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Using Non-Linear Support Vector Machines for Detection of Activities of Daily Living

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Abstract

Activities of Daily Living (ADL) refers to different daily routine type activities which includes walking, running, jogging, standing, sitting etc. Recognition of ADLs has been of considerable interest to researchers for health assessment purposes. Furthermore, since more and more people choose to live alone in their house. ADL recognition serves as the first step towards developing a monitoring system for such people. This work proposes an algorithm that can be used to perform ADL detection using three types of data from inertial sensors (accelerometer, gyroscope and orientation) captured using a smart phone using non-linear Support Vector Machines. We have used a representative dataset named MobiACT and extracting sensor readings for a 10s window, Autoregression modeling has been used to model the sensor readings and we have detected six types of ADLs using a Support Vector Machine. We achieve an overall detection accuracy of 97.45%. The given method has been tested and proven to outperform other algorithms for the purpose of activity recognition.

Keywords: Activities of Daily Living, Autoregressive Modelling, Inertial Sensor, Mobiact

1. Introduction

Activities of Daily Living (ADL) involves activities that constitute daily routines, such as walking, running, jumping, jogging, walking, eating, bathing, dressing, hopping etc. The detection of ADLs is an important task for fitness and health monitoring[1], assisted living and habit modeling[2]. Human motion analysis serves as the basis of activity recognition in the Smart Home scenario. This is applicable to both young people as well as the old, more so for the aged as with old age people tend to become less active

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which can lead to health deterioration. Moreover, old aged people may find it difficult to perform such activities and early detection of irregular patterns might point to illnesses.

Inertial Measurement Units (IMUs) have revolutionized the task of activity monitoring and recognition by allowing for the analysis of human gait to be used for this purpose. Sensors built in to these IMUs including accelerometers, gyroscopes and magnetometers combined with onboard data-processing capabilities means that the body kinematics could be estimated in near real-time. Furthermore, the ubiquities of smart phones that have these sensors built in to them provide a platform for not only the measurement but also processing of the measured data. Inertial sensors have been used before for the purpose of activity recognition as is evident from the work[3,4]. However, a big consideration in activity recognition using such sensors is the way in which the sensors are to be placed. Requiring IMU based activity recognition devices to be placed in a specific manner would hamper the usability of these devices that would make it cumbersome to be used in daily life. It is therefore necessary that activity recognition be performed in such a manner that doesn't put any positional restrictions on the way in which the devices are used. Considering this aspect, for ADL detection, we have considered the MobiACT dataset[5] which consists of three types of data from inertial sensors i.e. acceleration, gyroscope and orientation while subjects were asked to perform various activities of daily living captured using a smartphone without any directions on phone placement.

The rest of the paper is organized as follows, Section 2 provides the literature review, Section 3 discusses the MobiACT dataset that we have used in this research, Section 4 gives the methodology and Section 5 presents a discussion of the results achieved while Section 6 concludes our work.

2. Literature Review

There have been several approaches which have been previously utilized for ADL detection including cameras, thermal maps etc. we provide an overview of some works.

A dataset was introduced[6] who recorded inertial-sensor data using cellphones for detection of falls and recognition of activities. Through gyroscope and accelerometer sensors, recordings were made for nine dissimilar Activities of Daily Living (ADLs) and four different falls. They demonstrate the use of this data for activity recognition tasks.

The authors[7] proposed a threshold based method using inertial sensors for the purpose of activity recognition between running and walking. The inertial sensor used was an accelerometer. The threshold was applied on the variance of the accelerometer measurement. If the variance was below the specified value, the activity was identified as walking; else it was identified as running.

In Instance based methods with inertial sensors[8,9]. The current instance of the readings was matched with labeled instances present in the training data using K-nearest neighbors and a similarity measure was calculated to indicate to various activities.

A technique of using RGB-D cameras for recognizing ADL[10] utilized RGB-D cameras to recognize ADLs for old aged people. They show through experiments that their method works well in an indoor environment.

Kinematic features for recognizing and detecting events[11] uses the Microsoft Kinect for extracting human body joint information and perform tracking as well. These two methods can only be used indoors; moreover, they require extensive hardware deployment which reduces usability.

An activity recognition system based on inertial sensors that utilizes smart phones[12] uses acombination of logit boost, multilayer perceptron, Support Vector Machines

(SVM), J48 classifier was used that resulted in 91.15% detection accuracy with the user holding the phone in his hand. Furthermore six different types of ADLs were considered in this work. Other similar methods have been discussed[13,14].

An activity recognition solution from data containing activities of walking, jogging, running, walking up the stairs, walking down the stairs and hopping being performed by twenty seven people[15]. Twenty seven people15 places a smart phone in the user trousers' front pocket and a sampling rate of 50 Hz was used. The use of an Artificial Neural Network produced 93% accuracy in the activity recognition.

