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Kernel fusion based extreme learning machine for cross-location activity recognition

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ABSTRACT

Fixed placements of inertial sensors have been utilized by previous human activity recognition algorithms to train the classifier. However, the distribution of sensor data is seriously affected by the sensor placement. The performance will be degraded when the model trained on one placement is used in others. In order to tackle this problem, a fast and robust human activity recognition model called TransM-RKELM (Transfer learning mixed and reduced kernel Extreme Learning Machine) is proposed in this paper; It uses a kernel fusion method to reduce the influence by the choice of kernel function and the reduced kernel is utilized to reduce the computational cost. After realizing initial activity recognition model by mixed and reduced kernel extreme learning model (M-RKELM), in the online phase M-RKELM is utilized to classify the activity and adapt the model to new locations based on high confident recognition results in real time. Experimental results show that the proposed model can adapt the classifier to new sensor locations quickly and obtain good recognition performance.

1. Introduction

Human activity recognition (HAR) using inertial sensors has gained tremendous attention in recent years. It is useful not only for health-care monitor, but also for fall detection, gait measurement, and so on [1–7]. A major goal of wearable sensor-based research is to long-term monitor daily activities of people. By attaching sensors on different body locations, human activities can be tracked and monitored. Although the performance of HAR model could be significantly improved by applying several sensors, it is generally unrealistic and uncomfortable to wear them long time during daily activity.

To achieve high performance of activity recognition, identifying the optimal sensor deployment has attracted various researches in recent years [8–11]. Khan et al. [10] applied a single triaxial accelerometer attached to chest with particular orientation to identify fifteen activities including three static activities, eight transition activities, and four dynamic activities by hierarchical model, and an average accuracy of 97.9% has been achieved. A single accelerometer placed on thorax has been utilized to classify the activities (standing, sitting, lying, running, walking flat, walking upstairs and downstairs), and the recognition result has reached 80% by using decision tree (DT) [12]. Five small biaxial accelerometers worn on different body parts have been investigated using C4.5 and Decision Table, and C4.5 classifier has obtained the best results with an overall accuracy rate of 84% [13]. Accelerations from dominant wrist have been utilized for artificial neural networks (ANN) to recognize complicated daily activities, and an overall accuracy of 95.24% has been achieved [14]. A single triaxial accelerometer has been utilized by Cheng and Jhan [15] for fall detection with sensors placed on left ankle, right ankle, chest and waist, respectively. The optimal result of 98.48% accuracy rate has been obtained from the sensor data attached to the chest and waist.

Specifically fixed placement of sensors has been assumed by most of the aforementioned classification methods to train and test the classifier. However, this assumption may not usually hold true especially for user-centric smartphones monitoring. Consequently, the performance may be significantly degraded when the model trained on one location is applied to other sensor placements

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[16–18]. That is because when the device is placed on different locations, the embedded inertial sensors may exert different forces, and the distribution of sensor data from different locations is significantly different, even when the user is performing the same activity.

To tackle the cross-location human activity recognition problem, a fast and simple adaptive mixed and reduced kernel based extreme learning machine (M-RKELM) model has been proposed in this paper. The proposed approach involves data fusion at two different levels of abstraction [19]. First, with the aim of achieving more accurate, informative, and synthetic data than the original sources, we apply data-level fusion to the sensor readings along the three accelerometer axes and the magnitude of synthesized acceleration is used to extract features. Second, in the offline phase, M-RKELM is utilized to generate the initial recognition model. Finally, in the online phase, the high confident recognition results will be selected and produce the new training dataset, and based on this dataset, the recognition model will be retrained by taking the advantage of fast learning of a particular form of feature-level fusion, that is kernel fusion based online sequential extreme learning machine. Applying multiple sensors may increase the computational cost, the energy cost and discomfort, so this paper is focused on a single accelerometer based human activity recognition.

The main contributions of this paper are detailed as follows:

- In order to tackle the cross-location human activity recognition problem, extreme learning machine (ELM) is introduced in this paper. Considering the new locations, the online sequential extreme learning machine (OS-ELM) is introduced to update the recognition model.
- Considering the influence of kernel function on ELM for human activity recognition, kernel fusion method is proposed to increase the recognition results.

