Activities of Daily Life (ADL) Recognition using Wrist-worn Accelerometer

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Abstract—Activity recognition has become the necessity of smart homes, future factories, and surveillance. Activities independent of body posture predominantly exhibiting gestures involving both arm and the wrist motion supports the use of the wearable sensors for data acquisition. This paper uses an algorithm based prediction method to recognize the Activities of Daily Life (ADL) involving activities like mobility, feeding, and functional transfers. The classification of the various activities were carried out by using decision tree – J48 algorithm from the acquired dataset.

Keyword-Activities of daily life (ADL), decision tree, activity recognition, smart home, wearable sensor

I. Introduction

Human activity recognition study has been a vast area of research in recent days. Its application and need is growing rapidly in various automated environment of smart homes, surveillance, and robotics. Besides, human activity recognition has become an important feature for real time embedded systems. Conventionally, there is a problem with the sensors distributed over the environment to recognize activity of daily life. This limitation can be covered by using wearable sensors.

Activity recognition with machine learning approach using actigraph watch helped to obtain classified data of 91.39% classification accuracy using LogitBoost algorithm [1]. Actigraph sensor technology integrates real time health monitoring with ADL recognition. Comparatively it is expensive (approximately 225-275 USD) than an accelerometer. Which makes an actigraph sensor unsuitable for a common user. Previously, activity recognition using hierarchical framework have been tested for the daily morning activity of an individual which has involved six distinct activities [2]. The idea expressed in the paper was to define the probability and sequence of tasks carried out by the individual for the analyzed activity. It was found to give a new scope in designing an assisted smart living system. It can be emphasized that activity recognition using hierarchical framework could reduce the complexity in understanding and assisting the real world situations. Similarly, a two stage Markov model were built to communicate the relation and probability between a series of distinct activities [3][16].

ADL were monitored with a camera, by capturing one million of frames for machine learning and was found to give promising results. Eventually the data requirement of the method was very large and this supports the use of an accelerometer based sensor [4].

It was found that new approaches and methods are required to deal with the sensor data to recognize different activities and complexity. Ontology based approach has been proved to be a promising method to recognize different activities [5][6][7]. It was also emphasized that there is an immense necessity in developing a system that could understand complex real world situations.

Previously, wearable biosensors were used for real time continuous health monitoring. It is also used to provide personalized and affordable health care monitoring [8] and for sweat rate monitoring [9]. It was found that factors like simplicity, low cost, wearability and real time measurements uphold wearable sensors than any conventional system for real time application. Though wearable sensors were accepted widely, it carried several bottle neck criteria which need continuous attention in order to ensure optimal accuracy over its operation or in usage.

II. Literature Survey

ADL recognition is a challenging research field in Ambient Intelligence (AI). Similarly, motion primitive recognition has been proposed to carry out with Gaussian Mixture Modelling (GMM) and Gaussian Mixture Regression (GMR) to create activity models and also to compare the classification procedure for an automatic recognition system [11]. It is clear that acceleration data from the accelerometer is considered to give advantage in ADL recognition and for an easy run time classification [12]. The properties exploiting GMM and GMR were analyzed, which helps one to understand the importance of comparison procedure while dealing with acceleration data for ADL recognition.

Similar paper [13] investigated the optimum selection for number of Gaussians to build motion models, which is usually assumed to be a priori known. Also, the correlation among the three axes of the accelerometer were analyzed and found that the results were more accurate than the commonly adopted approach.

The conventional classification methods with crisp thresholds, brittleness and inaccuracy in system were analyzed for the uncertainty associated with the recognition [14]. It was found that modular techniques can be adopted by modifying the classifier approach in a minimal way, which is also applicable for classification of various domain.

Knowledge driven approach were used for continuous activity recognition using multi-sensor streams in smart homes based on ontological modelling and semantic reasoning. The domain knowledge was previously compared before giving a classification result and the focus of the system were to unify ontological modelling and representation for both sensor data and activities which facilitate domain knowledge reuse and the exploitation of semantic reasoning for activity recognition [15]. It is clear that the strength of traditional data-driven approach can be blended with knowledge-driven practices, which makes the approach more flexible and applicable.

