Personalized Human Activity Recognition

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CSS581 Term Paper

1. Abstract:

In this paper, author describes a method of improving the efficiency of a human activity recognition system by making them personalized to a particular user. This can be achieved by adding some user identification as an object feature when creating the classification model for predicting activity. Author looks into using clustering to get better user identification particularly for new users which do not exist in training data. Author also looks into using a classification model to predict the user group id when clustering has been applied for test data, before activity classification model can be applied.

2. Introduction:

Human activity recognition (HAR) is a method to identify the physical actions carried out by a person using data obtained from sensors attached on a person. These sensors can be part of a specialized wearable device like fitbit or it can make use of the different sensors on smartphones, which a person usually carries. HAR can be used by a person to plan for his physical activities. It can also be used to provide data to his medical provider, which can be used for various health related aspects. Currently there are a lot of customized devices such as Alta by FitBit and VivoSmart by Garmin. Furthermore there are a number of mobile applications available e.g. Apple health.

Human Activity Recognition has become a very important topic as it can be used to improve quality of life. It allows a person to track his daily physical activities. Through this information, people can bring changes into their life and by setting incremental goals. This will allow users to live a healthier life. Also this information can be used by health care industry to provide more objective and customized healthcare services. This can be used by insurance companies and healthcare industry to provide incentives to people who are more active, as physical activity can greatly decrease the likelihood of several diseases including coronary heart disease and type 2 diabetes. A lancet publication [1] estimates that physical inactivity causes 9% of all premature deaths worldwide.

Wearable sensors have been actively used for human activity recognition. The accelerometer is the most commonly used sensor for body motion signals [2]. Generally, accelerometer is used in multiple signal arrangement (e.g. triaxle accelerometers) or in combination with other sensors (e.g. gyroscope and heart rate sensors) [3]. These sensor arrangements can be attached on a wearable device which can be used to collect the data. An alternative can be a smartphone which supports number of sensors (e.g. accelerometer, gyroscope, GPS, video recorder, and microphone). Smartphone have several advantages over other wearable devices, as they are of no extra charge to the user since they are widely used nowadays. Also managing a wearable device becomes a hassle for the users whereas most people nowadays frequently use smartphones.

Human Activity recognition system uses physical data extracted from the wearable device or smartphones with accurate activity labels to first train a machine learning classification model. Then it uses the classification model to predict what activity a person is doing based on the new physical data. There has been a lot of research happening on how to predict activities accurately. In the next section, I will go through the literature review. My approach to the problem is a little different as I want to explore if adding the user id along with the sensor data for predicting activity will make the prediction more accurate, that is, whether personalizing the human activity recognition model will reduce the prediction error.

3. Related Work

There has been a lot of research happening on Human Activity Recognition system. Many researchers have used different combination of sensors, classification models and clustering model to recognize human activity. Investigators have used cameras [4], wearable computers and mobile devices [5]. In recent years, with smart phones being widely used, most of the research has been focused on using smartphones. A CenceMe application [6] was developed in 2008 which includes an activity classification engine that collects acceleration data from Nokia N95 phone to distinguish sitting, standing and falling. In 2009 [7] more research was performed using data extracted from Nokia N95 to distinguish activities into sitting, walking, running, standing, running, driving and cycling.

Guiry [8] used a combination of smartphone (Samsung galaxy SGT-I9000) and a PLUX sensor to accurately detect a human activity. He used a number of machine learning algorithms such as C4.5, CART, SVM, Multi-Layer Perceptrons, and Naïve Bayes along with his customized classifier. He showed that certain algorithms, including the popular C4.5 decision tree require the entire training set to be loaded into memory at once. While this may not be a problem when training these algorithms on a PC with a large, customizable heap, devices such as mobile phones are often limited by static heaps, of minimal size.

