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Cross-person activity recognition using reduced kernel extreme learning machine

Wan-Yu Deng[a,*], Qing-Hua Zheng[b], Zhong-Min Wang[a]

[a] School of Computer Science and Technology, Xian University of Posts & Telecommunications, 710121, China

[b] MOEKLINNS Lab, Department of Computer Science and Technology, Xian Jiaotong University, 710049, China

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ABSTRACT

Activity recognition based on mobile embedded accelerometer is very important for developing human-centric pervasive applications such as healthcare, personalized recommendation and so on. However, the distribution of accelerometer data is heavily affected by varying users. The performance will degrade when the model trained on one person is used to others. To solve this problem, we propose a fast and accurate cross-person activity recognition model, known as TransRKELM (Transfer learning Reduced Kernel Extreme Learning Machine) which uses RKELM (Reduced Kernel Extreme Learning Machine) to realize initial activity recognition model. In the online phase OS-RKELM (Online Sequential Reduced Kernel Extreme Learning Machine) is applied to update the initial model and adapt the recognition model to new device users based on recognition results with high confidence level efficiently. Experimental results show that, the proposed model can adapt the classifier to new device users quickly and obtain good recognition performance.

1. Introduction

Automatically recognizing motion activities is very important for many applications in many areas such as healthcare, elderly care and personalized recommendation. Many activity recognition approaches have been established which use specific purpose hardware devices such as in Dijkstra, Kamsma, and Zijlstra (2010) or sensor body networks (Mannini & Sabatini, 2010). Although the use of numerous sensors could improve the performance of a recognition algorithm, it is unrealistic to expect that the general public will use them in their daily activities because of the difficulty and the time required to wear them.

Since the appearance of the first commercial hand-held mobile phones in 1979, it has been observed an accelerated growth in the mobile phone market which has reached by 2011 near 80% of the world population (Anguita, Ghio, Oneto, Parra, & Reyes-Ortiz, 2012). With the development of micro-electrical mechanical systems, the accelerometers are miniaturized so that they can be embedded into small mobile devices, and we benefit from this to classify a set of physical activities (standing, walking, laying, walking, walking upstairs and walking downstairs) by processing inertial body signals through a supervised machine learning algorithm for hardware with limited resources. Compared with traditional wearable activity recognition (Roggen, Magnenat, Waibel, & Troster, 2011), the development of activity recognition applications using smart phone has several advantages such as easy device portability without the need for additional fixed equipment, and comfort to the user due to the unobtrusive sensing. One drawback of the smart phone-based approach is that energy and services on the mobile phone are shared with other applications and this becomes critical in devices with limited resources. Additionally when the device is used by varying users, the embedded accelerometer may exert different forces because the movement patterns of different users are distinct, even when the user is doing the same activity. The model learnt from a specific person often cannot yield accurate results when used on a different person. To solve the cross-person activity recognition problem, we propose a novel fast and simple adaptive model to be embedded in mobile devices that have the limited computing resource, storage and power. First, the readings along three axes are synthesized and the magnitude of synthesized acceleration is used to extract features. This can eliminate the orientation difference of the mobile device, at the cost of losing direction information. Second, RKELM (Reduced Kernel Extreme Learning Machine) is used to build up the initial recognition model in offline phase for its fast learning speed and good generalization ability. At last, to new users in the online phase, the high confident recognition results will be selected and generate the new training dataset, on which the recognition model will be updated through taking the advantage of fast incremental

* Corresponding author. Tel.: +86 34534534.
E-mail addresses: dengwanyu@126.com, wanyu.deng@gmail.com (W.-Y. Deng).

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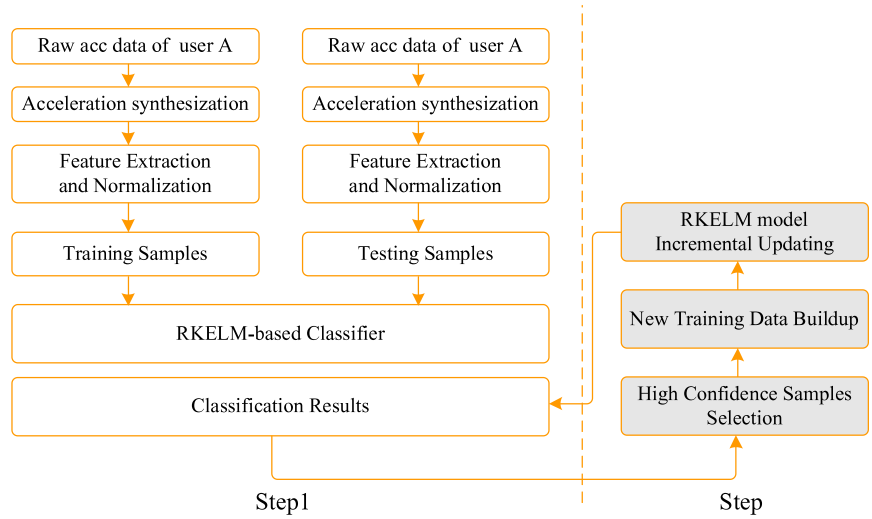

