INTELLIGENT HUMAN ACTIVITY RECOGNITION SCHEME FOR EHEALTH APPLICATIONS

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Abstract

Automatic activity recognition systems aim to capture the state of the user and its environment by exploiting heterogeneous sensors, and permit continuous monitoring of numerous physiological signals, where these sensors are attached to the subject's body. This can be immensely useful in healthcare applications, for automatic and intelligent daily activity monitoring for elderly people. In this paper, we present a novel data analytic scheme for intelligent Human Activity Recognition (AR) using wireless body sensors and smartphone inertial sensors which use information theory-based feature ranking algorithms and classifiers based on random forests, ensemble learning and lazy learning. Further, we propose a novel multimodal scheme based on combining multimodal three dimensional (x, y, z) accelerometer and gyro data from smart phone inertial sensors. Extensive experiments using different publicly available database of human activity show that the proposed approach can assist in the development of intelligent and automatic real time human activity monitoring technology for eHealth application scenarios for elderly, disabled and people with special needs.

Keywords: smart phone, body sensor, activity recognition, machine learning, assisted living

1.0 INTRODUCTION

The first commercial hand-held mobile phones appeared in 1979, and since then there has been an unprecedented growth in the adoption of mobile phone technology, reaching to more than 80% of the world population by 2011 [1]. Lately, smartphones, which is a new generation of mobile phones, are equipped with many powerful features including multitasking and a variety of sensors, in addition to the basic telephony. The integration of these mobile devices in our daily life is growing rapidly, and it is envisaged that such devices can seamlessly monitor and keep track of our activities, learn from them and assist us in making decisions. Such assistive technologies can be of immense use for remote health care, for the elderly, the disabled and those with special needs. However, currently, though there is good capacity for collecting the data with such smart devices, there is limited capability in terms of automatic decision support capability and making sense out of this large data repository. There is an urgent need for new data mining and machine learning techniques to be developed to this end. In this paper, we propose a new scheme for human activity recognition using smart phone data with potential applications in automatic assisted living technology. Activity recognition systems aim to identify the actions carried out by a human from the data collected via sensors and the surrounding environment. The current smart phones have motion, acceleration or inertial sensors, and by exploiting the information retrieved from these sensors, recognition of activities and events is possible. Our argument is that it is possible to develop cutting edge human assistive technologies, provided that we developed data driven approaches for automatic recognition of activities and events by processing the sensor data, and this can be done with appropriate machine learning and data mining techniques. We have developed an extensive algorithm pipeline of machine learning and data mining approaches to prove this hypothesis, and carried out an experimental validation on publicly available benchmark human activity recognition databases. For a baseline comparison, we examined a database with body worn sensors, the OPPORTUNITY database [1, 2], which is not smart phone based, and compared with smart phone based database [3]. As can be seen from experimental validation of these two strategies, the results obtained from single smart phone with few sensors is accurate and less intrusive to use.

The rest of the paper is organized as follows. The details of the research method and publicly available activity recognition databases used in this study are described in Section 2, which is next. In Section 3, we discuss the relevant background work done in this area, and the proposed automatic activity recognition approach is discussed in Section 4. The experimental validation of the proposed approach is described in Section 5, and the paper concludes with some outcomes achieved from this study and the plan for future research.

2.0 RESEARCH METHOD AND THE ACTIVITY RECOGNITION DATABASE

We used a quantitative and experimental research method for validating our hypothesis, and used two different real world, publicly available smart phone activity recognition (AR) databases [3] and OPPORTUNITY body sensor activity recognition database [1, 2]. The first database includes labeled data collected from 30 subjects in age group of 19 to 48 years. Each person performed different activities wearing a smart phone around the waist, and engaged in six different activities—walking on flat ground and up and down stairs, sitting, standing, and lying down. A Samsung Galaxy S2 smartphone was used for data collection, which contains an accelerometer and a gyroscope for measuring 3-axial linear acceleration and angular velocity respectively at a constant rate of 50Hz, which is sufficient for capturing human body motion. The database consists of two data sets: one raw pre-processing data from the sensors and another data set with features extracted. The raw data was then pre-processed by applying noise filters and then sampled with fixed-width sliding windows of 2.56 sec and 50% overlap. From each window, a vector of 17 features is obtained by calculating variables from the accelerometer signals in the time and frequency domain (e.g. mean, standard deviation, signal magnitude area, entropy, signal-pair correlation, etc.).