Anguita [9] used a smartphone Samsung S2 to detect human activity. He used a multiclass support vector machine approach to predict activities. The multiclass SVM employed for the classification of smartphone inertial data showed a recognition performance similar to previous work that used special purpose sensors, therefore strengthening the application of these devices for HAR purposes. Ortiz [10] published the results of competition which was helped with the data used by Anguita [9]. In this One Vs One (OVO) multiclass SVM with linear kernel was proposed for classification task. The method used majority voting to find the most likely activity for each test sample from an arrangement of 6 binary classifiers. An overall accuracy of 96.40% was reached on the test data and this method became the competition winning solution. For comparative purposes, they also evaluated the performance of a One-Vs-All (OVA) SVM and a KNN model which exhibited poorer accuracies (93.7% and 90.6% respectively)

Kwon [11] used a slightly different approach to use unsupervised learning for human activity recognition using smartphone sensors. This allowed him to consider unknown number of activities in his data. His experiment results show that the mixture of Gaussian exactly distinguishes those activities when the number of activities “k” is known, while hierarchical clustering or DBSCAN achieve above 90% accuracy by obtaining k based on Calin´ ski–Harabasz index, or by choosing appropriate values for e and MinPts when k is unknown. His approach provides a way of automatically selecting an appropriate value of k at which the accuracy is maximized for activity recognition, without the generation of training datasets by hand.

Ortiz [5] presents the Transition-Aware Human Activity Recognition (TAHAR) system architecture for the recognition of physical activities using smartphones. It uses real-time classification with a collection of acceleration and gyroscope sensors. Ortiz proposes two different implementations of the architecture. This is accomplished by combining the probabilistic output of consecutive activity predictions of a Support Vector Machine (SVM) with a heuristic filtering approach. The architecture is tested over three different data sets that involve data from people performing up to 33 different activities, while carrying smartphones or wearable sensors. Results show that TAHAR outperforms state-of-the-art baseline works and reveal the main advantages of the architecture.

4. Method & Approach

The approach which I used for human recognition activity system was different from what has been tried out before. In most of the previous systems for creating a classification model and predicting activities the data used was only the sensor data from smartphones or wearables and their corresponding labels. I am incorporating the user identification for the person into my model. My predicting model includes sensor data as well as the user identification of the person along with the activity labels. This will help to create a personalized human recognition model.

The reason why I want to add in the user identification data is that each person has a unique way of performing physical activities. It depends on a lot of personalized factors like their height, where they usually keep their cellphones or how they walk. I want to explore if I can increase the efficiency of the model if these factors are taken into account by adding the user identification.

4.1. Data

Data which I used for my experimentation is a publicly available dataset from the UCI repository [12] labeled as 'Human Activity Recognition Using smartphones'. Following is the link to the data:

http://archive.ics.uci.edu/ml/datasets/Smartphone-Based+Recognition+of+Human+Activities+and+Postural+Transitions

This data consists of 30 people who performed six basic activities (standing, sitting, lying, walking, walking downstairs, walking upstairs) and six postural transition activities (stand-to-sit, sit-to-stand, sit-to-lie, lie-to-sit, stand-to-lie and lie-to-stand). All the participants had strapped a Samsung galaxy S 2 smartphone on their waist. Data captured was 3-axial linear acceleration and 3-axial angular velocity at a constant rate of 50Hz using the embedded accelerometer and gyroscope of the device. This was video-recorded to label the data manually.

The data was pre-processed by applying noise filters and then sampled using sliding windows. For each window, a vector of 561 features was obtained by calculating variables from time and frequency domain. All of the preprocessing had already been implemented on the data in UCI repository. The only pre-processing which I did on the data was to apply principal component analysis (PCA) using Matlab to reduce the features size to 118, where I used a threshold of variance of 0.02 for getting to this point.

This data set has been divided into 70% training and 30% testing, where in training part of the data was from 21 people and in testing part of the data was from 9 other people. Training and testing did not include data from the same user id. I labelled this data division as '**Data Set 1**'. I also used a different method for dividing the data set. Instead of dividing the data based on the users, I divided the data for each user. So in this data set, 70% training data is from all 30 users and the other 30% training data is all 30 users as well. The data is divided 70% and 30% for each user. I labelled this as '**Data Set 2**'.

