Activity Recognition Using Hierarchical Hidden Markov Models on a Smartphone with 3D Accelerometer

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Abstract. As smartphone users have been increased, studies using mobile sensors on smartphone have been investigated in recent years. Activity recognition is one of the active research topics, which can be used for providing users the adaptive services with mobile devices. In this paper, an activity recognition system on a smartphone is proposed where the uncertain time-series acceleration signal is analyzed by using hierarchical hidden Markov models. In order to address the limitations on the memory storage and computational power of the mobile devices, the recognition models are designed hierarchy as actions and activities. We implemented the real-time activity recognition application on a smartphone with the Google android platform, and conducted experiments as well. Experimental results showed the feasibility of the proposed method.

Keywords: Hierarchical hidden Markov models, 3-axis accelerometer, activity recognition, Google android phone.

1 Introduction

As many types of smartphones such as Google Android phone and Apple iPhone are released and the use of smartphones increases, services using built-in sensors on a smartphone is also increasing. Accordingly, a lot of research is processing data collected from multiple sensors on a smartphone. Especially, some sensors like accelerometers have been used to recognize a person's activities in mobile devices before smartphones appear. Various studies on the user activity have been investigated to provide adaptive services on the mobile devices like healthcare systems for disabled or elderly people.

Some systems are developed to provide context aware services using a smartphone user's behaviors. Böhmer et al. developed a system to select suitable applications from a user's behavior on the Android platform [1]. Bellotti et al. developed a system named Maggiti which inferred a user's activities (Eating, Shopping, etc.) and recommended some content on Windows Mobile platform [2]. Probabilistic models are appropriate for dealing with vagueness and uncertainty in real life for context-aware services. However, it is difficult to apply them to mobile devices because it requires a lot of memory and CPU time. Hybridization of intelligent techniques is the combination of different computational intelligence techniques. The hybrid intelligent systems become

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popular to deal with many pattern recognition tasks [3][4]. In this paper, we proposed a hierarchical probabilistic model based approach to recognize a user's activities. It is applied to acceleration data gathered from an Android smartphone. Especially, it consists of two different kinds of probabilistic models which are continuous HMM and discrete HMM. Also, the feasibility of the method is shown by experiments.

2 Related Works

2.1 Activity Recognition with Accelerometers

There are many attempts to recognize a user's actions and behaviors with accelerometers. Table 1 summarizes some studies.

Table 1. Activity recognition using accelerometers

Author	Classifier	Contribution	Sensor	Year
Kwapisz et al. [5]	ANN, J48	Need for a little data size for recognition, fast recognition	Accelerometer	2010
Longstaff et al. [6]	NB, DT	Use of co-learning, high accuracy	GPS receiver, Accelerometer	2010
Maguire et al. [7]	kNN, J48	Fast recognition	Accelerometer, Heart-bit rate	2009
Gyorbiro et al. [8]	C4.5, NN	Real time recognition, efficient battery usage	Accelerometer	2009
Song et al. [9]	ANNs	Implementation on mobile environment	Accelerometer	2008
Zappi et al. [10]	HMM	Dynamic sensor selection	Accelerometer	2008
Yang et al. [11]	Neuro-fuzzy	Application of Neuro-fuzzy	Accelerometer	2007
Ganti et al. [12]	HMM	Implementation of middleware	GPS receiver, Accelerometer	2006

Many studies have typically been implemented in a mobile device as one of main contributions, and they also tried to recognize actions in real time with fast calculation speed. In this paper, we propose a novel method to use acceleration data for five seconds to recognize activities in real time.

2.2 Hierarchical Probabilistic Models

Hierarchical modeling approach is often applied to some probabilistic models such as Bayesian network [13], dynamic Bayesian network, hidden Markov model [14], etc. The approach is useful in most cases that patterns to recognize can be divided into smaller units with a hierarchical structure. Well designed hierarchical models improves accuracy and speed of recognition.

Table 2 summarizes some cases of hierarchical probabilistic models. In many cases, hierarchical model is used to recognize an activity that consists of some actions, or can be inferred from integration of each module which represents a part of a body. The approach is suitable to recognize a specific pattern from time-series patterns.

Table 2. Related works using hierarchical model

Author	Classifier	Contribution	Sensor	Year
Yang et al. [15]	HDBN	Activity recognition with multi-modal sensors	Accelerometer, wearable sensors	2009
Park et al. [16]	HDBN	Modularization using HDBN	Video camera	2004
Mengistu et al. [17]	HHMM	Understanding underlying semantics of words and sentences	Text data	2008
Wang et al. [18]	HDBN	Gesture recognition using HDBN	Video camera	2007
Du et al. [19]	HDBN	Hierarchical durational-state DBN	Video camera	2006

3 Proposed Method

The proposed structure consists of two steps of HMMs to analyze acceleration data and recognize a user's behavior. First, after acceleration data collected from a three-axis accelerometer on a smartphone, the acceleration data is transferred to low-level HMM to classify a user's actions. In the second phase, high-level HMM is used to recognize a user's activities from the set of actions. Figure 1 shows the process of the entire system.