The other database consists of vectors that contains 561 features each and represent 2.56 seconds of time. Each vector encodes characteristics such as the tri axial average, maximum, and minimum acceleration and angular velocity over the given interval, as well as more complex properties such as the Fourier transform and autoregressive coefficients.

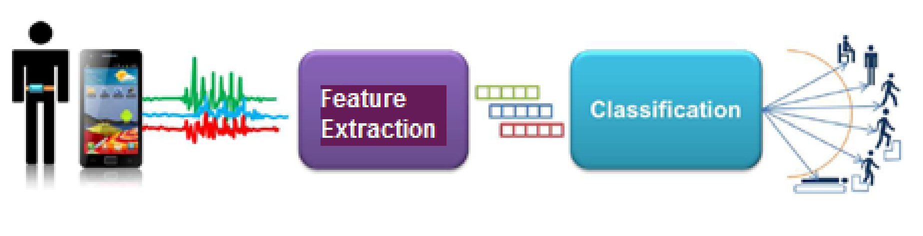


Fig. 1(a). Block Schematic for Activity Recognition Processing

The second database used for baseline comparison of smart phone based activity recognition database is the publicly available OPPORTUNITY database for Human Activity Recognition from Wearable, Object, and Ambient Sensors to benchmark human activity recognition algorithms [1, 2]. The activity recognition environment and scenario was designed to generate many activity primitives, yet in a realistic manner. Subjects operated in a room simulating a studio flat with a deckchair, a kitchen, doors, a coffee machine, a table and a chair.

The two databases provide thorough experimental validation of our proposed data driven algorithm pipeline, for smart phone automatic activity recognition technology development. Fig. 1(a) above shows the block schematic for smart phone acquired sensor data, and the body sensor placements for OPPORTUNITY database are shown in Fig. 1(b). The next Section discusses the related background work.

