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Recognizing Human Daily Activities From Accelerometer Signal

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Abstract

Automated recognition of human daily activities from wearable sensor signals has attracted a great deal of interests in many applications including health care, sports and aged care. In this paper, we presented a Hidden Markov Model (HMM)-based recognition method to recognize six human daily activities from sensor signals collected from a single waist-worn tri-axial accelerometer. All training signals from the same activity class are modeled as generated by a HMM, while a Gaussian Mixture Model (GMM) is used to model the continuous observation for each hidden state. A new test signal is classified to the activity class corresponding to the HMM that can produce the highest likelihood. In order to validate the performance of the proposed method, we collected 420 samples from seven subjects and 72 samples from six new subjects, while performing six daily activities including walking, standing, running, jumping, sitting-down, and falling-down. Two batches of experiments were conducted. The experimental results on the first dataset show that the proposed HMM classifier can learn acceleration signals well with low computational complexity, achieving a very high activity recognition accuracy of 94.8%. In the second experiment, the HMM classifier was evaluated by using new data contained in the second dataset and only two samples were misclassified, which demonstrates that the HMM-based recognition system has a good generalization capability. It can be concluded that the proposed method holds a potential in long-term in-situ assessment of human daily activities under ambulatory environment due to its robustness and computational simplicity.

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Keywords: acceleration signal; accelerometer; activity recognition; Hidden Markov Model (HMM); wearable system.

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1. Introduction

Motivated by every increasing needs for patient care, chronic disease management and promotion of life-long health and well-being for the aging population, automatic recognition and classification of a person's activity has received extensive research interests in computing communities. For instance, pressure sensors underneath a floor (GRF) were used to classify human movements based on the vertical component measurements of the ground reaction force such as fall detection, mobility analysis, behavior monitoring. Many others have developed machine vision technology for human behaviors analysis [1-3] in various applications, such as security, health care and aged care. These methods have the advantage of unobtrusiveness, since they do not require the attention and cooperation of the subjects under monitoring. However, the aforementioned methods may be only applicable in a well-controlled environment where a camera with sufficient illumination or pressure sensor floor is installed. In contrast, application of the aforementioned methods may be unrealistic or even impossible in in-situ monitoring and classifying human activities in ambulatory environment [4].

More recently, the development of increasingly powerful miniature electronic instruments with higher sensitivity and larger data storage capacity opens up new prospects for studying human and animal activity in ambulatory environment. Because of their light weight, small size, low energy consumption, accelerometer sensors embedded wearable system represents one of the newly emerging fields, which have found many applications in long-term in-situ activity monitoring and classification in ambulatory environment [5]. For instance, Picerno et al. [6] designed a wearable inertial measurement unit (IMU), containing a 3D accelerometer and gyroscope, to estimate countermovement jump height; Kun et al. [7] had developed a wearable monitoring system composed of accelerometers and magnetometers on lower limb for Knee-joint kinematics analysis; Bidargaddi et al. [8] detected walking activity in cardiac rehabilitation by using accelerometer; Kangas et al. [9] had compared low-complexity fall detection algorithms for body attached accelerometers and pointed out that a waist worn accelerometer coupled with a posture recognition algorithm might be optimal for fall detection; in our previous work [10], we developed a wearable system to automatically recognize human daily activities with relatively high accuracy, which is composed of a single waist-worn accelerometer sensor coupled with a support vector machine (SVM) classifier based on a wavelet-domain features and principle components analysis (PCA) dimensional reduction technique.

Although those wearable sensing technologies offer an optimal platform for recording daily activity patterns in terms of safety and comfort of the wearers, the success of a wearable system for automatic activity recognition in ambulatory environment relies on not only its robustness but also simplicity, like many other real-time applications.

In the last decade, Hidden Markov Models (HMM) based approaches have been successfully applied in real-time speech recognition and hand gesture recognition [11-12] for its low computational complexity and robustness. HMMs make use of both the similarity of shapes between test and reference signals and the probabilities of shapes appearing and succeeding in time series signals [13] and relate the pattern of one state to succession of stance [11]. In these HMM approaches, the current state is considered to be influenced by the previous state and is independent of the history state. Observation probabilities and transition probabilities are calculated via training input data. The subject corresponding to the highest posterior probability is chosen as the recognized result.

In light of this, we adopted HMMs to recognize human daily physical activities based on the acceleration signals collected by a single waist-worn tri-axial accelerometer in the study. Especially, we collected three channels of gravitation signals from the accelerometer sensor worn on the waist belt by each of the subjects recruited while performing six different activities and then concatenated them into a feature vector at each position to construct HMMs. Subsequently, we trained and evaluated HMM for recognition of each class of activities.