Accelerometer sensor was previously used for gait recognition which is a similar activity to ADL. The data from the accelerometer was used to authenticate by using histogram similarity and cycle length [16, 17, 18]. It was found that the accelerometer based gait recognition system had better precession than the vision based gait recognition system which reveals the use of an accelerometer based sensor for gesture or pattern recognition applications.

III. ADL Recognition System

Wrist wearable tri-axial accelerometer embedded in an ad-hoc sensing device was used to obtain data of ADL. Data acquisition was carried out with the sensor worn in the right hand of the volunteers. The specification of the accelerometer used for data acquisition can be found in Table-1. The average age of the volunteers was 57.4 and the minimum age of the volunteers is 19 and the maximum age is 81 and their average weight was 72.7 kg and the minimum weight and the maximum weight were 56 kg and 85 kg respectively. Initially the dataset had recordings from 16 volunteers performing 14 ADL, namely brushing teeth, climbing the stairs, combing hair, climbing down stairs, drinking from a glass, eating with fork and knife, drinking soup, getting up from the bed, lie down in bed, pouring water in a glass, sitting down on a chair, standing up from a chair, using telephone and walking. However, only 7 ADL were chosen for further study namely climbing the stairs, drinking from a glass, getting up from the bed, pouring water in a glass, sitting down on a chair, standing up from a chair and walking. Hence, the number of instances was comparatively lesser in the excluded classes of ADL which lead to biased classification.

TABLE 1. Sensor specification

Type	Tri-axial accelerometer
Measurement range	-1.5g to +1.5g
Sensitivity	6 bits per axis
Output data	32 Hz
Location	Right wrist
X axis position	Pointing towards the hand
Y axis position	Pointing towards left direction
Z axis position	Perpendicular to the plane of the hand

IV. STATISTICAL FEATURE

Classification cannot be carried by using the raw data obtained from the accelerometer. Hence, extraction of statistical features is inevitable. The descriptive statistical parameters such as kurtosis, mean, median, skewness, minimum value, maximum value, mode, standard error, standard deviation, sum, sample variance, range and count are the statistical features extracted from the obtained data of wearable sensors. The statistical feature was extracted for all 700 instances. The detailed information for the statistical features can be found from the extensive review.

V. DECISION TREE

A decision tree is a tree based knowledge methodology used to represent classification rules [19]. It is commonly used for various data mining application. Decision tree is represented in the form of inverted tree starting with root, branches, nodes and leaves, shown below in Fig 1. The J48 decision tree algorithm can be used to classify both categorical and numerical data. It gives a set of "if-then" rules to classify a given set of data points into different class. The if-then rules are graphically represented in the form of a tree, which is used to make decision or prediction. Also, a decision tree expresses the structural information available within the classified dataset; hence, the tree remains almost same for classification with any number of instances or data points

A decision tree is built on the basis of the criteria used for selecting a statistical feature/variable/attribute to split the classes and to select the optimum tree size. Various pruning factors are used in order to optimize the tree size. The root element and the order of significance of the statistical features or the attributes contributing to the decision tree are determined with the help of 'information gain'.

The "information gain" gives the measure of information that can be gained from a particular attribute or a statistical feature for a fast and efficient classification. The mathematical expression for calculating the information gain can be defined as, "the difference in entropy before splitting a parameter to entropy after splitting a parameter" for the given dataset and unit of information gain is 'bits'.

The decision tree is built on the basis of the entropy value of the training data. The value of entropy can either be high or zero. In this case, the entropy is high when the data points are equal for every class and zero when all data points belong to the same class. Hence, in the formula 'log base 2 of Pi' always produce a negative numerical to give entropy of positive value or zero and thereby balancing the mathematical expression with this case. The branch growth of a decision tree is dependent on the entropy of an attribute or statistical feature. The branch growth is stopped when the entropy is zero for an attribute or statistical feature.