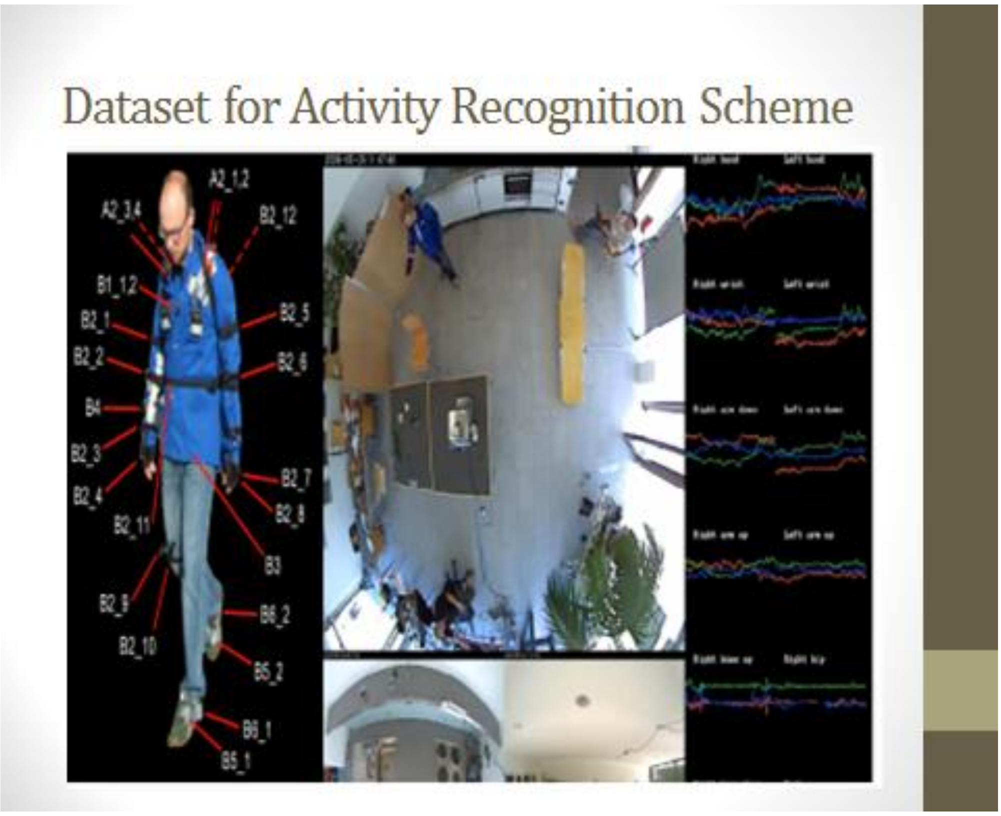


Fig.1(b). Sensor placement for Activity Recognition Data Collection

3.0 BACKGROUND

The role of smartphones for automatic activity recognition have several advantages such as device portability, and no requirement for additional fixed equipment that could be obtrusive and uncomfortable to the user. Other established activity recognition approaches are based on special purpose hardware set-ups and body sensor networks as in [4, 5, 6]. It is unrealistic, however, to expect in general home settings for people to wear those devices for their daily activities, though, such elaborate setups can enhance the activity recognition performance. Smart phones have the advantage over body sensors such as ease and convenience, along with the capability of multiple sensors, which can be exploited for activity recognition.

Appropriate machine learning and data mining methods need to be developed for processing these multiple sensor signals from smartphones for automatic and intelligent activity recognition. Though there have been several machine learning methods available [7, 8, 9, 10], it is not clear which algorithm can perform better for activity recognition with smartphones. If automatic activity recognition systems can be built based on intelligent processing of multiple sensor features on smart phones, it will be a great contribution to the eHealth, particularly for remote activity monitoring and recognition in aged care and disability care sector.

In this article, we examine several new machine learning and data mining approaches based on decision trees and ensemble learning techniques including random forests and random committee, and compare them with traditional naïve Bayes classifier and unsupervised k-Means clustering approaches for processing smartphone sensor signals for activity recognition. In addition, we propose a combination of different types of sensor signals for enhancing the recognition accuracy. For experimental validation, we validate our results with two different databases, one smartphone based database, and body sensors. . The next section describes the details of the research study for developing the smartphone-based automatic activity recognition technology.

4.0 INTELLIGENT DATA MINING SCHEME

In this section, we describe the existing intelligent data mining approach that are available for classifying different activities performed in activities of daily living. As the dimensionality of features is very high (561 features), which can severely affect the implementation in real time on smart phone devices, we propose an information theory based ranking of features as the preprocessing step for this purpose. In this approach the features or attributes are ranked using information gain as the criterion, and other insignificant features are discarded. This has worked surprisingly well as compared to other attribute selection methods, given that in this application context, we are dealing with very high-dimensional database, where we need to use around half the features of the database to achieve the same level of recognition performance.

Although several machine learning approaches are available in literature, many of them are not suitable in our case where we had to work with large multimodal sensor data in real time and in the same time achieve sensible results out of it. In the course of determining, after extensive testing, we found that some of the machines learning classifiers were more suitable than others when it came to achieving accuracy of results and efficiency of model building time. Now we briefly describe some of the machine learning classifiers which were examined in this study.

i. Naïve Bayes Classifier

This classifier is based around Bayes' theorem and computes probabilities in order to perform Bayesian inference. The simplest Bayesian method, Naive Bayes, is described as a special case of algorithm that needs no adaptation to data streams. This is because it is based on supervised learning, and it is straightforward to train the model, and performs well in terms of accuracy and generalization, making it a good method for baseline comparison. Further details of this classifier approach are given in [11, 12].