Fig. 1. The overview of TransRKELM activity recognition.

updating speed and low memory cost of OS-RKELM (Online Sequential Reduced Kernel Extreme Learning Machine). Experimental results show the efficiency and high recognition ability of the proposed model.

The rest of this paper is organized as follows. In Section 2, some related work will be illustrated. Section 3 introduces the proposed model. Experiments and results will be presented in Section 4. Finally, we conclude this paper in Section 5.

2. Relative works

Activity recognition (Taylor, 2009) based on mobile accelerometer has attracted a lot of attention for its widely applications in health care, personalized recommendation, advertisement serving and so on (Cambria & Hussain, 2012; Mital, Smith, Hill, & Henderson, 2011; Wollmer, Eyben, Graves, Schuller, & Rigoll, 2010). In the work of Ravi, Dandekar, Mysore, and Littman (2005) and Ward, Lukowicz, and Gellersen (2011), the authors used multiple accelerometers to classify different activities. Chen, Qi, Sun, and Ning (2010) used a smart phone to detect six activities in order to find the state switch point. These models can achieve high recognition accuracies because their testing and training samples are from the same batch of samples and follow the same distribution. But since accelerometer signals generated from different people follow different distribution, the performance of the model trained on one person will deteriorate when used to other people. Researchers have applied transfer learning to activity recognition when the activity persons, locations or labels change. For example, Zhao, Chen, Liu, Shen, and Liu (2011) propose a transfer learning-based algorithm which integrates a decision tree and the k-means clustering for personalized activity recognition model adaptation. Chen, Zhao, Wang, and Chen (2012) trained a classifier and used it to classify the sample of the target people, then the high confident samples were labeled and added into the training set, finally the model was retrained from a start. Zheng, Hu, and Yang (2009) trained a similarity function between the activities in the source domain and the target domain, then the data were transferred from the source domain to the target domain that have different label space. won Lee and Giraud-Carrier (2007) proposed a TDT (Transfer Decision Trees) algorithm. TDT assumed that the set of attributes of the source task be a proper subset of attributes of the target task. It learned a partial decision tree model from the source task and then transformed it as required by the training data in the target task. Torrey, Walker, Shavlik, and Maclin (2005) presented a method for transferring knowledge learnt in one task to a related task by reinforcement learning. They needed a human teacher in order to provide a mapping from the source task to the target task to guide this knowledge transfer. In Stikic, Van Laerhoven, and Schiele (2008), collaborative learning was introduced to add the unlabeled samples into the training dataset and achieved better models, but it needs two or more learners that were learnt from different feature sets separately, which is complicated and not power efficient.

3. The TransRKELM algorithm

In this section, we present the proposed cross-person activity recognition algorithm in detail. As illustrated in Fig. 1, the algorithm mainly contains two steps: Offline classification model construction and online adaptation for a new user.

Step (1) Offline classification model construction and online activity recognition. For offline classification model construction, first the readings of three axes are synthesized into magnitude series to get rid of orientation dependence. Statistic and frequency-Cdomain features are extracted from magnitude series of synthesized acceleration. Then, with the characters of fast learning speed and good generalization capability, RKELM is used to build the classification model. For online activity recognition, the unlabeled testing sample is generated with the same method as that used in the offline phase. Then the sample is classified by the RKELM classifier and the classification result is obtained.

Step (2) Activity recognition model updating. Based on the classification results, the confidence that a sample is correctly classified is estimated. The samples whose confidences are greater than a threshold, g, are selected to generate new training samples. Then, the RKELM model will be incrementally updated using OS-RKELM. As the new training samples are collected from a new user, the updated model would adapt to this user gradually (Chen et al., 2012).

3.1. Acceleration synthesization

Accelerometer detects and transforms changes in capacitance into an analog output voltage, which is proportional to acceleration. For triaxial accelerometer, the output voltages can be mapped into acceleration along three axes, a_x, a_y, a_z. As a_x, a_y, a_z are the orthogonal decompositions of real acceleration, the magnitude of synthesized acceleration can be expressed as: $a = \sqrt{a_x^2 + a_y^2 + a_z^2}$.