Driving Reform: Digital Health is Everyone's Business
A. Georgiou et al. (Eds.)

doi:10.3233/978-1-61499-558-6-62

Human Activity Recognition from Smart-Phone Sensor Data using a Multi-Class Ensemble Learning in Home Monitoring

Soumya GHOSE [1], Jhimli MITRA [1], Mohan KARUNANITHI [1] and Jason DOWLING [1]
[1] *Australian e-Health Research Centre, CSIRO, Digital Productivity Flagship.*

Abstract. Home monitoring of chronically ill or elderly patient can reduce frequent hospitalisations and hence provide improved quality of care at a reduced cost to the community, therefore reducing the burden on the healthcare system. Activity recognition of such patients is of high importance in such a design. In this work, a system for automatic human physical activity recognition from smart-phone inertial sensors data is proposed. An ensemble of decision trees framework is adopted to train and predict the multi-class human activity system. A comparison of our proposed method with a multi-class traditional support vector machine shows significant improvement in activity recognition accuracies.

Keywords. Activity recognition, support vector machines, random forest

Introduction

The number of Australians aged 65 and over is expected to increase rapidly from 13 per cent of the population to 25 per cent of the population by 2042 [1]. Managing the ever increasing cost of delivering healthcare to the ageing population is a major challenge. Assisting the chronically ill and aged population accounted for over 70% of Australia's 103.6 billion dollar health expenditure during 2007-2008, that is only likely to increase [2]. This expenditure may be reduced by remote monitoring of aged or chronically ill patients that in turn may potentially reduce the frequency of hospitalisations. Helping patients self-manage their conditions at home through the provision of tele-health services and remote monitoring by health workers enables timely intervention. The success of such a system often requires prediction of the patient activities such as sleeping and walking.

In remote monitoring of patient, often specific sensors measuring heart rate, blood pressure, blood glucose and body temperature are used to collect patient-specific data. Recent advances in sensor technology have allowed the integration of these sensors in smart-phones, thus, allowing seamless tracking of activities with smart-phone sensors such as accelerometer and GPS. For example, activity monitoring like walking or lying

[1] Corresponding author: Soumya Ghose, The Australian e-Health Research Centre, CSIRO, Level 5 - UQ Health Science Building 901/16, Royal Brisbane and Women's Hospital, Herston Qld 4029 Australia; E-mail: Soumya.Ghose@csiro.au

is of critical importance for an elderly person or sick patient. Therefore, sensor data from the smart-phone GPS or accelerometer may be used in identifying the patient's state.

Activity recognition aims to identify the actions carried out by a person given a set of observations from inertial sensors such as accelerometer and gyroscope. The primary objective of this work is to use multi-class ensemble learning to predict a set of physical activities like standing, walking, laying, and walking upstairs and downstairs from the accelerometer and gyroscope sensor data. The data from the smart-phone can be uploaded to a remote server at a certain time interval and then the machine learning framework can predict the patient's activity state from that data. The sampling rate of the procedure is however application dependent. For example, a chronically ill patient may be monitored more frequently compared to an elderly person with health conditions only related to ageing.

All such remote monitoring however generates large amount of data and it is time consuming to manually predict a patient's activity from the sensor data. Multi-class classifiers provide an elegant solution to such a problem. In this work, an ensemble of decision trees (random forest) is trained with the sensor data related to a set of physical activities. Given a new set of sensor data, the random forest classifier predicts the patient's activity from the learned model.

The rest of the paper is structured in the following manner; the state of the art in activity recognition is presented in Section 2, methodological details of the multi-class ensemble of decision trees classifier is presented in Section 3 and the results are presented in Section 4.

1. Related Work

The use of smart-phone in remote monitoring of patient activities has several advantages. Smart-phones are portable, convenient to use and relatively in-expensive compared to full-body sensor apparel [3]. The use of numerous sensors may improve activity prediction accuracies and with technological advancements, smart-phone sensors are increasingly becoming more accurate. One major drawback of smart-phone based sensors, however, is sharing of resources like processing power and memory with other applications. Nonetheless, smart-phones have become an integral part of our life allowing easy collection of sensor data. These data may be further analysed with machine learning methods to classify an activity.