ii. K-Means Clustering

Clustering is an unsupervised learning approach, and here the dataset does not need to have labelled data. The instances are grouped and if they are either the same or related to each other they are placed in one group and those that are different or un-related are placed in another group. k-Means is known to be the simplest and the most popular algorithm and based on some criterion (Euclidean distance or Manhattan distance), it analyses instances that can be clustered without having any previous knowledge about them. Due to its simplicity, and capability to work on unlabeled data, it is a good candidate for baseline reference for examining classifier performance. Further details of this classifier approach are available from [13].

iii. Decision Trees

A decision tree is a predictive machine-learning model that decides the target value (dependent variable) of a new sample based on various attribute values of the available data. The internal nodes of a decision tree denote different attributes; the branches between the nodes tell us the possible values that these attributes can have in the observed samples, while the terminal nodes tell us the final value (classification) of the dependent variable. The attribute that is to be predicted is known as the dependent variable, since its value depends upon, or is decided by, the values of all the other attributes. The other attributes, which help in predicting the value of the dependent variable, are known as the independent variables in the dataset. The J48 Decision tree classifier (used in our experiments) uses the following simple algorithm:In order to classify a new item, it first needs to create a decision tree based on the attribute values of the available training data. So, whenever it encounters a set of items (training set) it identifies the attribute that discriminates the various instances most clearly. This feature is able to tell us most about the data instances so that we can classify them the best is said to have the highest information. The details of J48 decision tree classifier are provided in [14, 15].

iv. Random Forests

Random Forests are an ensemble of decision trees, and are based on ensemble learning methods (also thought as a form of nearest neighbor predictor) for classification and regression that construct a number of decision trees at training time and outputting the class that is the mode of the classes output by individual trees (Random Forests is a trademark of Leo Breiman [14], for an ensemble of decision trees). Single decision trees often have high variance or high bias. Random Forests attempts to mitigate the problems of high variance and high bias by averaging them to find a natural balance between the two extremes. Considering that Random Forests have few parameters to tune and can be used simply with default parameter settings, they are a simple tool to use without having a model or to produce a reasonable model fast and efficiently.

v. Random Committee

Random committee is also a form of ensemble learning approach and based on the assumption of improving performance by combining classifiers. It involves building an ensemble of randomizable base classifiers, with each base classifier built using a different random number seed (but based on the same data). The final prediction is a straight average of the predictions generated by the individual base classifiers, that consists of several classifiers and outputs the class based on the outputs of these individual classifiers [14, 15, 16].

vi. Lazy IBk Classifier

Lazy learners store the training instances and do no real work until classification time. IBk is a k-nearest neighbour classifier [8, 15, 16]. A variety of different search algorithms can be used to speed up the task of finding the nearest neighbours. A linear search was used for this study, but the performance can also be enhanced by using kD-trees or cover trees. The distance function used was Euclidean distance. The number of neighbours that we used was only one, with no weighting based on distance from the test instance.

5.0 MULTIMODAL ACTIVITY RECOGNITION SCHEME

The algorithm described in the Section 4, are based on processing single data mode. We extended the investigations to examine the performance of activity recognition scheme based on learning the multimodal three dimensional (x, y, z) accelerometer and gyro data from smart phone inertial sensors available from the same dataset. Further, we develop a new supervised and unsupervised machine learning strategy for combining inertial sensor signals, using a novel approach based on deep canonical correlation analysis (or dCCA*).*

Deep canonical correlation analysis is a method for learning complex nonlinear transformations from two different modalities of data (including accelerometer and gyro data), leading to output representations that have a high linear correlation. For this method, the parameters of transformations of both modalities are jointly learned to maximize the total correlation. It is a nonlinear extension to well-known canonical correlation analysis (CCA), and is an alternative to the kernel version of CCA (kCCA), but superior to both in terms of learning correlations.

Canonical correlation analysis (CCA) is a well-known statistical technique for finding linear projections of two random vectors that are maximally correlated. Kernel canonical correlation analysis (kCCA) is an extension of CCA in which maximally correlated nonlinear projections, restricted to reproducing Kernel Hilbert spaces with corresponding kernels, are found. Both CCA and kCCA are techniques for learning representations of two data views or modalities, such that representation from each modality is simultaneously the most predictive of, and the most predictable by, the other. CCA and kCCA have been used for unsupervised data analysis when multiple views are available [17, 18, 19].

