Cross-mobile ELM based Activity Recognition

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Cross-mobile ELM based Activity Recognition

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Abstract

Activity recognition using mobile phones has great potential in many applications including mobile healthcare. In order to let a person easily know whether he is in strict compliance with the doctor's exercise prescription and adjust his exercise amount accordingly, we can use a mobile phone based activity reporting system to accurately recognize a range of daily activities and report the duration of each activity. A triaxial accelerometer built-in the mobile phone is used for the classification of several activities, such as staying still, walking, running, and going upstairs and downstairs. To build an activity recognition model, we usually employ one or some specific persons and a specific mobile phone to collect the training samples. However, the world doesn't have the same two mobile phones. The model learnt on one mobile phone may perform poor on another one due to the different offset o, sensitivity s and sampling frequency f values. To solve the cross-mobile problem, we propose an algorithm known as TransELMAR(Transfer learning and Extreme Learning Machine based Activity Recognition) that integrates the transfer learning technique and extreme learning machine algorithm for activity recognition model adaptation. Tested on a real-world data set, the results show that our algorithm outperforms several traditional baseline algorithm.

Keywords: *Extreme Learning Machine, Activity Recognition, K-means Algorithm, Transfer Learning*

1. Introduction

To keep fit, it is necessary to do exercise and the amount of exercise required by each person can be quite different. Aiming to help people stay healthy and improve health, doctors often prescribe exercises, such as walking, running, climbing upstairs, going downstairs, etc., to patients. In the doctor's prescription, time is the most important metric that measures the amount of exercise. If a person can easily check the time he has spent in an exercise, he will know whether he is in strict compliance with the doctor's prescription and adjust his exercise amount accordingly. This is a crucial factor to enable people to improve their quality of exercise. A population of people with good health can save the government's cost in medical care.

In this paper, a mobile phone based portable activity reporting system is presented, which uses a triaxial accelerometer to accurately recognize a range of daily activities, such as staying still, walking, running, and climbing upstairs and downstairs, and report the duration of each activity.

When the activity recognition model is trained for a specific mobile and a specific person, the system performs well. However, it performs poor when transplanted onto a different mobile. There are several reasons. 1) Different mobiles may have different types of built-in sensors, for example, they have different sampling frequency. 2) The same type of sensors may have the different drift of sensitivity and offset on every axes of the built-in accelerometer due to the manufactural technology.

To solve the above cross-mobile activity recognition problem, it is better to train a new model. However, collecting sufficient samples, extracting features and training the model need much manual effort and computing time. To consider the convenience of the user and the limited resource of the mobile phone, it needs a simple and fast method to automatically train a new model for the new mobile. To achieve this aim, a transfer learning technique that integrates extreme learning machine (ELM) and k-means clustering algorithm is proposed. Firstly, an activity recognition model, ELM_A, is trained offline, which uses the samples from mobile A and contains the knowledge about a range of daily motion activities. When the ELM_A model is applied on mobile B, it can automatically calibrate the offset, scale the data, calculate the sampling frequency, collect and label new samples, and train a new model, ELM_B, for the new mobiles.

The contributions of our work can be described as follows: 1) We propose a novel fast and simple self-adaptive model embedded in mobile phones that have the limited computing resource, storage and power. 2)We experimentally evaluate the effectiveness of the model by testing how to transfer the model from a low sampling frequency mobile to a high sampling frequency, while maintaining accuracy.

2 Activity Reporting System

2.1. Overall System

As shown in previous research, if done regularly and over a long time, even a limited amount of physical activity can be beneficial for people's health. A proper amount of exercise is very important to prevent and control diseases, especially for the elderly. In order to help monitor the daily activities of the elderly, we have built a motion recognition system named Activity Reporting System, which is a software system that embedded in a mobile phone. With the mobile phone, the activities of a user change the readings of an accelerometer. The artificial intelligence (AI) module of the activity reporting system collects the readings of the accelerometer, and recognizes the pattern of each activity using a classifier that has been trained offline and measures the total time of each activity. Then, a user, such as an elderly person, can easily know whether he reaches his prescribed amount of exercise.