4.2. Data – Effect of adding user identification

Firstly, I explored whether there was any effect of adding the user identification number as a feature to the classification model accuracy. For this purpose, I used the data set 2 since it contained the same user id in both test and training data sets. I conducted a baseline test without the user id added as a feature and then another test with user id added as a feature. The classifier models I used for this test were K-nearest neighbor, support vector machine with linear kernel, support vector machine with polynomial kernel, discernment analysis, naïve bayes and neural network. For neural network testing, I had to find the global minimum for getting the best accuracy.

4.3. Clustering

Next, I tried to cluster users in similar group id using various clustering algorithms. I used hierarchical clustering and k-mean clustering with variable number of cluster group on data set 2. This test was conducted to see how alike different user groups were and if it would be possible to use the cluster model to accurately predict, when a new user is added to an existing group. One challenge I faced was that cluster groups were formed of clustered activates rather than clustering based on user. To fix this, I used just one activity, walking, from the data set and just clustered user group for that particular id.

4.4. Calibration

Calibration is a process which can be used for personalized HAR where you do not need to cluster models each time data is received. It is assumed that the user who is using the sensor will not change and the device is going to be calibrated to his specifications. The process for calibration would require the user to walk for a fixed duration for the first time he uses the device. This data would then be used in the models to figure out which clustered user group he belongs to and then add to the activity classification model respectively. For my testing purposes, I am using the first ten walking activity sets for each user as calibration data and then using it to determine his user group.

4.5. System 1 –Clustering -Classification

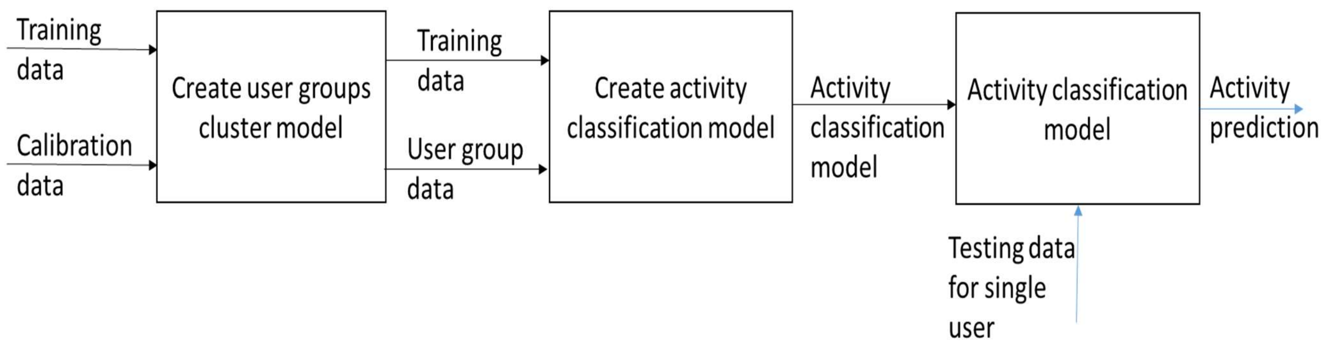

Figure 1.

The figure 1 above is the first model I devised for personalized human activity recognition system. This includes a clustering and a classification model. First, the training set data for walking activity and calibration data is used to create a clustering model. The results from clustering model is used to add the clustering group ids as a feature for each training data object and for the calibration data. The calibration group id is added as a feature to the testing data. A classification model is created and is used to predict the activing label for the user. I have tested this model with various different classification models. A challenge with this model is that for it to work, a classification and clustering model needs to be created each time new calibration data is provided. This will take a lot of processing power which will be a concern on a smartphone or a wearable device.