While kCCA allows learning of nonlinear representations, it has the drawback that the fixed kernel limits the representation. Also, since it is a nonparametric method, the time required to build the model based on kCCA features increases with increase in training data, making it a very computational intensive approach. In this study, we consider learning flexible nonlinear representations via deep networks. Deep networks do not suffer from the drawbacks of nonparametric models as in kCCA, and given the empirical success of deep models on a wide variety of tasks, they could be more promising in terms of learning highly correlated representations.

Deep networks have been used widely to learn representations of single data, for example using deep Boltzmann machines, deep auto encoders, and deep nonlinear feedforward networks [17, 18, 19]. For learning representations of multimodal data that has inherent nonlinear correlations, we use deep CCA (dCCA) which simultaneously learns two deep nonlinear mappings of two views or modalities (3D x, y, z, dimensional accelerometer and gyro data) that are maximally correlated. This can be loosely thought of as learning a kernel for kCCA, but the mapping function is not restricted to live in a reproducing kernel Hilbert space. This representation could be used in an unsupervised setup, leading to better accuracy and model building time.

6.0 EXPERIMENTAL RESULTS

Different sets of experiments were performed to validate the proposed intelligent human activity recognition scheme. It is important to reiterate that there is not much previous study done on such automatic schemes, particularly in the eHealth application context. Therefore, to ensure the validity of results, we utilised different benchmark publicly available datasets, and a standard protocol for carrying out the experimental validation of our approach. It is a widely accepted norm in machine learning data mining community, particularly for cutting edge, innovative technology development.

a. Single Mode Experiments

To evaluate the performance of the proposed machine learning and data mining approach for automatic human activity recognition from smartphone data, we used the part of the dataset [3], with pre-processed feature set with 561 features and represents 2.56 seconds of time from each database. Each record in the feature set consists of several attributes, such as, triaxial acceleration from the accelerometer (total acceleration) and the estimated body acceleration, triaxial angular velocity from the gyroscope, a 561-feature vector with time and frequency domain variables, its activity label, an identifier of the subject who carried out the experiment.

Table 1. Performance Comparison: Recognition Accuracy and Model building time

(a): Recognition Accuracy (%)

NumFeat	KM	NB	J48	RF	RC	IBK
2	38.00	49.45	56.30	55.60	60.10	53.18
8	68.40	48.26	61.39	63.01	63.03	60.18
16	69.00	48.57	69.02	71.27	71.10	67.84
32	70.00	52.34	70.24	74.17	75.10	71.74
64	59.00	56.10	77.30	77.51	83.73	77.51
128	59.50	55.31	91.46	94.29	95.10	92.97
256	57.00	53.86	93.81	95.63	96.28	97.55
561	60.00	79.00	94.00	96.30	96.90	97.89

(b): Model building time (seconds)

NumFeat	KM	NB	J48	RF	RC	IBK
2	15.1	0.0	0.9	7.3	14.4	0.0
8	20.6	0.0	7.4	16.8	17.7	0.0
16	37.4	0.3	11.4	19.7	23.4	0.0
32	67.9	0.9	25.7	25.7	25.4	0.0
64	119.4	1.7	38.0	29.1	31.5	0.0
128	217.0	4.4	64.6	31.7	30.7	0.0
256	457.5	3.3	52.7	20.1	25.7	0.1
561	582.1	5.8	247.4	14.7	27.0	0.5

As can be seen from Table 1, the Naïve Bayes Classifier performs reasonably well for such a large dataset, with 79% accuracy, and it is fastest in terms of building the model taking only 5.76 seconds. However, random forests, one of the ensembles learning approach is better in terms of both accuracy and model building time, with 96.3% accuracy and 14.65 seconds model building time. Though, the other ensemble learning classifiers (random committee and random subspace) perform well in terms of classification accuracy (~ 96%), their model building time is higher. As expected, the k-Means clustering being an unsupervised approach performs poorly with 60% classification accuracy, and 582 seconds. For benchmarking the results, we repeated the experiments with readings from dataset taken from OPPORTUNITY database, and those algorithms that provided equal and better performance with Smartphone dataset is shown here in Table 1.