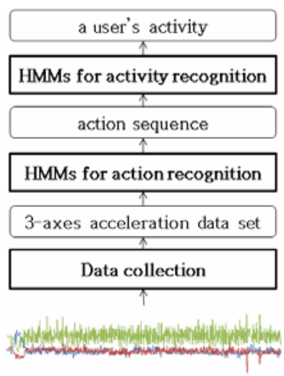

Fig. 1. The flow of the whole process

3.1 HMMs for Action Recognition

In general, there are two methods, which are quantization and continuous HMM, to process continuous data. In this paper, continuous HMMs with Gaussian distribution are used to recognize a user's actions from the acceleration data.

Mostly continuous HMM training requires more time than discrete HMM learning, and it may burden real time pattern recognition with additional computation. Here, complexity and time required for the computation is not too large because we acceleration data for short time are used. A set of actions recognized by low-level HMMs are four kinds of actions such as stand, walk, run, stair up/down. Each HMM for each action has five hidden states. The frequency to collect acceleration data is 12hz, and data length for action recognition is five seconds. The data window size for action is 60.

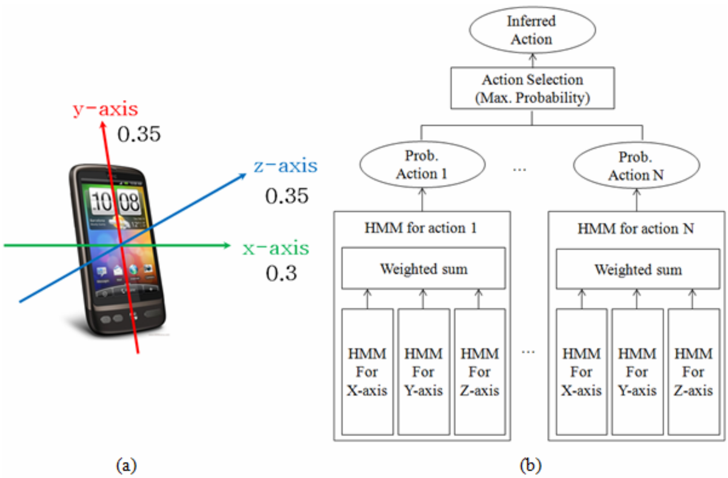

Fig. 2. (*a*) Directions and weights of X, Y, Z axes (b) HMM structure for action recognition

Acceleration data include x, y, z axis values as shown in Figure 2(a). In order to handle three-dimensional acceleration data, we train a HMM for each axis and integrate probability values of three axes with a weighted sum approach. Weight for each axis is shown as Figure 2(a). Figure 2(b) shows the structure of low level HMM for action recognition.

3.2 HMMs for Activity Recognition

In order to recognize a user's activities, previously recognized actions in step 1 are used as input data. In general, an activity consists of a number of actions. It is possible to recognize the user's activities if and only if the acceleration data should be collected over an enough period of time. The data window size for activity is 3600.

If a single-layered HMM is used to recognize the user's activities, the increase of the length of the acceleration data accompanies the increase of the number of state transitions. Many state transitions make the probability very small and require additional

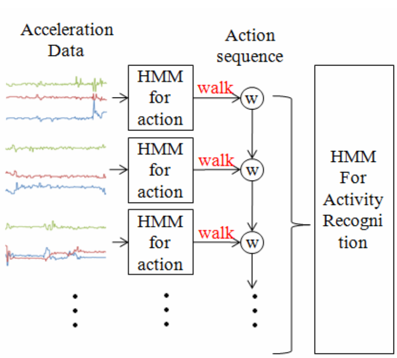

Fig. 3. HMM structure for activity recognition

calculations such as log function. However, a sequence of actions are used as input for the HMM for real-time activity recognition on a mobile device without using the acceleration data directly. It can reduce the required time for calculation and can enhance the precision. Figure 3 shows the basic structure for the activity recognition.

4 Experimental Results

4.1 Data Collection

Android OS based HTC Desire was used as a platform for data collection. Participants were three graduate students between 20-30 years old. They grasped the smartphone by hand for data collection. The amount of collected data for training action/activity recognition is shown in Table 3.

Table 3. Training HMMs for data size

Type	Class	Data size
Action	Stand	315 seconds
	Walk	463 seconds
	Stair Up/Down	1,178 seconds
	Run	213 seconds
Activity	Shopping	1,435 seconds
	Taking Bus	5,478 seconds
	Moving (by walk)	11,264 seconds

4.2 Evaluation of HMMs for Action Recognition

Figure 4(a) showed the performance of HMMs for action recognition. The experiment was done with 4-fold cross validation. Recognition for 'stand', 'run', 'walk' actions show good performance except for 'stair up/down' action. It is difficult to classify 'stair up/down' and 'walk' actions sometimes. There were various types of stairs, and some stairs have similar properties with undulating ways. Classification between 'stair up' and 'stair down' was conducted for a more detailed analysis of the precision evaluation.