In this case, suitable methodology is efficiently used to bring out the structural information from the analyzeddataset and presented in Fig 1 and the description for the denoted attributes are defined and categorized in Table 2**.**

TABLE 2. Activities of daily life (ADL)

Sl. No.	**Activities of daily living (ADL)**	**Motion primitive(s)**	**Denoted by**
1	Mobility	Climbing the stairs	A
2	Feeding	Drinking from a glass	B
3	Functional transfers	Getting up from the bed	C
4	Feeding	Pouring water in a glass	D
5	Functional transfers	Sitting down on a chair	E
6	Functional transfers	Standing up from a chair	F
7	Mobility	Walking	G

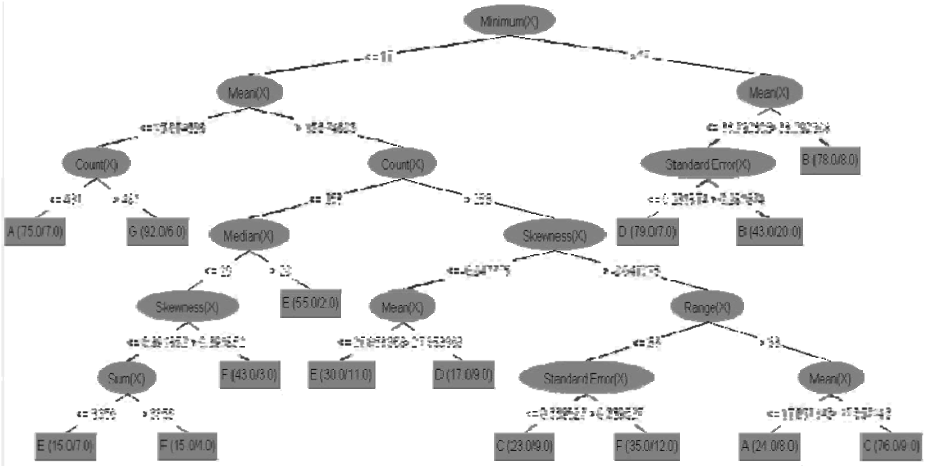

Fig. 1. Final decision tree

The following inferences were obtained from the decision tree:

- Only 11 statistical features were used by the classifier, the 'sample variance' and 'mode' does not affect the classification result; hence, they can be excluded for further study.
- 'Minimum' is the most significant descriptive statistical feature contributing towards classification.
- Through extensive analysis, the set of 'if-then' rules from the decision tree can be extracted and used as rules for fuzzy classifier.

VI. RESULTS AND DISCUSSION

The classification was carried out for the data recorded from the wrist worn accelerometer for daily activity which comprises dataset with 700 instances for 100 instances in each class. Initially the acceleration data in the X, Y and Z axis was analyzed with J48 decision tree algorithm. It was found that acceleration data in the X axis give better classification accuracy over the other for the same event.

A. Effect of features and feature selection:

The descriptive statistical features for the X axis acceleration data were extracted for the events and the classification was done. Also, every single feature may not yield higher classification accuracy. Hence, the most significant features contributing towards the classification was selected through preliminary study and was found that only 11 descriptive statistical features contribute towards the classification. The root feature of the general decision tree is the most significant feature, followed by the hierarchy of features contributing towards classification from the decision tree.

Table 3 (a) Feature Selection

Features (In the order of significance)	
1	Minimum
2	Mean
3	Sum
4	Count
5	Skewness
6	Median
7	Standard deviation
8	Standard error
9	Range
10	Kurtosis
11	Maximum
12	Sample variance
13	Mode

Table 3(b) Feature Selection

Features	Correctly Classified Instances (%)
1	38.8571
2	57.4286
3	72.1429
4	73.4286
5	77.5714
6	79.4286
7	80.4286
8	80.1429
9	80.8571
10	79.8571
11	79.4286
12	79.4286
13	79.4286

The feature selection was carried out by choosing features for classification in the hierarchy of its significance and Table-3 shows that the outcome was found that the classification yield maximum accuracy of 80.8571% with first 9 significant features. However, lesser the number of features required for classification reduce the time required for classification. Hence, the first seven most significant features were selected and were found to give80.4286%classification accuracy which does not deviate to a large extend from the maximum classification accuracy.

B. Effect of minimum number of objects

The minimum number of objects (*m*) is the most important pruning factor in J48 decision tree algorithm. The most significant '*m*' is found by varying it in the range of 1 to 100. From Fig 2 it is found that for the value of '*m*' as '1', the classification accuracy is high. However, the classification carried out with minimum number of objects as '1' cannot be standardized as it has higher level of uncertainty over filtering. Also, decision tree algorithm is proposed to have simple interpretation and better understanding over the classified event. Hence, a suitable decision tree and an acceptable classification accuracy of 78.5714% were found with '*m*' value of '15'in order to form a class.

