A Review On Human Activity Recognition Based On Smart Phone Using Supervised Learning

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Abstract: *Human activity recognition systems are in wide diversity of applications and also in a large field of research and development. Identifying complicated activities will continue as a challenge in research area currently with focusing mainly on advanced machine learning algorithms. This article concentrates on activity recognition based on a particular dataset of UCI Machine learning repository .Some basic activities like walking, walking up stairs, walking down stairs, sitting, standing, laying are being focused. A comparison is also made between different approaches .The aim of this paper is to discuss about the different approaches which can be applied on HAR dataset.*

Keywords—*Performance Evaluation, Supervised Learning, Human activity recognition (HAR)*

I. INTRODUCTION

Human activity recognition systems aims to recognize the actions carried out by human from the data collected. Many sensors are used in human activity recognition systems to assist in the prevention, management, and treatment of patients. The data of Images-based is also analyzed for visual activities monitoring, such data is more developed in terms of spatial and temporal information than other types of sensor- based data. However, image-based data has its own numerous challenges related to complex data processing and high dataset scarcity. These limitations can be overcome by integrating camera data along with body sensor data. The current smart phones have motion acceleration or inertial sensor by exploiting through this sensors recognition of different activities can be done. This can help for human recognition of human continuous activities or to monitor patient's movements who need round –the –clock care, such as the elderly people.

Smartphone's emerged from the integration of new services and features to mobile phones that complement the traditional telephony service (e.g. Internet access, gaming, location– based services and multisensing capabilities, etc.). They are playing an important role in the exploration of novel alternatives for the retrieval of information directly from the users. It is foreseen that these devices will be able to monitor and learn from our actions effectively and unobtrusively and consequently assist us to better decide about our future behavior [Cook and Das, 2012]. Human Activity Recognition (HAR) is a research field in which the aim is to identify the actions carried out by one or more subjects through the gathering and understanding of the information about the user state of action and its surrounding environment. This is done by the exploitation of environmental and on-body sensors, and distributed computing resources. Accelerometer is one of the Mechanisms used for the retrieval of body motion information and which has been applied for the recognition of human activities

Experimental Data Collection:

The study in this paper is mainly focused on UCI Machine learning repository in which the database was built from the recordings of 30 subjects performing activities of daily living by carrying of a waist-mounted smart phone with embedded inertial sensors.

The experiment for collection of dataset was real time were the group of 30 volunteers within an age difference of 19-48 years have participated. Each person has performed six different activities (WALKING, WALKING_UPSTAIRS, WALKING_DOWNSTAIRS, SITTING, STANDING, LAYING) wearing a smart phone on the waist. By using the embedded accelerometer and gyroscope, the 3-axial linear acceleration and the 3-axial angular velocity at a Constant rate of 50Hz was captured. The experiments have been video-recorded for labeling the data manually.

The dataset is randomly partitioned in two parts, where 70% of volunteers were selected for generating the training data and 30% the test data. Sensor signals containing the accelerometer and gyroscope needed some sort of pre- processing to be applied on it. So, by applying noise filters and then sampling in fixed-width sliding windows of 2.56 sec and 50% overlap. By using a Butterworth low-pass filter into body acceleration and gravity the sensor acceleration signals were separated. Gravitational force is always seen to have only low frequency of components; therefore a filter with 0.3 Hz cutoff frequency was used.

Vector features were obtained by calculating the variables from the time and frequency domain in each of the window. The dataset contains attributes for each record that is the triaxial acceleration from the accelerometer which is the total acceleration and also the estimated body acceleration. The Triaxial Angular velocity through the gyroscope, 561-feature vector with time and frequency domain of the variables .Its activity labels . An identifier of the subject who has carried out the experiment.

II. LITERATURE SURVEY

Information theory based ranking of features in preprocessing step for the purpose of classifying different activities were carried out. In this approach the features or attributes were ranked using information gain as the criterion, and other insignificant features are discarded. [1]. This has worked surprisingly well as compared to other attribute selection methods, this application context is, dealing with very high-dimensional datasets, where we need to use around half the attributes for achieving the same level of recognition performance.

Extensive experiments with different features were also carried out based on navies bayes classifier, K-means Clustering, Decision tree and random forest .The comparison of classifier performance was made between the recognition accuracy and model building time. The total data size comprised of 10,000 samples, 5-fold cross validation technique was applied on dataset to partition it into training and testing.

The work presented [3] to develop a method for the detection of set of activities for daily living using the five body-worn accelerometers and then employing well known ML classifiers. Frequentist and Bayesian models have been well covered throughout HAR literature, they involve predictive models such as binary decision trees and threshold-based classifiers [5, 6], geometric approaches including K-Nearest Neighbors (KNN), Artificial Neural Networks (ANN) and Support Vector Machines (SVM) [11, 7, 10], and probabilistic classification methods as for example Naive Bayes classifiers, and Hidden Markov Models (HMM) [8, 9].

[15]Set of experiments were carried out for performance of MC-HF-SVM based on AR Dataset. Learning of SVM models with different number of k bits for β estimation and then comparing their performance in terms of test data error against the standard floating-point Multiclass SVM (MC- SVM)
The experiment showed us that for the dataset k = 6 bits were sufficient for achieving a performance comparable with the MC-SVM approach that uses 64-bit floating-point arithmetic.
Test errors remained stable (around 1% variation) for k values from 64 to 6 bits, but it increases noticeably to 15% when it reaches 5 bits.
The graph shows that some values of k produced smaller errors than the one obtained with the MC-SVM**.** The classification results of the MC-SVM and the MC-HF-SVM for k = 8 bits 2 for the test data were depicted through the means of a confusion matrix, where estimates of the overall accuracy, recall and precision were also mentioned. Overall 789 test samples were evaluated with equal number of samples per class.

III COMPARITIVE STUDY BASED ON EVALUATION METRICS

OVO Multiclass linear SVM with majority voting gives 96.40% accuracy [12] while the Kernel variant of learning vector quantization with metric adaptation gives 96.23 % accuracy [13]and Confidence-based boosting algorithm Conf-AdaBoost.M1 gives 94.33% accuracy[14].

The Naïve Bayes Classifier performs reasonably well for such a large dataset, with 79% accuracy,[1] and it is fastest in terms of building the model taking only.5.76 seconds. However, random forests, which is ensemble learning approach is better in terms of both accuracy and model building time, with 96.3% accuracy and 14.65 seconds model Building time. The other learning classifiers which are random committee and random subspace though perform well in terms of classification accuracy (~ 96%). As expected, the k-Means clustering being an unsupervised approach performs poorly with 60% classification accuracy, and 582 seconds. The classifier which is seen to be best performed is IBk classifier, which is based on lazy learning, resulting in an accuracy of more than 90% for 128 features and 256 features.

In the comparative study of MC-SVM and MC-HF-SVM. The confusion matrices of both MC-SVM and MC-HF-SVM show similar outputs varying slightly in the classification accuracy of the activities walking downstairs and walking upstairs. They also show some of the false predictions mostly in the dynamic activities. Static activities instead perform better, particularly the laying activity which obtained an accuracy of 100%.

IV CONCLUSION

In this paper we have made comparisons and found that between MC-SVM and MC-HF-SVM that even with reduction in bits of 6 the MC-HF-SVM model parameter β, it is possible to substitute the standard MC-SVM.The experimental results confirmed that it is possible to substitute the standard Multiclass SVM model with more efficient fixed- point representations but further experimentation is required to evaluate the system in more realistic conditions, such as when the Smartphone system shared resources are allocated for different application.

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