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Nonparametric discovery of movement patterns from accelerometer signals[☆]

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ABSTRACT

Monitoring daily physical activity plays an important role in disease prevention and intervention. This paper proposes an approach to monitor the body movement intensity levels from accelerometer data. We collect the data using the accelerometer in a realistic setting without any supervision. The ground-truth of activities is provided by the participants themselves using an experience sampling application running on their mobile phones. We compute a novel feature that has a strong correlation with the movement intensity. We use the hierarchical Dirichlet process (HDP) model to detect the activity levels from this feature. Consisting of Bayesian nonparametric priors over the parameters the model can infer the number of levels automatically. By demonstrating the approach on the publicly available USC-HAD dataset that includes ground-truth activity labels, we show a strong correlation between the discovered activity levels and the movement intensity of the activities. This correlation is further confirmed using our newly collected dataset. We further use the extracted patterns as features for clustering and classifying the activity sequences to improve performance.

1. Introduction

Physical activity directly affects human physical and mental health. The 2007–2009 Canadian Health Measures Survey [1] notes that only 15% of adults meet the recommended physical activity guidelines. The survey states this as one of the main reasons for the increasing trend of various diseases such as obesity, diabetes, high blood pressure and cardiovascular disease. Asztalos et al. [2] further show a positive relationship between physical activity and mental health. Long term activity monitoring can help improve the intervention of these diseases. Moreover, it can provide guidelines for changing one's life style to reduce their risk.

Recent advances in wearable sensor technology provide the opportunity to measure human physical activity or movement instead of inferring them from a survey or human observation. The accelerometer is the most popular sensor for this task due to its small size and low energy consumption [3]. It is also widely used in a recent arising trend of devices and applications to monitor physical activity for health monitoring and fitness assistance. Some examples are Fitbit[1] devices and various mobile phone applications on iOS and Android for activity tracking. Although these devices and applications help the user keep track of her daily activities, most of them are only focus on step counting. However, different intensity levels and their duration may have different effects on people's health [4]. The step count might not be efficient to reflect all aspects of a user's activities. Thus, there is a need to detect the intensity levels and duration of the activities.

In this paper, we propose an approach to detect the body movement intensity levels from the accelerometer data. By investigating the public USC-HAD dataset [5] that includes the labeled sequences of various activities, we find a feature that reflects the intensity of body movement. As this feature is continuous, we need to discretize it to obtain the activity levels. The levels can be modeled as a mixture of normal distributions and inferred from the data by clustering approaches, e.g. Gaussian mixture model (GMM). These methods, however, require the number of levels to be specified in advance. This information is not always available and may vary among the users. They also require the data to be aggregated into a single flat structure. As the data points in an activity sequence might have some mutual correlation, this flat structure might not be adequate to model the hierarchical and grouping nature of the data. We address these problems by employing the hierarchical Dirichlet process (HDP) model [6].

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[1] http://www.fitbit.com .

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The HDP model organizes the data into documents, which are usually bags of words. In our case, a document is a set of accelerometer signals obtained from an activity sequence. The HDP model can discover the clustering structures within the documents and also share the structures among them. Due to the use of Dirichlet process priors on the parameters, the model can automatically discover the number of activity levels from the data. To demonstrate the effectiveness of the discovered activity levels, we use them as the features for clustering activity sequences. The activity clusters are consistent with the labels provided in the dataset.

Although providing a good benchmark dataset for analyzing human activity, the USC-HAD dataset was collected in a control setting under the observation of a researcher. We, therefore, further collect a new dataset in our lab using the Sociometric badge [7]. We provide a badge to each participant to wear during working hours for three weeks. Motivated by the experience sampling framework [8], we use the Magpi application[2] running on mobile phones to collect the ground-truth in the most possible natural way. The participants answer the questionnaire about their latest activities through the application when they can spare some time. They can choose multiple labels for an activity sequence, which is a common scenario. We then obtain the activity sequence preceding to the answer time and assign the chosen labels to it. We repeat the experiments using the HDP model on this data to obtain the activity levels that are consistent with the labels provided by users. We then use the mixing proportions over the activity levels of the sequences as the features to perform a multi-label classification. The classification performance using these features outperforms that using the fast Fourier transform (FFT) features.