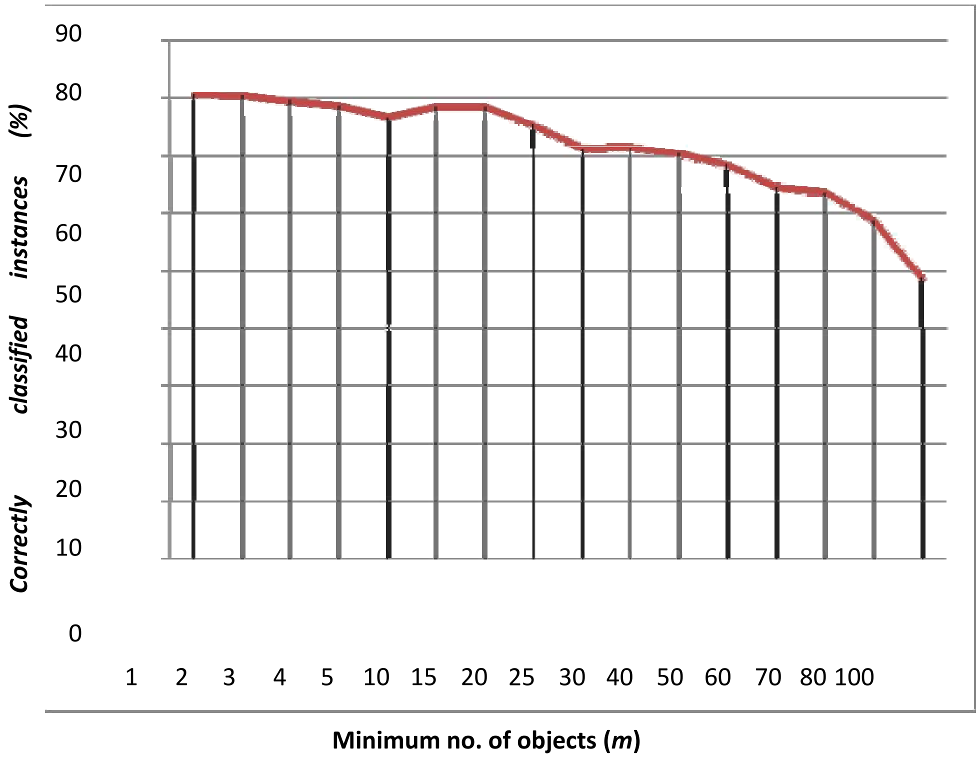

Fig 2: Effect of minimum number of object

C. Effect of confidence factor

The value of confidence factor lies between 0 and 1. The optimum value of '*c*' was found by varying 'c' within 0 and 1. From Fig 3, it was found that the classification yields maximum classification for a confidence factor value from 0.55 to 0.95. Although, value of '*c*' is chosen as 0.55 being the least and no significant change in classification can be noted for the values between 0.55 and 0.95.