The activity reporting system can be installed on a smart phone, which the user can hold in hand, put in a pocket, wear on the waistband, or hang in front of the chest. While the user is doing exercise, the activity states can be displayed on the screen. When the user wants to know the statistical information of each activity, he can change to the corresponding interface via shortcuts on the screen.

2.2. Embedded Activity Recognition Module

It is hard to generate a one-size-fits-all model that can fit all the mobile phones. When the phones have the same parameters, such as sampling frequency, the drift of sensitivity and offset on every axes, they can share the same model. However, the world doesn't have the same two mobile phones. Especially, the model built on the low frequency mobile cannot take full advantage of the high frequency mobile.

In this paper, to solve the above problem, we propose an embedded transfer learning technique [1] for the problem. Our solution integrates the k-means clustering algorithm and the extreme learning machine algorithm [2] together. We call our system TransELMAR, which stands for transfer learning and extreme learning machine based activity recognition. As shown in Figure 1, firstly, we build Model_A with the labeled samples collected on mobile A. Secondly, we classify the unlabeled samples collected on mobile B. These data are used to adapt Model_A to yield a new personalized model, Model_B, for mobile B. Experiments using real-world samples show that the TransELMAR algorithm performs well using the generated personalized model.

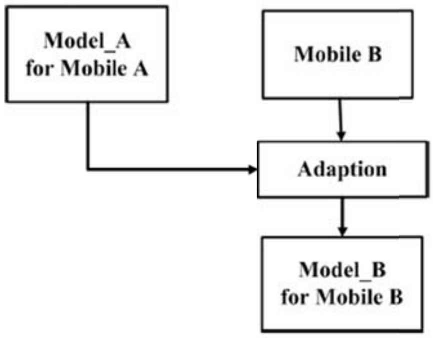

Figure 1. Cross-People Motion Activity Recognition

The rest of the paper is as follows. In Section 3, related works are reviewed. In Section 4, TransELMAR is presented in detail. In Section 5, experiments on TransELMAR are given. Section 6 concludes the paper.

3. Related Work

To improve the training speed, a novel learning machine ELM is developed since 2004 by Huang etc. Serious works proved the high performance of ELM on the aspects of training speed, predicting accuracy and generalization [3]. For our case, we need to train the classifier on the resource limited mobile phone. Therefore ELM is the right one algorithm to solve our problem.

Some of the existing literature has explored activity recognition based on accelerometers. In the work of [4] , the authors used multiple accelerometers to classify different activities. Chen [5] used a smart phone to detect six activities in order to find the state change 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 data distribution. All these above literature did not consider the cross-people activity recognition problem.

Some literature has mentioned the cross-people problem. For example, in the 4 work of [6], the authors used multiple sensors to detect activity types. When subject-specific training data was used, the average accuracy is 49%. When the leave-one-subject-out validation was used, the average accuracy dropped 26%.

4. The TransELMAR Algorithm

In this section, we present the TransELMAR algorithm in detail. Our algorithm runs in the following high-level steps. We first calibrate mobile A, collect samples of each activity and generate an ELM_A model for mobile A using the ELM algorithm. We then collect samples on mobile B. In this phase, we calibrate mobile B and use a sub-sampling technique to fit ELM_A. Then, the samples are classified by the ELM_A model. We then use the classified data as the initial cluster centers for mobile B and start the one step K-means algorithm. After this step, a labeled sample set is built. We select k-nearest samples to the centers as the high confident samples and based on them we can learn the ELM_B' model using the ELM algorithm. Finally, we repeat Step 2 to Step 4 in a loop, until the algorithm converges. Then, the result is an ELM_ B for mobile B.