The remainder of the paper is organized as follows. Section 2 gives the details of the experimental data collection including apparatus, subjects and description of collected data. The classification method based on HMM is explained in Section 3. Section 4 analyzes the experimental results associated with our method on the collected data. Finally, conclusion and future works are given in Section 5.

2. Data Collection and Experimental setup

2.1. Apparatus and Methods

The data collection device consists of a tri-axial accelerometer (MMA7260, Freescale) and a microcontroller (C8051F020, Silicon Laboratories Inc.) with a 12-bit analog-to-digital convertor (ADC). The acceleration data along three orthogonal axes is collected by the tri-axial accelerometer with a sampling rate of 50Hz (since human activity frequency is less than 20Hz [14]) and a full-scaled affection set at $\pm 4G$ (where G represents acceleration due to gravity: 9.81 m/s). The resolution of the accelerometer is nearly 0.000122 G/division. The collected data by the microcontroller is input to a laptop with USB interfaces with a communicating rate at 9600bps.

The sensor is oriented in a way that x-axis is aligned with the vertical direction, y-axis along the lateral axis and z-axis with the anterior-posterior axis while a subject is standing. The waist belt with the accelerometer mounted was worn by human subjects to capture the three channels of acceleration signals.

2.2. Subjects and data collected

Thirteen healthy volunteers were recruited. Their profiles vary in age from 26 and 50 years, in weight from 51kg to 75kg and in height from 158cm to 179cm. The labels of six daily activity classes and their corresponding instructions are shown in Table I.

Tab. I. Activity labels and instructions

Class	Activity	Instruction/ Manner
1	falling	fall forward down
2	jumping	jumping at origin
3	running	running forward
4	sit down	sit down on a chair
5	standing	remain standing straight
6	walking	walking forward

Seven volunteers were randomly chosen to perform six daily activities for ten times each while three channels of acceleration signals were recorded simultaneously by the waist-worn accelerometer they were wearing, forming the first dataset. The six remained subjects performed the six activities twice each and the data collected formed the second dataset. Thus, a total of 492 sequences were obtained.

3. Activity Classification

3.1. Acceleration signals and their charactersitcs

The acceleration signal along the vertical axis is a modulation of the measured gravitation signal for upwards and downwards movements, while the signals along the anterior-posterior and lateral directions characterize the forward/backward movements and lateral movements, respectively. Fig. 1 shows some examples of acceleration signals of six activities, i.e., standing, jumping, sitting-down, walking, running and falling performed by one of the volunteers.

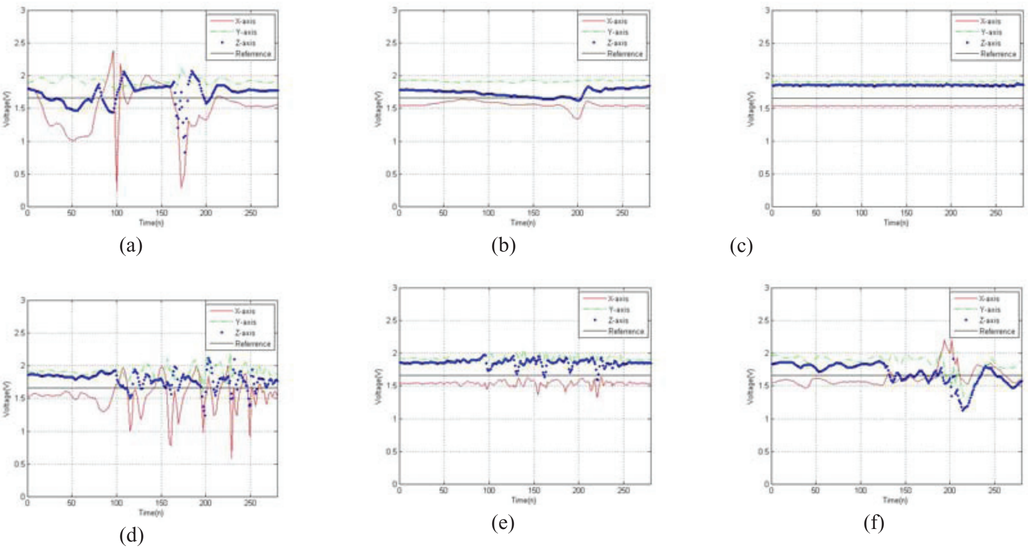

Fig. 1. Examples of acceleration readouts from one subject performing six different physical activities. (a)-(f): “jumping”, “sitting-down”, “standing”, “running”, “walking” and “falling-down”.