4.6. System 2 Clustering-Classification-Classification

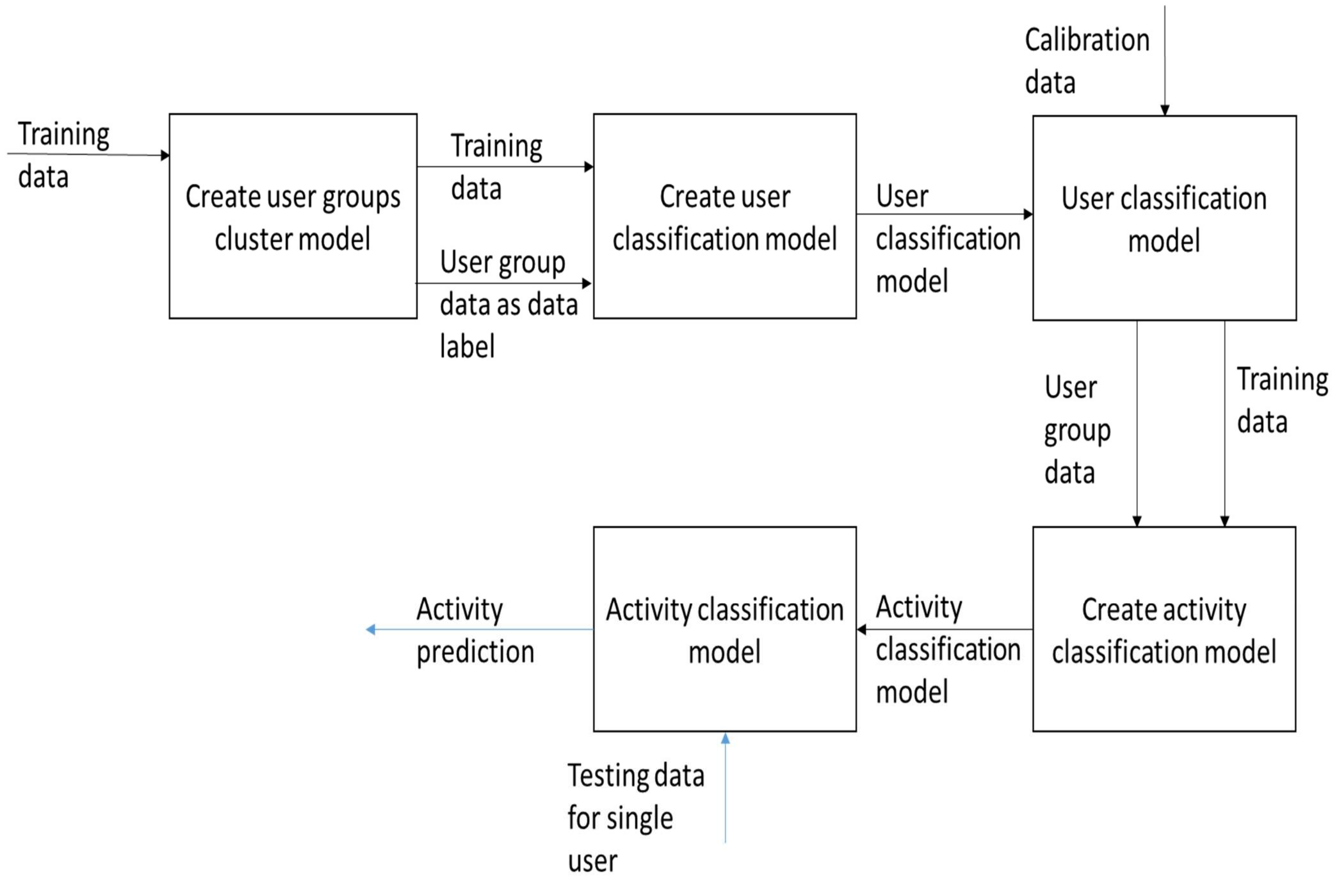

Figure 2.