4.1. Learn ELM_A Model Using ELM in the Offline Phase

In the offline phase, for mobile A, we calibrate it, collect the accelerometer data for each activity, assign labels to them, extract features from the raw data with the slide window technique and train an ELM_A model using ELM method. For the time series data, we can record the time at which each data are collected and calculate the sampling frequency. Therefore, we can generate an ELM_ A model with the sampling frequency f_A.

4.1.1. Calibrate the Mobile Phone

Some literature [7, 9] have addressed the calibration problem. Their methods are already good enough for calibrating accelerometer. For our case, we focus on the frequency problem that affects the cross-mobile accuracy. Therefore, we introduce a semi-automatic calibration process that is easy to operate for the user and needs less computation.

Collect samples of stationary motion. Phone has six surfaces as a cubic object. Put each surface of the phone on a smooth desk for several seconds. These data are stored in a vector, named *Acc_Stationary*.

Find the maximum and minimum of each axes. We traverse the *Acc_Stationary* vector and get the positive and negative readings of every axes, (a_x , a_y , a_z) and (a_x', a_y', a_z') respectively.

Calculate the offsets and scales. Then, the offsets are calculated as $O = (O_x, O_y, O_z) = (\frac{a_x+a_x'}{2}, \frac{a_y+a_y'}{2}, \frac{a_z+a_z'}{2})$, the scales are calculated as $S = (S_x, S_y, S_z) = (\frac{a_x-a_x'}{2}, \frac{a_y-a_y'}{2}, \frac{a_z-a_z'}{2})$.

Calibrate the *sample* of activity. Then, for each sample $X = (a_x, a_y, a_z)$, the calibrated sample $X' = (\frac{a_x-o_x}{s_x}, \frac{a_y-o_y}{s_y}, \frac{a_z-o_z}{s_z})$.

4.1.2. Calculate the Sampling Frequency

On mobile phone, applications can get the current system time via API functions. When collecting samples of activity, we can give each sample a time stamp. Therefore, we can get the sampling frequency by enumerating the samples in a one second time window.

4.1.3. Learn the Model using ELM

The ELM is a recent neural network algorithm, which is known to achieve good performance in complex problems as well as reduce the computation time compared with other machine learning algorithms [2]. The ELM algorithm does not train the input weights or the biases of neurons, but it acquires the output weights by using the norm least-squares solution and Moore-Penrose inverse of a general linear system [2]. By finding the node giving the maximum output value, we decide the final result.

Figure 2 shows the network structure of ELM with a single hidden layer used for our experiments. We used 50 hidden neurons and the sigmoid activation function.

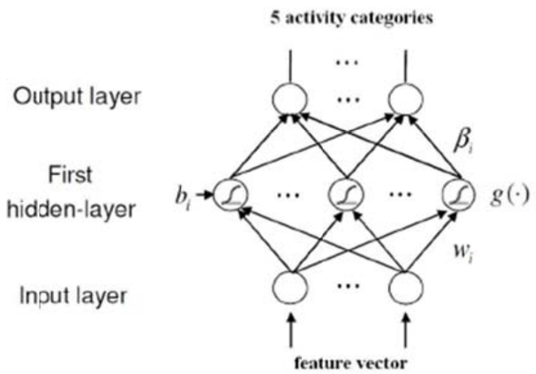

Figure 2. the ELM algorithm

4.2. Learn ELM B Model in the Offline Phase

4.2.1. Collect and Classify Samples on Mobile B

When applied on mobile B, ELM_A model can easily calculate the sampling frequency of it, f_B . If f_B is greater than f_A, it is possible to get a better model than ELM_A model.

Collect samples on mobile B. As described in some existing literature, the time window, *T*, is used to collect samples. In a window, we collect the raw accelerometer data using the frequency f_A and store them in a vector, V_f_A. At the same time, we also collect the raw accelerometer data using the frequency f_B and store them in a vector, V_f_B. We extract the same features from them respectively and generate the feature vectors, F_f_A and F_f_B.