Table 2: Different performance measures for different classifier models

Features	TPR	FPR	PR	RC	F-m	ROC
IBK(256)	0.976	0.005	0.976	0.976	0.976	0.985
RC(256)	0.963	0.008	0.963	0.963	0.963	0.998
RF(256)	0.956	0.009	0.956	0.956	0.956	0.998
RC(128)	0.951	0.01	0.951	0.951	0.951	0.996
RF(128)	0.943	0.012	0.943	0.943	0.943	0.996
J48(256)	0.938	0.012	0.938	0.938	0.938	0.971
IBK(128)	0.93	0.015	0.93	0.93	0.93	0.957
J48(128)	0.915	0.017	0.915	0.915	0.915	0.96
RF(64)	0.837	0.035	0.839	0.837	0.838	0.969
RC(64)	0.837	0.035	0.839	0.837	0.838	0.969
IBK(64)	0.775	0.049	0.776	0.775	0.776	0.863
J48(64)	0.773	0.048	0.774	0.773	0.774	0.891
RC(32)	0.751	0.053	0.755	0.751	0.752	0.943
RF(32)	0.742	0.055	0.746	0.742	0.743	0.942
IBK(32)	0.717	0.06	0.72	0.717	0.718	0.826
RF(16)	0.713	0.061	0.716	0.713	0.714	0.929
RC(16)	0.711	0.061	0.714	0.711	0.712	0.923
J48(32)	0.702	0.063	0.701	0.702	0.701	0.857
J48(16)	0.69	0.065	0.69	0.69	0.689	0.873
IBK(16)	0.678	0.067	0.681	0.678	0.679	0.812
RF(8)	0.63	0.079	0.63	0.63	0.63	0.889
RC(8)	0.63	0.078	0.633	0.63	0.631	0.872
J48(8)	0.614	0.082	0.61	0.614	0.611	0.868
IBK(8)	0.602	0.084	0.606	0.602	0.603	0.791
J48(2)	0.563	0.092	0.565	0.563	0.562	0.888
NB(64)	0.561	0.093	0.57	0.561	0.515	0.878
RF(2)	0.556	0.093	0.558	0.556	0.557	0.876
NB(128)	0.553	0.09	0.644	0.553	0.523	0.928
NB(256)	0.539	0.092	0.662	0.539	0.505	0.928
IBK(2)	0.532	0.097	0.539	0.532	0.533	0.854
NB(32)	0.523	0.102	0.517	0.523	0.453	0.873
NB(2)	0.495	0.108	0.512	0.495	0.418	0.865
NB(16)	0.486	0.11	0.494	0.486	0.417	0.86
NB(8)	0.483	0.11	0.489	0.483	0.413	0.859

A trade-off between accuracy and model building time is necessary for a smartphone based activity recognition system, as real time activity monitoring requires the model to be built dynamically from the captured data, and faster model building time with good recognition accuracy is the best to aim for. Further, additional performance measures such as True Positive Rate (TPR), False Positive Rate (FPR), Precision, Recall, F-measure and Receiver Operating Characrteristics (ROC), as described in [20], need to be taken into consideration for choice of best algorithm for building automatic activity recognition systems. Table 2 shows these additional performance measures. The confusion matrix for IBk classifier (the best performing classifier) for 128 and 256 ranked features is shown in Table 3. The confusion matrix shows how the classifier confuses and misclassifies one class for another (Actual Class (AC-0 to AC5) vs. Recognized Class (RC-0 to RC-5). As can be seen in Table 3, the classifier that performs well, has the least confusion in recognising the Class 6 (Laying) and Class 1 (walking activity) out of 6 different activities (WALKING, WALKING_UPSTAIRS, WALKING_DOWNSTAIRS, SITTING, STANDING, LAYING). The activities cause confusion (incorrect classification) between walking upstairs and walking downstairs, and there is similar confusion (incorrect classification) between sitting and standing. With just one smartphone tied to the waist, this is a significantly better performance for recognising each activity.