Several machine learning methods including Naïve-Bayes classifiers, support vector machines (SVM), threshold based methods and Markov models have been used for activity recognition [3]. Activity recognition with a multi-class SVM produced promising results [3]. Traditionally, SVM is a binary classifier. The classifier was extended to a multi-class classifier using a one-versus-the-rest classification strategy [4]. SVM provides a linear decision surface maximising the margin of separation between two classes. Non-linear kernel functions may be chosen for SVM where the data is not linearly separable; however, the choice of such a kernel is not straightforward. In many cases, the projection of data into a higher dimension does not capture the intrinsic properties of the features that can actually discriminate between the classes. A random forest [5] on the other hand provides a non-linear decision surface as an aggregation of piece-wise linear decision surfaces obtained from the decision trees. Therefore, in this work we have used the multi-class random forest classifier that can be easily applied for the multi-class activity recognition problem and compared its performance with the one-versus-the-rest multi-class SVM classifier performance [4].

2. Method

A random decision forest is a supervised learning method and is an ensemble of decision trees. A decision tree is a set of two types of nodes, the split nodes and the leaf nodes. In order to train a model, the training feature space is randomly sampled with uniform sampling of the feature thresholds at each split node with the aim of maximising the information gain [5]. Therefore, each split node stores a decision function, while the empirical distribution of the posterior probability $p(y \mid x)$ of assigning label y to the training data x is stored at the leaf nodes.

To predict the label of a new data x, the feature is pushed down through the learned split functions and once it reaches the leaf node, the stored distribution $p(y \mid x)$ is used to predict the label. The overall prediction of the forest with T decision trees is finally obtained by averaging the individual tree prediction as follows,

$$p_t(y \mid x) = \frac{1}{T}\sum_{t=1}^{T} p_t(y \mid x) \tag{1}$$

Each of the decision trees in a random forest is a weak classifier and an aggregate of their individual predictions is used to obtain a final prediction. A single decision tree is known to suffer from over-fitting [6], while, a random forest offers better generalisation capabilities by randomising the features and feature threshold values at the split nodes. In this work, the number of trees was fixed to 200 and depth was fixed as 7 to reduce over-fitting.

A public dataset from [7] was used to evaluate the classifier performance. The experiments were carried out on a group of 30 volunteers within an age bracket of 19-48 years. The experiments were further video tagged to aid in data labelling. Each participant performed six activates (sitting, standing, walking, laying, walking upstairs and walking downstairs) wearing a Samsung Galaxy S2 smart-phone. The data from the accelerometer and gyroscope, measuring 3-axial linear accelerations and angular velocity respectively at a constant rate of 50Hz were captured for activity recognition. The sensor data were pre-processed by applying a Gaussian noise reduction filter and then re-sampled in fixed-width sliding windows of 2.56 sec with 50% overlap. From each window, a vector of time and frequency domains features of the accelerometer signal is extracted. Mean, standard deviation, signal magnitude area, entropy, signal-pair correlation, and Fourier Transform were used to extract the frequency components of the signal. The features were used as inputs along with the activity label to train a random forest classifier.

3. Results

The public dataset was randomly partitioned into 70% training and 30% testing samples. The common evaluation metrics like the true positive rate, false positive rate and precision were measured. The metrics were computed as follows:

$$\mathrm{TPR} = \mathrm{Sensitivity} = \mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}},$$

$$\mathrm{FPR} = \frac{\mathrm{FP}}{\mathrm{FP}+\mathrm{TN}},$$

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}}.$$

The Receiver Operating Characteristic (ROC) curves for each class prediction along with the average prediction by random forest are presented in Figure 1. In Figure 1, we can observe both true positive rate (TPR) and the false positive rate (FPR) of the multi-class classifier are very high.

As observed in Table 1, the classifiers scores a perfect or near perfect scores in terms of precision and recall in activity recognition of walking, standing, sitting and laying. The classifier scores comparatively low in terms of precision and recall for walking upstairs and walking downstairs. We believe this is more related to gyroscope values that were recorded. A more sensitive gyroscope sensor is probably needed to distinguish between walking upstairs and downstairs.

In this work we quantitatively compared the activity recognition accuracy results with a previously published work of Anguita et al. [4] validated on the same public dataset (Table 1). Anguita et al. used an extended SVM to adapt to a multi-class activity recognition framework. As observed in Table 1, our proposed random forest classifier performs better in all the activity classes in terms of precision and recall. A maximum value of 1 for precision and recall was achieved for the "Laying" class by both the compared approaches.