Classify samples on mobile B. F_f_A are classi_ed by ELM_A model and each sample is assigned to a label. Therefore, we get an initial labeled set, Label f_A. After F_f_B and Label f_A are combined to each other, we get the coarsely labeled sample set, TrainSet_f_B.

4.2.2. The One Step K-means algorithm

On one hand, the ELM_A model can be seen as a weak classifier which can classify a new user's samples with the accuracy higher than random guess. On the other hand, the K-means algorithm can cluster samples into several classes, but its clustering quality and iteration number are related to the initial K cluster centers and the algorithm can be very slow to converge with a bad initialization. In our solution, we combine the merits of ELM_A model and the K-means algorithm to realize cross-mobile activity recognition.

Firstly, the target mobile's samples, TrainSet_f_B, can be classified by the ELM_A model into classes, TrainSet_f_B =$\{(\mu_j, \mathrm{Label}_j, V_j)\}_{j=1}^{m}$, where m is the number of classes, Label_j is the label of the jth class, μ_j is the center of the jth class.

Secondly, we prepare the initial conditions of k-means clustering algorithm and calculate the centers of every class, $\mu_j = \frac{\sum_{i=1}^{|V_j|} x_i^j}{|V_j|}$.

Thirdly, each sample x is redistributed to a class by the distance metric.

$$j = \mathrm{argmin}_i |x - \mu_i|$$

This completes the one-step K-means algorithm.

After the above one step K-means method, we can get the labeled samples.

4.2.3. Learn ELM B Model

Using the well labeled sample set TrainSet_f_B =$\{(\mu_j, \mathrm{Label}_j, V_j)\}_{j=1}^{m}$ and the ELM algorithm, we can learn the ELM_B Model for mobile B.

Firstly, for each class, we select the k-nearest samples to the center as the high confident samples, *ConfTrainset*.

Secondly, using *ConfTrainset* and ELM, we train the ELM_B' model for mobile B.

Thirdly, we repeat above 2 steps in a loop until the algorithm converges. The converging condition is βnew - βold < Thd, where βnew is the weight got in the current iteration and βold is the weight got in the previous iteration.

5. Experiment

5.1. Data Collection

The information of mobile phones with accelerometer. To address the cross-mobile problem, we collect several off-the-shelf mobile phones with built-in accelerometer. Those mobile phones from Nokia have the same parameters. Although the accelerometers built-in them can achieve 100 or 400 Hz, the sampling frequency has been reduced to approximately 32 Hz by calling the Nokia Accelerometers plug-in API. Therefore, we can only collect the data with a frequency not great than 32 Hz. To be convenient to do fast fourier transform(FFT) on the samples, we use the frequency 1,2,4,8,16,32 Hz to collect sample on the Nokia mobile phones. For the HTC and Samsung mobile phones listed in Table 1, they all employ the Android operating system and the API provides four frequencies, such as SENSOR DELAY FASTEST, SENSOR DELAY GAME, SENSOR DELAY NORMAL, SENSOR DELAY UI, which are corresponding to 46_48 Hz, 22_23 Hz, 12_13 Hz, 4_5 Hz. With the same reason as Nokia mobile phones, we collect samples with the frequency 1,2,4,8,16,32 Hz.

The information of activity samples on different mobile phones. In our experiments, an activity database is constructed from the data collected from those above devices. In this database, there are 10 participants and five activities. The sliding window method is used to extract the features. Our chosen window size is two seconds and the overlap time is one second. Thus a complete action can be included in the window. Feature extraction on windows with 50% overlap has demonstrated successful in previous work. In each window, features are extracted from each of the three axes of the accelerometer. The features are: Mean, Standard Variance, the Fast Fourier Transform energy and the correlations between every pair of axes. So there are a total of 12 features extracted from one window and these features are processed into a single sample. The number of samples of every activity are listed in Table 1.