Table 3 Confusion Matrix for IBk classifier (best performing classifier)

	RC-0	RC-1	RC-2	RC-3	RC-4	RC-5
AC-0	1717	3	2	0	0	0
AC-1	12	1513	19	0	0	0
AC-2	9	25	1372	0	0	0
AC-3	0	0	0	1471	235	71
AC-4	0	0	0	231	1658	17
AC-5	0	0	0	71	28	1845

(128) ranked features

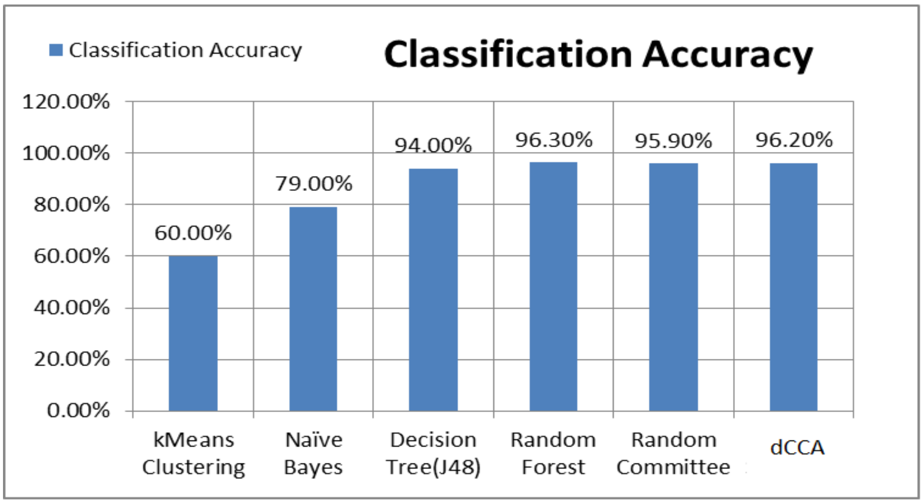
	RC-0	RC-1	RC-2	RC-3	RC-4	RC-5
AC-0	1716	5	1	0	0	0
AC-1	3	1541	0	0	0	0
AC-2	1	15	1390	0	0	0
AC-3	0	1	0	1648	127	1
AC-4	0	0	0	97	1809	0
AC-5	0	0	0	1	0	1943