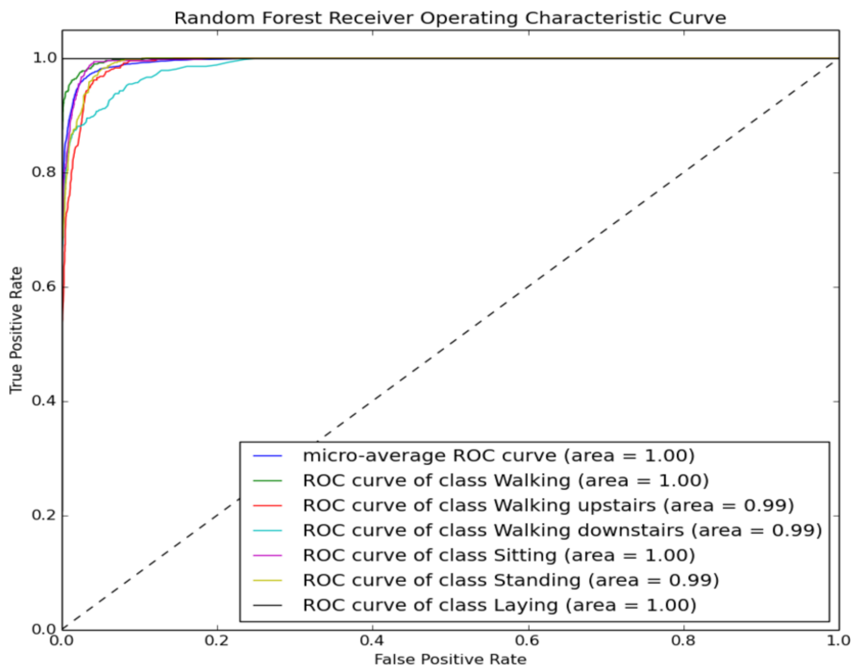

Figure 1. Random forest activity recognition ROC curves for each activity class and the average ROC.

Table 1. Quantitative comparison of SVM [4] and our proposed random forest framework.

Activity	Metrics	SVM [4]	Random Forest (proposed)
Walking	Recall	0.95	0.99
	Precision	0.87	0.99
Walking Upstairs	Recall	0.72	0.97
	Precision	0.81	0.94
Walking Downstairs	Recall	0.79	0.98
	Precision	0.74	0.95
Standing	Recall	0.92	1
	Precision	0.97	0.98
Sitting	Recall	0.96	0.99
	Precision	0.94	0.98
Laying	Recall	1	1
	Precision	1	1

4. Conclusion

An automatic activity recognition system has been proposed with a random forest classifier. The proposed method performs slightly better than support vector machine proposed by [4]. The method however, needs to be validated with a larger dataset. In future, this work may be extended to develop a risk prediction system from patient's activity state to alert health personnel. Accurate activity prediction system for the elderly with the proposed model may potentially reduce the risk associated with remote monitoring. Additional sensor data from heart rate monitoring and body temperature may be easily incorporated as features in the classification system to design a patient – specific and illness-specific remote risk assessment system.

References

[1] Australian Government, Australia's Demographic Challenges, http://demographics.treasury.gov.au/content/_download/australias_demographic_challenges/html/adc-04.asp, accessed on [14th March, 2015]

[2] CSIRO, Home Monitoring of Chronic Disease for Aged Care, http://www.csiro.au/en/Research/DPF/Areas/Digital-health/Improving-access/Home-monitoring, accessed on [14th March 2015].

[3] A. Mannini et al., Machine Learning Methods for Classifying Human Physical Activity from On-Body Accelerometers,Sensors, vol. 10, pp. 1154-1175, .

[4] D. Anguita et al., Human Activity Recognition on Smartphones using a Multiclass Hardware-Friendly Support Vector Machine, Proc. IWAAL, pp. 216-223, 2012.

[5] Andy Liaw and Matthew Wiener, Classification and Regression by Random Forest, JML. R News, pp. 18-22, 2002.

[6] L. Breiman, Random forests. Machine Learning, vol. 45, 2001.

[7] UCI machine learning repository, Human Activity Recognition Using Smartphone Dataset,archive.ics.uci.edu/ml/datasets/Human+Activity+Recognition+Using+Smartphones, accessed on [14th March 2015].