Table 1. The Information of Activity Samples on Different Mobile Phones

Manufacture	Phone Type	Sampling Frequency	Activity Name	Sample Number
Nokia	N95 8GB E66 N82 N86	1 2 3 4 8 16 32	Stationary Walking Running Climbing Upstairs Climbing Downstairs	600000
HTC	Hero(G3)			150000
Samsung	Anycall I9008			150000

All samples are formatted into {Manufacturer, PhoneType, UserID, Frequency, Activity, Feature1,Feature2, … }.

5.2. Accuracy vs Frequency

As mentioned in section 5.3, the sampling frequency can affect the accuracy of activity recognition. On N95 mobile, using the ELM method, we test the accuracy of activity recognition under the condition that samples are collected with different frequency. We have verified the ELM algorithm with a full data set of the 10 participants. For each participant, 500 samples were randomly selected as the training samples and 500 samples in the remaining as the testing samples. This step was repeated 10 times. The average accuracies were listed in Figure 3.

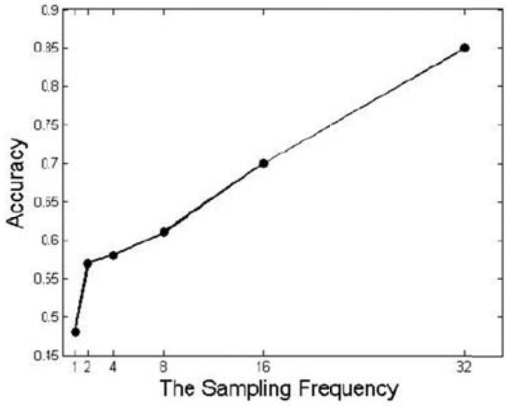

Figure 3. Accuracy vs Frequency with ELM

As can be seen from Figure 3, when the sampling frequency is 1 Hz, the accuracy of activity recognition is about 47% that is only better than the random guess, which is 20% for 5 classes. The accuracy of the ELM model increases significantly when the sampling frequency varies from 1 Hz to 32 Hz.

5.3 Cross-Mobile Accuracy without TransELMAR

To get a direct impression of the cross-mobile problem, we illustrate the results of our experiment in Figure 4. As we focus on how to transfer an ELM model from a low sampling frequency mobile to a high one, We only list the corresponding results. The training samples are collected on a low sampling frequency mobile. We use them to train an ELM model. Then, we use the model to classify the testing samples collected on a high sampling frequency mobile. All the mobile phones mentioned in Table 1 are used. The frequencies we used are 1,2,4,8,16,32 Hz. All the mobiles used are calibrated and the sensitivity is scaled to [-9.8,+9.8]. Every experiment is repeated for 10 times and the average accuracy is calculated.

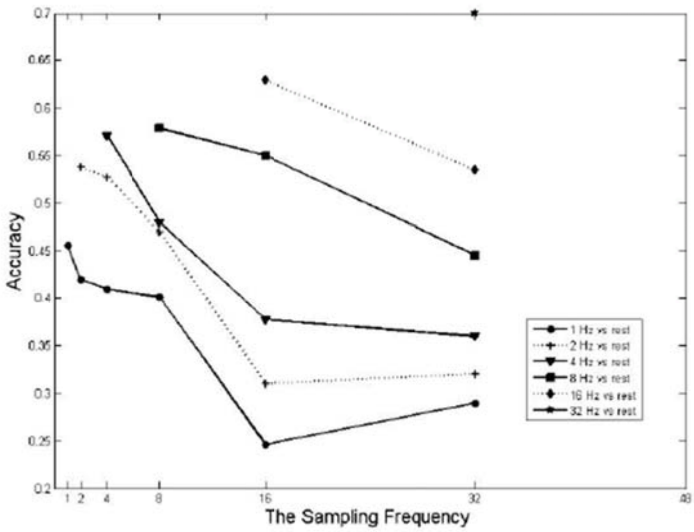

Figure 4. Cross-Mobile Accuracy without TransELMAR

As can be seen from Figure 4:

- When the target mobile's sampling frequency is closer to the source one, the accuracy that the source ELM model classifies the target samples can be closer to that classifying the source samples.
- With the increasing of the source mobile's sampling frequency, the source ELM model's performance are getting better and better.