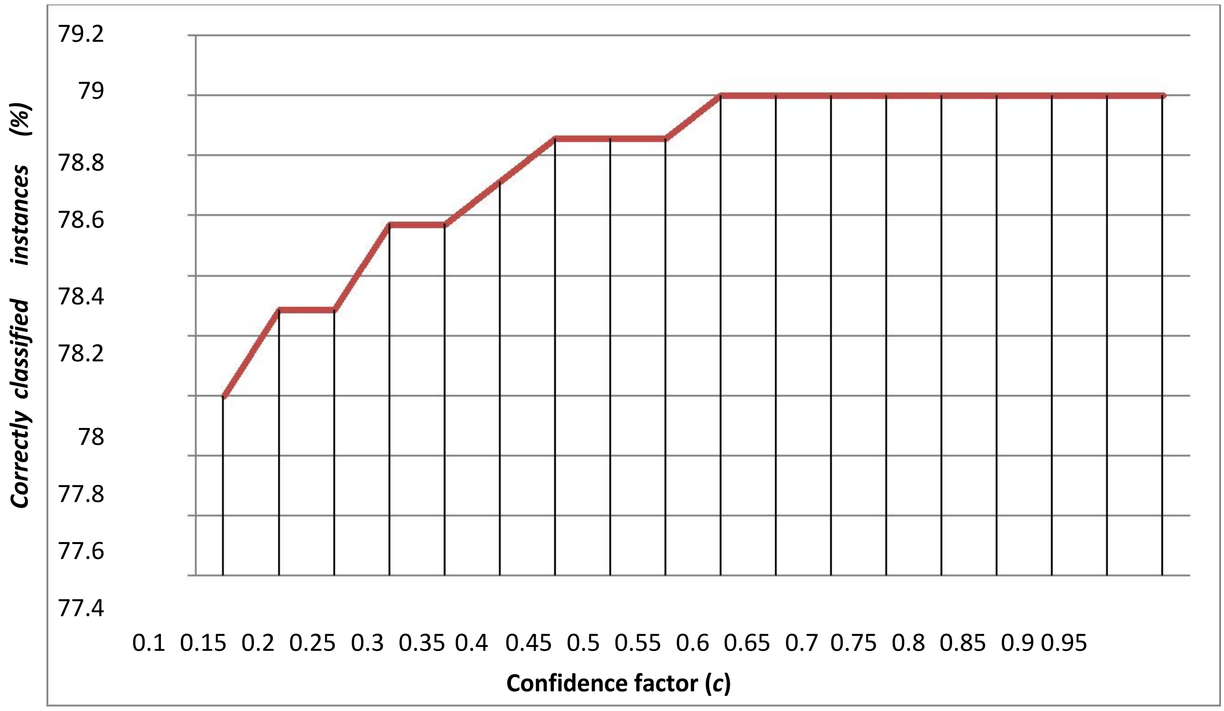

Fig3: Effect of confidence factor

The detailed class wise accuracy gives better understanding over the classification. From Table-4 true positive rate (TP rate) and false positive rate (FP rate) are shown which is of most importance. For a better classification accuracy, the TP rate should be closer to '1' and the FP rate should be closer to '0'. It is found that the built model is good.

TABLE 4. Detailed accuracy by class

	TP Rate	FP Rate	Precision	Recall	F-measure	ROC Area	Class
	0.79	0.023	0.849	0.79	0.819	0.929	A
	0.87	0.03	0.829	0.87	0.849	0.951	B
	0.8	0.052	0.721	0.8	0.758	0.942	C
	0.82	0.042	0.766	0.82	0.792	0.959	D
	0.73	0.035	0.777	0.73	0.753	0.94	E
	0.65	0.052	0.677	0.65	0.663	0.88	F
	0.87	0.12	0.926	0.87	0.897	0.941	G
Weighted Average	0.79	0.035	0.792	0.79	0.79	0.934	

The classification accuracy of the C4.5 decision tree algorithm is represented in the form of confusion matrix shown in Table-5. From the Table, the following inferences were derived:

- The correctly classified instances by the classifier are represented as the diagonal elements of the confusion matrix.
- The first element of the first row in the confusion matrix gives the number of data points belonging to the class or event "climbing the stairs" i.e. 'A'.
- The second element of the first row gives the number of data points belonging to class of "climbing the stairs (A)", however misclassified under class of "Drinking from a glass".
- Similarly, number of misclassified instances in each class can be found individually. Computing the total number of misclassified instances the total error percentage of the classification is found to be 21%.

TABLE 5. Confusion matrix

a	b	c	d	e	f	g	Classified as:
79	0	4	0	5	6	6	**a** = A
0	87	0	12	1	0	0	**b** = B
3	0	80	4	4	8	1	**c** = C
0	14	1	82	3	0	0	**d** = D
0	3	6	3	73	15	0	**e** = E
7	1	16	5	6	65	0	**f** = F
4	0	4	1	2	2	87	**g** = G

VII. CONCLUSION

Initially, the data were acquired with respect to all the three axis of the accelerometer sensor.Through the study it was found that the data acquired from the x-axis alone plays a predominant role in ADL prediction with a significant classification accuracy. The J48 decision tree algorithm was used to determine the significant features required for the prediction of an ADL and to explore the hidden information available in the acquired data. The proposed approach yields promising result and more significantly, the use of single axis sensor data which drastically reduces the computational time of the system. Besides, this reduction in computation time of the ADL recognition system gives a better scope in the development of similar technology in future.

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