The proposed HDP model can deal with not only univariate data but also multivariate data. We further use it to discover the activity patterns in a multivariate setting on two features—the *mean* and *standard deviation* of signal magnitude. Using this setting, we can discover an extra type of activity compared to the univariate setting.

Our main contributions in this paper are: (1) A new collection method for human activity data in a natural setting. The ground-truth is collected using experience sampling on mobile phones. (2) An extraction of physical activity levels using the HDP model. The number of levels is inferred automatically. (3) A demonstration of the effectiveness of the extracted patterns for clustering and multi-label classification toward improved performance. (4) An extraction of the activity patterns using the HDP model in a multivariate setting on two features: the mean and standard deviation of the signal magnitude.

The rest of this paper is organized as follows. Section 2 reviews the related work in activity data collection and recognition methods. Section 3 introduces the datasets used in this paper, including the public USC-HAD dataset and the Sociometric dataset that we collected in our research lab. Section 4 presents the HDP model for activity level detection. Section 5 reports our experimental results. And finally we conclude our paper in Section 6.

2. Related work

This section reviews the related work on accelerometer-based activity recognition. We focus on the following two aspects: the data acquisition and the recognition methods.

2.1. Data collection

The data collection setting affects the performance of activity recognition in many aspects. Two main factors are sensor setting including the number and placement of sensors, and the label collection setting.

2.1.1. Multiple sensors vs single sensor

Early work in activity recognition uses multiple sensors to enhance the recognition. Bao and Intille [9] use five bi-axial accelerometers placed at different parts of user's body (thigh, ankle, arm, wrist and hip). Olguín and Pentland [10] use three accelerometers worn at right wrist, left hip, and chest. They examine the classification using four different combinations of these positions. Parkka et al. [11] use two accelerometers placed at chest and wrist. Huynh et al. [12] use two accelerometers put in the right hip pocket and on the right wrist. Atallah et al. [13] use six accelerometers worn at chest, upper arm, wrist, hip thigh, ankle and ear.

In spite of the high classification performance, it is obtrusive for the users to perform real-life activities while they are wearing such complicated systems. Thus many recent studies have shifted to a single sensor setting. Ravi et al. [14] use an accelerometer worn near the pelvic region. Karantonis et al. [15] use an accelerometer worn at the waist to classify activities and detect fall.

A recent work [16] systematically examines the accelerometer setting for activity recognition including the number of sensors and their placement. The work states that the recognition performance is not improved using more than two accelerometers and the hip and chest are the two best places for activity recognition using one single accelerometer. In this paper, we do not focus on fine-grain activity recognition, thus we use an accelerometer integrated in the Sociometric badge worn at one's chest. Wearing the badge is similar to wearing a name tag, thus it is less obtrusive than other positions. Our early work along this line of research has been reported in [28].

2.1.2. Label collection

The label collection method depends on the data collection setting. Under a laboratory setting, the subjects are required to perform a particular activity during a particular time interval. The activity label can be easily recorded under the observation of a researcher. However, it is difficult to obtain the labels when the data is collected outside the laboratory without the supervision of researchers. Under this setting, the labels are usually provided by the users themselves. For example, in [9], the users perform each of 20 different activities and annotate the activity along with start and end time stamp. Recent studies utilize smart phones to collect labels. Typical approach is using an application to allow users selecting the activity that they perform and click start and end button before and after the activity, respectively [17]. However, there is a bias in this approach as the users know the activity while they are performing it. In this paper, we collect the data in a totally natural way as described in Section 3.2.

2.2. Recognition methods

A wide range of machine learning methods have been used for activity recognition. The most popular ones are the supervised learning algorithms. Some examples are decision tree [9,15], k-nearest neighbor (kNN) [9,14], naive Bayes [9,12,14], hidden Markov models (HMM) [10,12], support vector machine (SVM) [12,14]. Cleland et al. [16] recently compare these algorithms and conclude that SVM is the best algorithm for this task. However, these methods are suitable for single-label data only. As each sequence in our data may have multiple labels, we use a multi-label classification algorithm.

The features used for activity recognition vary from time domain to frequency domain. Huynh et al. [12] use a topic model to extract the features for the task. Our approach can be seen as a nonparametric version of the topic model in [12]. A recent work [18] uses the HDP model for activity and routine recognition, but the features are extracted using the Dirichlet process mixture model (DPM).

[2] https://www.magpi.com/ .