The figure 2 is the second model for personalized human activity recognition system. This does not require the clustering or classification models to be created each time calibration data is received. In this system, the walking label training data is clustered into similar user group at first. Next, the training data and the user group data is sent to the next classification model. This classification model uses user groups as the labels. For this model, I have used K-nearest neighbor as the classifier. It is used to predict what user group calibration data belongs to. The results from clustering model is used to add the clustering group ids as a feature for each training data object and for the calibration data. The calibration group id is added as a feature to the testing data. A classification model is created and is used to predict the activing label for the user. I have tested this model with various classification models

5. Experiment Details and Results

5.1. With User ID

For this experiment, I used the data set 2 and used different classify functions from Matlab to conduct a test to evaluate if adding the user identification as a feature will change the error in the models. In Table 1, five different models were tested and for most of them there was improvement in the accuracy. The same data was tested on all models to make it easier to compare the result.

Before conducting the user ID test, the models were optimized. Particularly for neural networks model, different layers, neurons, transfer functions and bias were tested. One challenge I faced with neural networks was that the model was converging on local minimum instead of the global minimum. In order to solve this problem, I randomly allocated weights and ran the function with different weight 25 times.

Model	Error (without user id)	Error (with user id)
KNN	4.4%	3.6%
SVM – linear kernel	3.1%	3.0%
SVM – polynomial 2-order kernel	3.2%	3.2%
Discriminant Analysis	5.5%	5.9%
Naïve Bayes	11.4%	11.4%
Neural Network	3.9%	3.7%

Table 1.

5.2. Cluster

Next I used clustering on data set 2 to cluster training and test data into different groups. For this I started with clusters to be 6 and moved from there. I found that hierarchical clustering with clusters size 8 provided the best results. Next I used the user id available with the training data, to compare the number of cluster group each user was placed in. Out of the 30 users, I found that 27 users had 90% of their objects placed in one user group. But for 3 users, their objects were divided into 2 groups 60% to 40%. For next step I allocated the cluster group for each user based on the maximum frequency of the user groups and added it as a feature. I did the same thing with test data. The test results below show that there was some improvement in efficiency and error was reduced by 10% for the best performing support vector machine with linear kernel model.

Model	Error (without user id)	Error (user id)
KNN	4.4%	4.3%
SVM – linear kernel	3.1%	2.8%
Neural Network	3.9%	3.8%

Table 2.

5.3. Data Set 2

Next I applied the system 1 and 2 defined earlier for data set 2. The results for System 1 were very similar to clustering results. For system 2 the KNN and SVM were worse, this was to be expected since were are adding more errors in the system by using an extra classification model. Figure 4 provides confusion matrix for the best performing model that is the support vector machine with a linear kernel on data set 2 and system 1.

Model	Error (without user id)	Error (System 1)	Error (System 2)
KNN	4.4%	4.2%	8.33%
SVM – linear kernel	3.1%	2.8%	2.9%
Neural Network	3.9%	3.5%	3.6%

Table 3.

Figure 4.

5.4. Data Set 1

This is the first time I used data set 1 for my analysis. Most research papers have used this data division in their analysis. It doesn't show much of an improvement from the baseline error when no user id was used. Neural network for System 1 shows a little bit of a promise. A reason attributed to it is that for this data set, classification model is just being applied on 21 users instead of 30 users for data set 2. Also the testing data set users are new and are not already there in the training data set. I am expecting a data set of larger user group will be able to provide better results.

Model	**Error (without user id)**	**Error (System 1)**	**Error (System 2)**
KNN	14%	17%	15.6%
SVM – linear kernel	6.3%	6.3%	6.3%
Neural Network	6.7%	6.2%	6.7%

Table 4.

6. Conclusion and Discussion (Future Work)

In this paper, I have presented a way to improve the accuracy of human recognition model by adding the user identification as a feature. As you can see from the results stated above, it works well when the user or similar user already exists in the training dataset. For the best accuracy SVM- linear model I was able to reduce error by 10%. But it doesn't make much difference if a unique user is tested. Neural network model was able to reduce error by 1.5%. In future I would like to work on a larger and more diverse user group data set to evaluate what kind of effects a new unique user has when we have a larger data set.

7. References

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