5.4. Cross-Mobile Accuracy with TransELMAR

In this experiment, we test the TransELMAR algorithm. Without loss of generality, for mobile A with frequency frq_a and mobile B with frequency frq_b, where frq_ a <= frq_b, firstly, we use mobile A to collect N activity samples and train an ELM model, ELM_A. Secondly, we apply the ELM_A model to mobile B. ELM_A collects samples with frequency frq_a and frequency frq_b respectively on mobile B. Thirdly, ELM_A classified the samples collected with frequency frq_a and labeled the samples collected with frequency frq_b. Fourthly, with the results of the 3th step as the initial class centers of the k-mean algorithm, after several iterations, we can get the well labeled samples. Fifthly, using the labeled samples, we train an ELM model for mobile B, ELM_ B.

As can be seen from Table 2 and Figure 5:

(1)When frq_a is 1 Hz, for each frq_b, the ELM B model performs poor when Frq_b increases. It is due to the low frequency that leads to not capture sufficient information.

(2)When frq_a is greater than 1 Hz, the performance of the ELM_B model increases significantly than it is 1 Hz. Especially, when frq_a is 16 Hz, the performance of the ELM_B model can achieve 75% that is good enough for activity recognition.

(3)When frq_a and frq_b are 32 Hz, the accuracy of the ELM_B model is close to 80%. We think when frq_b is greater than 32 Hz, the performance of the ELM_B model can be improved.

Table 2. Cross-Mobile Accuracy with TransELMAR

	1 Hz	**2 Hz**	**4 Hz**	**8 Hz**	**16 Hz**	**32 Hz**
1 Hz	0.451	0.442	0.434	0.426	0.415	0.412
2 Hz		0.540	0.557	0.564	0.576	0.583
4 Hz			0.562	0.578	0.583	0.592
8 Hz				0.588	0.619	0.630
16 Hz					0.653	0.748
32 Hz						0.797

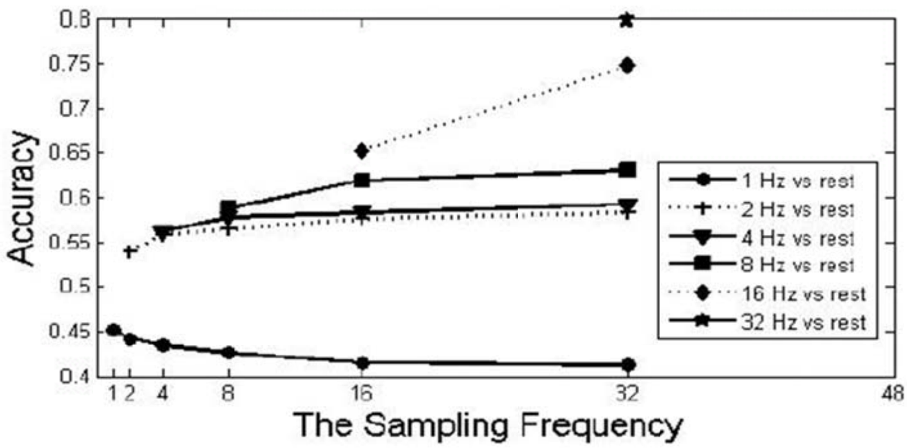

Figure 5. Cross-Mobile Accuracy with TransELMAR

6. Conclusion

In this paper, we have proposed the TransELMAR algorithm to solve the cross-mobile activity recognition problem. Empirical evaluations have shown that:

1) The TransELMAR model can be used to transfer the knowledge on user activities and address the cross-mobile problem.

2) The source and target sampling frequency can a_ect the performance of the ELM model. When the source frequency is not smaller than 16 Hz and the target frequency is not smaller than 32 Hz, the ELM B model can outperform the ELM A model, which means it can take the advantage of high sampling frequency.

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