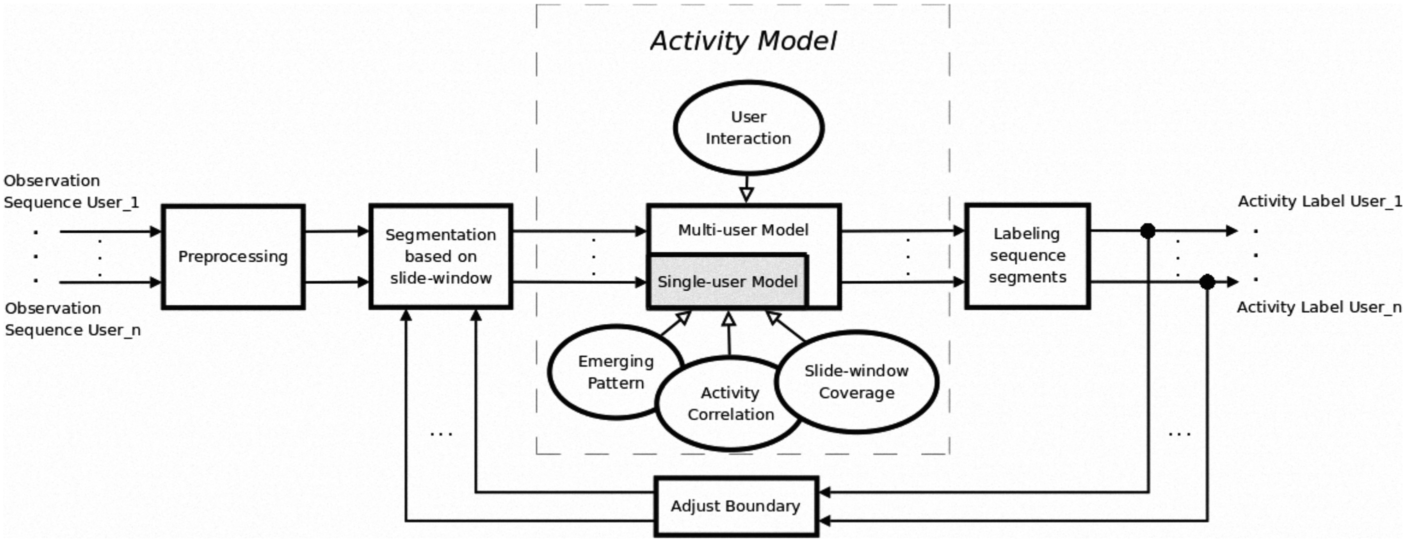

Fig. 1. Overview of the *epMAR* recognizer.

recursively. For each pair of consecutive sequence segments, we design an algorithm to detect and adjust the boundary. This algorithm serves as a feedback loop in our system aiming to label sequence segments accurately and overcome the drawback of a slide-window based segmentation method.

B. Activity Model

1) Single-user Model: The single-user model is designed to recognize activities of a single user. It is composed of three elements: *EP score*, *Slide-window Coverage score* and *Activity-Correlation score*. The details are described as follows:

EP score: This score element provides a measurement on a fraction of EPs contained in a test instance.

Slide-window Coverage score: This score element is used to measure how many irrelevant observations contained in a test instance for a particular activity.

Activity-Correlation score: This score element is used to measure correlations between activities. We use condition probability to model correlations between activities.

Finally, we propose our single-user model using a linear combination of the above three elements:

$$\begin{aligned} single\_user\_score =& c_1 * ep\_score + c_2 * coverage\_score \\ &+ c_3 * correlation\_score \end{aligned}$$

where c_1, c_2 and c_3 are the coefficients, representing the importance of an individual score element.

2) Multi-user Model: The multi-user model is capable of recognizing activities of multiple users. It extends our single-user model by taking user interactions into account.

Interaction score: This score element is used to measure the interaction between different users.

We propose our multi-user model using a linear combination of single-user model and interaction score:

$$multi\_user\_score = single\_user\_score + c_4 * inter\_score$$

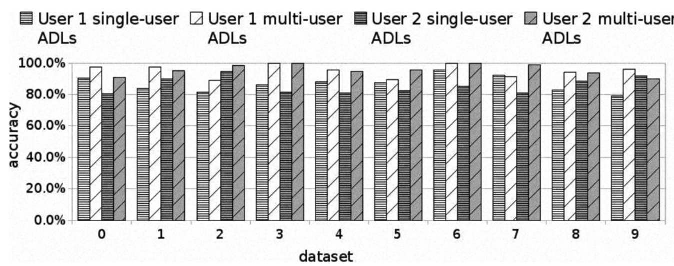

Fig. 2. Accuracy Breakdown in Users and ADLs

where c_4 is the coefficient representing the importance of $inter\_score$.

V. Experimental Studies

We now move to evaluate our proposed algorithm. Data collection was done by two volunteers over a period of two weeks in a smart home environment. We use ten-fold cross-validation for our evaluation. We evaluate the performance of our algorithm using the time-slice accuracy.

The detailed breakdown in users and ADLs are shown in Fig. 2. The overall accuracy of both users for both *Single-user* and *Multi-user ADLs* achieves 89.72%, demonstrating that the *epMAR* recognizer is effective for recognizing activities in a multi-user scenario.

VI. Conclusions

In this paper, we study the fundamental problem of recognizing activities for multiple users from sensor readings in pervasive computing. We design our sensor platform and conduct a real-world trace collection. We propose a novel activity model based on Emerging Pattern and design the *epMAR* recognizer to recognize both *Single-user ADLs* and *Multi-user ADLs*. The results demonstrate both the effectiveness and reliability of our system.

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