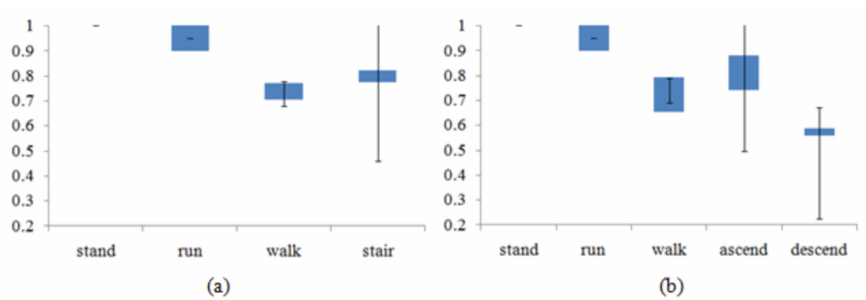

Fig. 4. (a) Precision of action recognition (b) Precision of action recognition (*stair up/down*)

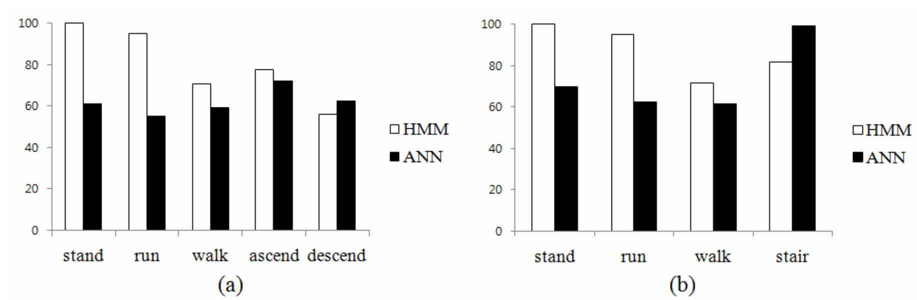

Fig. 5. Comparison of precision (*HMM and ANN*)

Figure 4(b) shows the result of the evaluation for more detailed actions including 'stair up' and 'stair down.' The result showed decrease of precision of 'walk' action. It implied that walk and stair up are confusing. Also, it meant that classification between 'stair up' and 'stair down' is very difficult by using a built-in accelerometer on a mobile phone. Also, Figure 5(a) and (b) shows the result of comparison with ANN(artificial neural network).

4.3 Evaluation of HMMs for Activity Recognition

We attempt to recognize three kinds of activities which can be determined by acceleration data. They are shopping, taking bus, and moving by walk. It is assumed that there are some acceleration patterns for all activities. For instance, when a user is shopping in a department store, he or she is going to repeat walking and standing regularly. If a user takes a bus, the acceleration pattern may be similar to 'standing' action for sitting in a seat. When a user moves for a long time, the user's acceleration pattern may show 'walking' and 'stair up/down'. Figure 6 shows the comparison among hierarchical HMM, HMM, and ANN for activity recognition. The two step hierarchical HMM shows better average performance than original HMM and ANN.

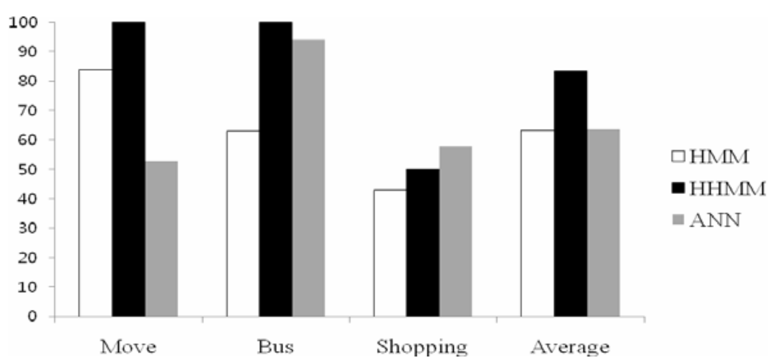

Fig. 6. Comparison of precision (*HHMM , HMM and ANN*)

5 Summary and Future work

In this paper, we attempt to recognize actions in real time on the Android platform, and recognize the user's activities from a recognized set of actions. The two step HMM structure is appropriate for mobile environment to reduce computational complexity. Looking at the results of action recognition, there is confusion between 'stair up/down' and 'walk' actions. Careful data selection and training will improve the performance of recognition. Also, 'shopping' and 'taking a bus' activities have some difficult patterns to classify, and it is necessary to use more sensors such as a GPS receiver, Wi-Fi, etc.

There still are many problems to be solved on the mobile activity recognition such as integration of multi-modal sensor data, and modeling user's variations. Moreover, the comparison with other methods such as DTW, and BN is also a very important issue to be considered as a future work.

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