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Compressed sensing method for human activity recognition using tri-axis accelerometer on mobile phone

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Abstract

The diversity in the phone placements of different mobile users' dailylife increases the difficulty of recognizing human activities by using mobile phone accelerometer data. To solve this problem, a compressed sensing method to recognize human activities that is based on compressed sensing theory and utilizes both raw mobile phone accelerometer data and phone placement information is proposed. First, an over-complete dictionary matrix is constructed using sufficient raw tri-axis acceleration data labeled with phone placement information. Then, the sparse coefficient is evaluated for the samples that need to be tested by resolving L1 minimization. Finally, residual values are calculated and the minimum value is selected as the indicator to obtain the recognition results. Experimental results show that this method can achieve a recognition accuracy reaching 89.86%, which is higher than that of a recognition method that does not adopt the phone placement information for the recognition process. The recognition accuracy of the proposed method is effective and satisfactory.

Keywords activity recognition, compressed sensing, mobile phone accelerometer, phone placements

1 Introduction

Smart mobile phones in which an accelerometer is embedded can sample the tri-axis acceleration data of mobile users in real time, which allows instantaneous recognition of their activities, such as standing, walking, and running. As compared to an activity recognition method that uses specified wearable body sensors, that which uses a mobile phone's accelerometer has many advantages. For example, it does not require users to wear additional devices and can record and process activity data within mobile phones for a wide range of applications, including daily activity monitoring, intelligent health assistance, falling detection for elderly people, etc. Therefore, mobile user activity recognition has become an active topic in the mobile computing and ubiquitous computing research field [1–3]. In recent years, researchers have proposed different methods that use the tri-axis acceleration data of mobile phones to recognize human activities. Most of these methods extract features from the captured acceleration signals and then build a classification model to recognize various activities. For example, Parviainen et al. proposed a Bayesian model [4], Lee et al. proposed a mixture-of-experts model [5], Deng et al. proposed a reduced kernel extreme learning machine model [6], Büber et al. proposed a *k*-nearest neighbor (KNN) model [7], and Zeng et al. proposed a convolutional neural networks model [8] to recognize activity.

It should be noted that the place in which different users habitually carry their mobile phone differs, and therefore, the phone placements are diverse during sampling of the tri-axis acceleration data. This uncertainty increases the difficulty of activity recognition, because the data sampled may be completely different when the user is performing the same activity but carrying the phone in different body locations. Most recognition methods calculate the synthetic acceleration data by combing tri-axis acceleration data, and use synthetic acceleration data to

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avoid the problem caused by the varying placement of mobile phones. To address this problem, various methods have been proposed using different approaches. For example, Wang et al. proposed a method to transfer raw tri-axis acceleration data into a different coordinate system to obtain higher recognition accuracy [9]. Zhu et al. proposed a method that uses the similarity of activities to achieve placement-independent results [10]. Wang et al. proposed a method that uses the fast Fourier transformation (FFT) curve to achieve a result that is placement-independent [11]. However, according to the results of our study and experiments, we argue that phone placement information, when used appropriately, can be a factor that facilitates the recognition of human activity. Further, in our method the additional operations that in order to achieve activity recognition to exclude the placement information are not necessary.

In this paper, we propose a solution for recognizing human activity by means of a compressed sensing method using both acceleration data and phone placement information. Compressed sensing theory was originally used to reconstruct a signal using limited or incomplete samples if the signal is sparse in a certain transformation domain [12]. It can also be applied to pattern recognition fields, such as image, face, and speech recognition. Studies have been conducted on human activity recognition in which compressed sensing theory was applied. Zhang et al. proposed a sparse representation method to recognize human activity that uses wearable sensors data [13]. AKimura et al. proposed a compressed sensing method for human activity sensing that uses mobile phone accelerometers data [14]. Xu et al. proposed a compressed sensing method to recognize human activity in wearable body sensor networks [15]. In our previous study, we developed a compressed sensing method to recognize human activity that uses mobile phone acceleration data, which achieved satisfactory results [16]. However, we did not introduce phone placement information into this recognition method. In the present study, we took advantage of phone placement information for activity recognition and achieved a method that yields an even better recognition rate than that of the former method. Our experimental results show that by using the proposed method five human activities (standing, walking, running, walking upstairs, and walking downstairs) can be recognized with an accuracy rate of up to 89.86% when the mobile phones are carried in three different places (in the hand, trouser pocket, and handbag).

The remainder of this paper is organized as follows. In Sect. 2, the theory of compressed sensing, and the existing work on human activity recognition by using a compressed sensing method are introduced. In Sect. 3 the human activity framework are described. The experimental results and analysis are presented in Sect. 4. Finally, the conclusions are shown in Sect. 5.

2 Related work

2.1 Compressed sensing theory

Compressed sensing theory exploits the fact that many natural signals are sparse and compressible in the sense that their representations are concise when expressed in an appropriate basis. Random observation matrixes are used to project raw data into the required transformation domain. Suppose that $\boldsymbol{\alpha}$ is a vector of unknown, $\boldsymbol{y}$ denotes the available observed measurements, and $\boldsymbol{A}$ is the data matrix to describe the relation between $\boldsymbol{\alpha}$ and $\boldsymbol{y}$. Then, we have

$$\boldsymbol{y} = \boldsymbol{A\alpha} \tag{1}$$

where $\boldsymbol{y} \in \mathbb{R}^{N\times1}$, $\boldsymbol{A} \in \mathbb{R}^{N\times M}$ and $\boldsymbol{\alpha} \in \mathbb{R}^{M\times1}$.

For applications where the number of measurements is much smaller than the number of unknowns ($N<<M$), data matrix $\boldsymbol{A}$ is also called an over-complete dictionary matrix. In this case, Eq. (1) represents an underdetermined system and $\boldsymbol{\alpha}$ cannot be uniquely reconstructed from matrix $\boldsymbol{A}$ and measurements $\boldsymbol{y}$. However, in situations where $\boldsymbol{\alpha}$ is sufficiently sparse, we can reconstruct $\boldsymbol{\alpha}$ with the L0 sparsity formulation to obtain the approximate solution of $\boldsymbol{\alpha}$

$$\left.\begin{aligned} &\hat{\boldsymbol{\alpha}} = \arg\min \|\boldsymbol{\alpha}\|_0 \\ &\text{s.t.} \\ &\quad \boldsymbol{y} = \boldsymbol{A\alpha} \end{aligned}\right\} \tag{2}$$

Eq. (2) represents a determined system and its solution is stable. However, it is intractable, because it is an NP hard problem. The traditional heuristic to approximate the sparsity L0 is to use the minimal energy L2 instead. It is well-known that L2 is a least square formation and can be efficiently resolved. As the energy minimization L2 is not necessarily equivalent to the sparsity L0 in most cases, with high probability the solution of Eq. (2) is the same as the L1 minimization:

$$\left.\begin{aligned} &\hat{\boldsymbol{\alpha}} = \arg\min \|\boldsymbol{\alpha}\|_1 \\ &\text{s.t.} \\ &\quad \boldsymbol{y} = \boldsymbol{A\alpha} \end{aligned}\right\} \tag{3}$$