These acceleration signals are empirically known to be closely correlated with the activities that the wearers are undertaking. It can be observed that the signals of jumping and falling activities have distinguishable characteristics compared to the other four activities. However, the patterns of the signals collected from the same subjects during walking and running look similar, though there is substantial difference in the signal amplitude between them. It can be also seen that the sensory data collected from different people performing the same activities such as running and walking exhibit different kinematic characteristics (not displayed here). On the other hand, one subject’s running characteristics could be similar to another’s walking action in terms of frequency and/or amplitude of the signals.

3.2. Hidden Markov Model

The Hidden Markov Model (HMM) is a statistical method based on Markov process. In the regular Markov process, the state is directly visible and only there is a need to estimate the transition probability between the states. More than that, the Markov process has its unique characteristic: the conditional probability distribution of the state $x(t)$ at time t, depends only on the distribution of the state $x(t)$ at time $t-1$, that is to say, the state at time $t-2, t-3, ..., 2, 1$ not have influence on the state at time t, i.e., $P(q_t = S_j \mid q_{t-1} = S_i, q_{t-2} = S_k, ...) = P(q_t = S_j \mid q_{t-1} = S_i)$. Fig. 2 gives an example of a left-to-right HMM.

In the hidden Markov model, the state is not directly visible to the observer anymore. The observer could only obtain the value of output, which is dependent on the value of the state. It is likely that there is more than one state in the process, and each state has a probability to generate an output value. For a N states and M observation HMM, there are three parameters $\lambda = \{\pi, A, B\}$ to be trained [11]:

1) the initial state distribution $\pi = \{\pi_i\}$, where $\pi_i = P(q_1 = S_i), 1 \le i \le N$;

2) the state transition probability distribution $A=\{a_{i,j}\}$, where $a_{i,j}=P(q_{t+1}=S_j \mid q_t=S_i), 1\le i,j\le N$;

3) the output value generated based on the observation symbol probability distribution in state j, $B=\{b_j(k)\}$, where $b_j(k)=P(X_k(t)\mid q_t=S_j), 1\le i\le N, 1\le k\le M$.

There are three fundamental problems for HMM: the probability of an observation sequence O given a model $\lambda=\{\pi,A,B\}$; the corresponding state sequence given an observation sequence O and a model $\lambda=\{\pi,A,B\}$, and the model parameters $\lambda=\{\pi,A,B\}$ given a set of sequences observed.

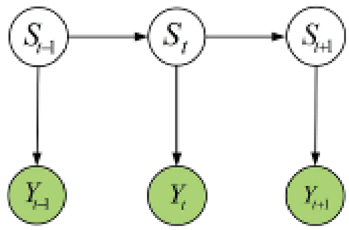

Fig. 2. A left-to-right HMM. Shaded nodes are observed while unshaded ones are hidden.

3.3. Classification by HMM

A HMM is trained for each class of action. The number of hidden states is specified empirically (i.e., $N=3\sim 8$). A mixture Gaussian distribution is adopted to model the continuous observations for each state. The model parameters $\lambda=\{\pi,A,B\}$ are randomly initialized and estimated iteratively by Baum-Welch algorithms [11].

As there are multiple signal series for one action class, the distribution of each sequence within one action class is summed up in the parameter estimation to train the HMM model. Once the parameters $\lambda=\{\lambda_1,\lambda_2,...\lambda_C\}$ for all the C classes are obtained a test signal sequence with length T, $O=\{O_1, O_2, ... O_T\}$, can be classified to the action class corresponding to the HMM based on which the likelihood computed is highest, i.e., $c^* = \arg\max_i P(O_1, O_2, ... O_T \mid \lambda)$. In other word, a new acceleration signal is classified as an activity class corresponding to the HMM that can produce the highest likelihood.

4. Experiment results

4.1. Leave-one-out Test

In this trial, the data in the first dataset described in Section II were used to perform the leave-one-out cross validation. Specifically, we treated ten samples corresponding to one activity performed by one subject as the test data, while all the remaining samples are regarded as the training data. Each acceleration sequence is normalized to be zero mean and standard variance.

We trained a HMM for each activity class. A test sequence is assigned to a label corresponding to the HMM based on the highest likelihood computed. As the observed sequence in HMM is a continuous signal, a mixture Gaussian distribution is used to model the continuous observation for each state.