(256) ranked features

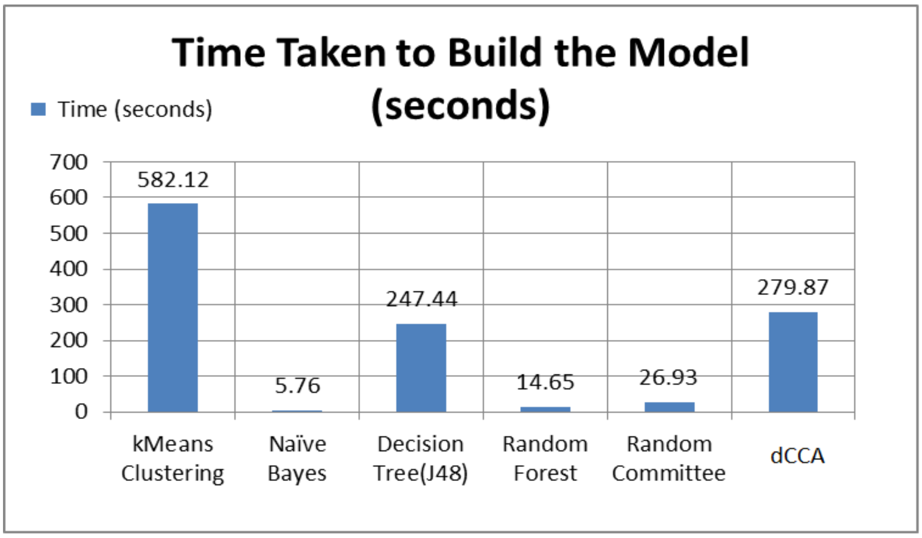
b. Multimodal Experiments

The next stage of experiments involves multiple sensor signals available in the databases. We conducted a number of experiments to examine the performance of different learning approaches in a supervised or unsupervised setup, and in a subject independent manner, for recognizing human activity. For supervised setups (where output class labels were provided for building the models), the total data size for training and testing comprised around 10,000 samples. We used 5 fold cross validation for partitioning this large database (10,000 samples) into training and testing subsets. Fig. 2 shows the comparative performance for each classifier in terms of Classification Accuracy and Time taken to build the model. Table 4 and 5 show details of other measures of performance in terms of TPR (True Positive rate), FPR (False Positive Rate), Precision, Recall, F-measure and confusion matrix.

The dCCA approach shown in Fig. 2 almost has a matching performance, as the random forests/random committee providing around 96% recognition accuracy, despite the fact that it is used in an unsupervised setup. The dCCA features are essentially the learning features here, in that, the experimental setup with dCCA features uses an unsupervised setup (with no class labels provided during the training phase), and involves extraction of dCCA features and k-Means clustering of dCCA features. However, their performance is much better than the simple *k*-Means Clustering technique. This could be due to better modelling of inherent nonlinear correlations between different modalities of inertial sensor signals at a deeper level using dCCA approach. A trade-off however, between accuracy and model building time, is necessary for a smartphone based activity recognition system as real time activity monitoring needs the model to be built dynamically from the captured data.



(a) Recognition Accuracy



(b) Model building time

Fig. 2: Comparison of Performance of Recognition Accuracy Vs. Model building time

Table 4: Different performance measures for different classifier models

Classifier Model	Accuracy	TPR	FPR	Precision	Recall	F-measure	ROC Area
Naïve Bayes	79.00%	0.788	0.041	0.807	0.788	0.786	0.963
Decision Tree(J48)	94.00%	0.939	0.012	0.939	0.939	0.939	0.972
Random Forest	96.30%	0.963	0.008	0.963	0.963	0.963	0.998
Random Committee	95.90%	0.959	0.008	0.96	0.959	0.959	0.997
dCCA	96.20%	0.961	0.008	0.961	0.961	0.961	0.998

Faster model building time with better recognition accuracy is the best to aim for. Furthermore, additional performance measures such as TPR, FPR, Precision, Recall, F-measure and ROC area need to be taken into consideration for choice of best algorithm for building automatic activity recognition systems. Table 4 and 5 show these additional performance measures. Once again, we provide the results for only those algorithms here for which smart phone based database resulted in equal or better performance than the OPPORTUNITY database.

Table 5: Confusion Matrix for Random Forests (best performing classifier)

Random		Actual Class					
Forests		a	b	c	d	e	f
	1	1698	12	12	0	0	0
Predicted	2	25	1498	21	0	0	0
Class	3	30	40	1336	0	0	0
	4	0	1	0	1682	87	7
	5	0	1	0	140	1765	0
	6	0	3	1	0	5	1935

7.0 CONCLUSIONS AND FURTHER PLAN

In this study, we proposed a novel automatic activity recognition scheme based on single model and multimodal combinations of smart phone sensor signals, based on several data driven novel approaches. The experimental validation of the proposed algorithm pipeline was provided by comparing the performance with two different publicly available benchmark databases. For single model experiments, we found optimal attribute selection techniques based on information theory based ranking leads to better performance. For multimodal experiments, a combination of supervised and unsupervised yields best performance. In particular, random forests ensemble learning method and dCCA learning features turn out to be best performers in terms of activity classification accuracy, model building time, and confusion matrix.

Further research would involve adapting the proposed data fusion approach based on a performance threshold, where the contribution from different sensor signals, type of features and learning schemes can be adapted dynamically based on the threshold set on recognition accuracy and model building time. This can be customised to a different eHealth application context, depending on age, disability or a critical care scenario. Also, other active and novel unsupervised learning approaches need to be investigated, as model building in real time on resource-constrained smartphones could be restrictive.

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