The reminder of the paper is organized as follows: after the introduction, the description about related work will be presented in Section 2. The method proposed in this paper is summarized in Section 3. In Section 4 our approach is experimentally evaluated. Finally, conclusion remarks are drawn in Section 5.

2. Related work

In this section, two main topics related to this paper will be overviewed: (1) feature selection for varying device locations; (2) the related adaptive recognition model.

(1) *Feature selection for varying device locations*

Signal data from gyroscopes and accelerometers has been combined by Kunze and Lukowicz [20] to reduce the negative influence of rotation and translation, and the result shows that the displaced recognition accuracy has increased from 24% to 82%. Genetic programming based feature extraction method is proposed by Forster et al. [21] to extract effective features that are robust to sensor displacement for activity and gesture recognition, and the results demonstrate that the proposed method is superior to a feature selection based on standard features on the two used datasets. Online unsupervised self-calibration classifier has been proposed by Forster et al. [22] to tackle the context recognition problem with sensors displaced on body segments, and the results demonstrate that after calibration the accuracy has increased by 33.3% in the human computer interface (HCI) scenario and 13.4% in the fitness scenario. An unsupervised adaptive algorithm, which updates itself by the online version of expectation-maximization, has been proposed by Chavarriaga et al. [23] to tackle the feature distribution problem caused by the change in the sensor location, and the results show that the method is more robust to rotation than general classifier and the performance of classifier linear discriminant analysis (LDA) decreases after rotation of about 15°. C4.5 decision tree, specifically tailored for detection of the accelerometer location on the body, has been utilized by Guo [24] to improve the classification performance of everyday activities, and better performance with 85.2% precision and 82.9% recall has been achieved by the proposed algorithm. Though many efforts have been made to solve this location displacement problem, these methods mainly focus on the selection of displacement-invariant features and cannot offset the information loss caused by sensor variability. In addition, these algorithms are computational complex and difficult to implement on smartphones.

(2) *The adaptive model for HAR*

Differently from traditional elderly-body-posture analysis, collaborative sensors have been utilized by Lai [25] to analyze body posture for judging which behavior is occurring. These sensors are attached to six body locations of an elderly person: the neck, the waist, the left wrist, the right wrist, the left thigh and the right thigh, respectively. Subtractive clustering method (SCM), which is acted as the threshold for posture judgment, has been proposed to calculate the center position of the habitual inclination angles for each posture and adequate performance has been achieved. Transfer learning Embedded Decision Tree (TransEMDT) has been proposed by Zhao [26] to solve the cross-people activity recognition problem using a smartphone with an embedded triaxial accelerometer, which integrates the decision tree and K-mean clustering method, and the average accuracy has been increased by 20% after using the proposed model. With similar goals, transfer learning reduced kernel extreme learning machine has been proposed by Deng et al. [27]; the proposed algorithm is based on a fast and efficient reduced kernel extreme learning machine to initial activity recognition model in the offline phase, while in the online phase, online sequential reduced kernel extreme learning machine has been proposed to adapt the recognition model to other users, and the results has demonstrated that after adaptation, the accuracy is improved more than 1%. However, only the model adaptation across different users has been taken into consideration by aforementioned works. To our knowledge, there are few researches related to human activity recognition model adaptation across different locations.

3. The TransM-RKELM method

In this section, the proposed cross-location activity recognition algorithm is detailed . It mainly involves two steps, as depicted in Fig. 1:

(1) *Offline classifier construction and online activity recognition*

For offline classification model construction, with the aim of achieving more accurate, informative, and synthetic information, we apply data-level sensor fusion to the readings of triaxial signal into magnitude series to get rid of orientation dependence. Statistical and frequency-domain features are subsequently extracted. Then, PCA is utilized to reduce the dimension and obtain efficient features. With the features of fast learning speed and high generalization capability, mixed kernel based ELM algorithm is utilized to build the classification model. For online activity recognition, the unlabeled testing samples are generated with the same method as that used in the offline phase. Then, the samples are classified by the M-RKELM classifier and the classification results are obtained.

(2) *Activity recognition model retraining and updating*

Based on the classification results, the confidence that samples are correctly classified is estimated. The samples whose confidences are greater than a predicted threshold, θ, are selected to build up new training dataset, together with the training samples in Step 1. Then, the ELM classification model will be retrained and updated. As the new training samples may be collected from a new