Another work[16] considered three different.... different decision tree models based on 1. The activity performed by the user and the position of the smartphone (vector), 2. Only the position and 3. Only the activity. Fifteen users were asked to perform the activities of walking, running, walking up the stairs and walking down the stairs and remaining stationary with the smartphone was put into a carrying bag, the pocket of the trouser or the hand. Samples of length of ten seconds of accelerometer readings were recorded for each different kind of activity and position of smartphone. They achieved an accuracy of 88.32%.

WISDM dataset is proposed based on a smartphone-based recognition system, in which a combination of Multilayer Perceptron, LogitBoost and J48 classifiers reached an overall accuracy of 84.90% when the user held the smartphone in his hand[17]. The volunteers were asked perform six different activities: walking, jogging, stairs up, stairs down, sitting and standing. The sampling rate for the recordings was set at 20 Hz while a window of 10 seconds with no overlap was used for feature extraction.

17 IMUs inertial sensors to determine four different activities in Parkinson's Disease (PD) patients, standing up, walking, turning and sitting down[18]. They are able to provide very high detection rates of 100%. However, the sheer number of sensors employed and the placement makes this scenario very specific.

Table 1. Different types of ADLs contained in the MOBIACT dataset[5]

Name of Activity	No. of Trials	Time period	Description
Car Step In (CSI)	6	6s	Step in a car
Car Step Out (CSO)	6	6s	Step out of a car
Walking (WAL)	1	5m	Normal person walking
Jumping (JUM)	3	30s	Continuous jumping
Stand (STD)	1	5m	Standing with precise movements
Jogging (JOG)	3	30s	Jogging
Sit chair (SCH)	6	6s	Sitting on a chair
Stairs down (STN)	6	10s	Walk down the Stairs (10 stairs)
Stairs up (STU)	6	10s	Walk up the Stairs (10 stairs)

3. MobiAct Dataset

The MobiAct dataset was developed for the purpose of developing machine learning algorithms for the detection of Activities of Daily Living and falls. It involves data recorded from 57 people in the age range from 20 to 47 while performing different types of activities and falls. Data was recorded using a Samsung S3 smartphone placed in the front pocket of the subject through the phones inertial sensors, accelerometer and gyroscope. During the capturing of the data, no restrictions were imposed on the placement of the phones which makes this dataset a representative dataset for activity recognition tasks. Table 1 lists the details of ADLs that are present in the MobiACT dataset.

4. Methodology

A three step procedure that involves preprocessing, feature extraction and classification is used in our work. Preprocessing consists of down sampling and segmentation, feature extraction includes features which are extracted using Autoregressive modelling and the last step is classification where classification is performed using non-linear Support Vector Machines as given in Figure 1. SVM has been chosen in this work as its cheap computational complexity as well as speed[19].

4.1 Pre-Processing of the Inertial Sensor Data

In the first stage, depending on the type of activity and the nature of the captured data, this may involve either one of two operations being performed.

4.1.1 Re-Sampling

Since the MobiAct dataset measurements from sensors which vary over trials in terms of sampling frequency[6]. They need to be resampled to a uniform single frequency before they can be processed. This sampling frequency was chosen to be 20 Hz and all sensor readings were resampled in this manner. Previous work in[5] has shown a sampling frequency 20 Hz to be sufficient for use in activity recognition tasks.

4.1.2 Segmentation

Trials of some activities contained various instances of the activity being performed, for e.g. standing and jogging.

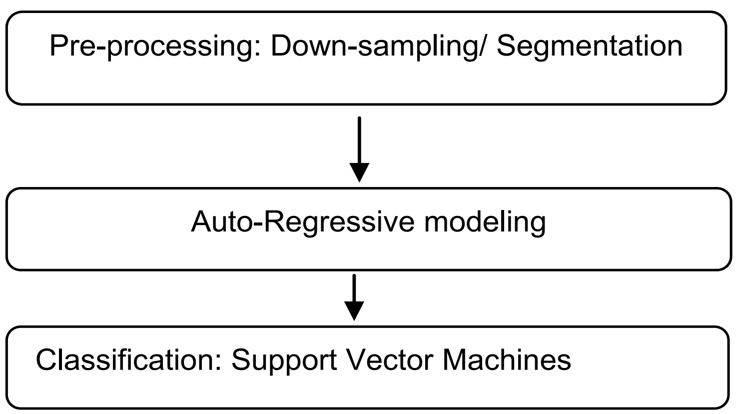

Figure 1. Flow chart of ADL detection scheme.

Table 2. Segmentation details of considered ADL signals

Name of Activity	Time Period	N.o of Subjects	N.o of Trials	N.o of Segments
Walking (WAL)	5 m	57	1	1710
Jogging (JOG)	30 s	57	3	513
Stairs Up (STU)	10 s	57	6	342
Stairs Down (STN)	10 s	57	6	342
Sit chair (SCH)	6 s	57	6	342
Standing (STD)	5 m	57	1	1710

Therefore, it was necessary to extract suitable windows of these activities for consideration. Windows of 10s were formed from individual sensor readings for each activity. The total number of Segments for each ADL activity is shown in Table 2.