The number of hidden states of HMM and the number of mixture components of GMM are two key parameters which usually affect the classification accuracy significantly. The recognition results with respect to the number of hidden states and the mixture components obtained in this study are reported in Table II. It can be seen that the recognition result is relatively stable when the number of hidden states is greater than 4 and the number of mixture components is set to be larger than 2. The highest recognition accuracy of 94.8% is achieved when the number of hidden states and mixture components are set to be 7 and 3, respectively.

Table II. Recognition Accuracy in the Leave-one-out

States / Mixture	3	4	5	6	7	8
1	65.2%	81.2%	80.0%	85.0%	87.4%	87.6%
2	88.8%	91.7%	94.0%	93.4%	92.9%	94.5%
3	86.9%	90.1%	93.1%	94.3%	**94.8%**	93.6%
4	90.7%	91.7%	93.1%	94.5%	93.8%	94.0%

It is necessary to investigate what kinds of activities are prone to misclassification with the other activities. Fig. 3 demonstrates the confusion matrix for the recognition result with 7 hidden states and 3 mixture components. Each row of the confusion matrix gives the number of samples that are classified to certain activity classes labeled by the columns. Each diagonal element in the matrix gives the number of samples belonging to one activity that are correctly classified. It can be found that only 22 out of 420 samples are misclassified. The activities "sit" and "fall" are less discriminative than the others in this case.

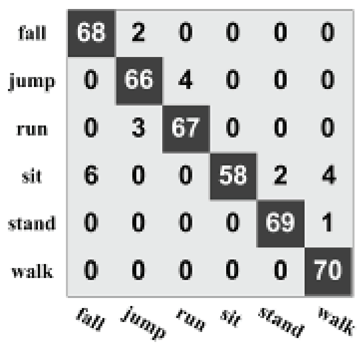

Fig. 3. Confusion matrix of Leave-one-out test.

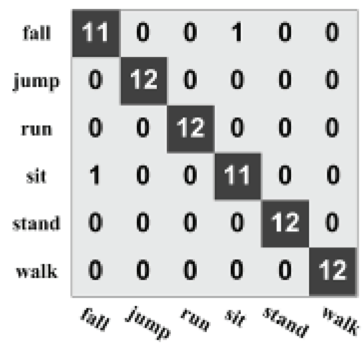

Fig. 4. Confusion matrix of recognition on other subjects.

4.2. Test on other subjects

We also validate the generalization ability of HMM, by using 72 samples in the dataset two which were collected from six new subjects. The confusion matrix of the recognition results is shown in Fig. 4. It can be seen that only two out of 72 test samples, i.e., one "fall" and another "sit", are misclassified, yielding a high recognition accuracy of 97.2% for the new subjects. This result indicates that the HMM is not only able to learn the correlation between acceleration signals and activity classes, but also capable of generalization of the activities.

5. Conclusion and future works

In this preliminary work, we presented an effective and efficient algorithm based on a Hidden Markov Model (HMM) with lower computing complexity to automatically recognize human activities from acceleration signals collected by a single waist-mounted tri-axial accelerometer in a garment.

Three channels of acceleration signals from each activity class were concatenated as feature vectors to construct a HMM to recognize 6 daily activities including walking, standing, running, jumping, sitting-down and falling-down. 492 samples were collected from 13 subjects for two experiments. In the first trial, we performed leave-one-out cross test on 420 sequences from seven subjects performing six activities. A high recognition accuracy of 94.8% was achieved by our method. The two important parameters, i.e., the number of hidden states and mixture components of GMM, were also experimentally investigated. It demonstrates that the recognition accuracy is relative stable with respect to these parameters. In order to investigate the system's capacity to recognize activities from new subjects, i.e., generalization ability, we validated the algorithm using 72 new samples in the second dataset collected from six new subjects. Only two of them were misclassified, which proved that the system can not only learn the activity signals very well but also has a good generalization capability.

However, it may be noted that we have not considered all classes of activities in daily life in this study. More exhaustive work need to be carried out in the future to meet more complex activity recognition requirements by a wider range of people, such as aged, young, injured or disable people. In addition, this recognition algorithm was based on the segmented acceleration readouts with each containing only one activity which was assigned a unique label. For real-time applications, we will incorporate some state-space models such as Conditional Random Field (CRF) to automatically segment and detect multiple activities in a continuous sequence. As such, a wearable system with robust and efficient activity recognition algorithms coupled with a single waist-mounted wireless accelerometer sensor and Bluetooth connected microchip will be assembled for real-time applications in the future.

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