4.2 Feature Extraction

An Auto-Regressive (AR) model is linear time invariant system and a digital all pole Infinite Impulse Response filter that can be used to model signals, for health[20] and also is shown to work better than statistical features[21]. The AR model results in coefficients that can be used to recreate the modeled signal. Mathematically, it is given in Equation 1

$$y(t) = \sum_{i=1}^{m} a(i).y(t-i) + \varepsilon(t) \quad (1)$$

In Equation 1, y(t-i) represents the time series under consideration, the coefficients of the determined AR model of order 'm' are given a(i). The number of previous samples which are used for the estimation of the current value of the signal is determined by m. ε(t) represents the output of uncorrelated errors. We have used the Yule-Walker method[22] to determine the ARM model. The was used to compute the AR model coefficients of order 3, therefore each sensor segment is represented by five values resulting in a combined feature vector of 36 values for all three sensor readings.

4.3 Classification

This work uses Support Vector Machine (SVM) to perform classification. The SVM is a linear classifier that attempts to fit a line between two classes of data in order to separate them and has been shown to work well in activity recognition. It finds applications in classification and regression tasks. Since the feature space of the feature set in this work is non-linear, we have used an SVM with a sigmoid kernel which is given in Equation 2.

$$\text{Sigmoid: } K(x_i, x_j) = \tanh(\Gamma(x_i - x_j) + c) \qquad (2)^{23}$$

Where Γ (Gamma) is 1/num_features, K (x_i, x_j) is the hypothesis space according to kernel, C controls the tradeoff between the margin and error and ($xi-x_j$) is difference of the Feature space.

5. Results and Discussion

To test the algorithm we have modelled each of the segmented window with a fourth order AR model and provided the coefficients of the model as input to the Support Vector Machine. Furthermore, to ensure no bias is present, we have considered an equal number of segments of each activity. Table 3 shows the confusion matrix for the classification.

From Table 3, sixty two segments of each activity were used for testing of the developed scheme. Out of the six activities considered, the activity of Standing (STD) and Walking (WAL) was recognized with an accuracy of 100% by the proposed method, with the activities of Jogging (JOG) and Sitting (SCH) being recognized with accuracies of 98.611. The activities of walking up the Stairs (STN) and walking down the Stairs (STN) were classified with accuracies of 93.055% and 94.44%. As expected, the activities involving stairs had some of the segments classified incorrectly with 3 segments of STN being classified as STU and 3 segments of STU being classified as STN. The overall accuracy of the proposed method involving autoregressive modeling and Support Vector Machines comes out to be 97.45% which is a significant improvement on previous methods using the same dataset as shown in Table 4.

It can be observed from Table 4 that the proposed method outperforms the methods of[5,17], in the activities of walking upstairs, walking downstairs, sitting and standing. However, it provides a slightly less effective performance for the activity of jogging. However, the overall accuracy 97.45% is higher than that of the work produced in[5,6]. It is to be noted that the authors in the compared work use a feature set that consists of 64 values whereas

Table 3. Confusion matrix

No. of samples of each activity	Activity Name	WAL	JOG	STU	STN	SCH	STD	Detection Percentages
72	**WAL**	72	0	0	0	0	0	**100**
72	**JOG**	0	71	1	0	0	0	**98.611**
72	**STU**	2	0	67	3	0	0	**93.055**
72	**STN**	1	0	3	68	0	0	**94.44**
72	**SCH**	0	0	0	0	71	1	**98.611**
72	**STD**	0	0	0	0	0	72	**100**

Table 4. Comparison results (% accuracy) (No overlap, 10s window size)

Activity	SVM + AR	Kwapisz et. al. (2011)	Vavoulas et.al. (2015)
Walking	100	95.314	99.810
Jogging	98.611	99.000	99.620
Upstairs	93.055	79.321	92.500
Downstairs	94.44	69.411	91.511
Sitting	98.611	94.605	98.000
Standing	100	90.421	99.410
Average	97.45	88.102	96.815

our work consist of 36 values thus it saves on the computational complexity of activity detection process.

6. Conclusion

In this work we have used measurements from the Accelerometer, Gyroscope and Orientation sensors in a smart phone to perform activity recognition. After pre-processing (resampling and segmentation) was performed, we extracted features using third order Autoregressive modelling for six different types of activities of daily living. Classification was performed using a non-linear Support Vector Machine. The results show that the proposed method improves upon previous methods of activity recognition using the same dataset. The use of data that does not require any positional arrangement of the sensing unit (in this case the smart phone) is a fundamental requirement for activity recognition tasks.

Future work in this direction is to determine the performance of individual sensors for use in activity recognition so as to determine the most suitable choice, also, another thing of interest is to use a smaller window size to speed up the recognition process.

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