

Activity recognition from body worn accelerometers - toward real-time event detection

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Abstract Inadequate physical activity is a leading risk factor in public health and inactive people are more vulnerable to having chronic diseases. In addition, levels of physical activity may be an indicator of health problems in elderly individuals, a particular problem in many societies where there is a growing ratio of elderly people. Identifying levels of physical activity may have a significant effect on reducing healthcare costs in the future. As a consequence, finding approaches for measuring the individuals' activities is a persistent need, in order to provide a view about their quality life and to observe their current health status. This may be best achieved by using low-cost wearable technologies such as accelerometer based inertial sensors. In this work, accelerometer data was projected onto a sphere of radius g (magnitude of acceleration due to earth gravitate) and the angle between the posture of the individual's trunk and the gravity vector was used together with the dot product of two successive accelerations to extract significant features from accelerometer data. Two datasets were used, the first had been collected for SPHERE project from individuals with Parkinson's disease in their home and the second is a public domain benchmark data set. Decision Trees and Naïve Bayes classifiers were used on both datasets. The classification results of a small set of activities of single individual from first dataset show that Naïve Bayes have a higher overall accuracy rate, which is 85.41% compared with 78.56% for Decision Trees. The second dataset of daily household activities is used to provide a comparison with one state-of-the-art approach in the literature. The result shows that Decision Trees with the proposed features outperform the literature approach by having an overall accuracy rate exceeded 91%.

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1 Introduction

According to the World Health Organization, inadequate physical activity is a leading risk factor in public health resulting in more than three million deaths each year [1]. In addition, a considerable number of studies showed that physically inactive people are more susceptible to chronic illnesses and may have poorer levels of health when compared to physically active people [2]–[5]. The United Nations report for world population shows that there is an increasing rate of elderly people around the world [6]. For example, in 2015, the report estimates that people aged 60 or over comprise a 12% of the world’s population and this sector of the population has grown steadily by 3.26% per year [6]. These factors cause a substantial impact on healthcare costs [7]. As a consequence, there is a persistent need for methods to assess the individuals’ activities of daily life (ADL) in order to monitor their current health status and present a view about an individual’s quality life. If early detection of specific health threat factors can be made a timely and effective intervention can be considered [8]. New intelligent technologies might enable transparent detection and evaluation of the activities of daily life [9]. Recently, there has been a noticeable interest in health monitoring by using the latest advances in wearable technology [8], [9]. This technology could be used as a way of assessing health and might enable elderly people to live independently and in safety at home [8].

Accelerometer based sensors are a widely investigated technology to facilitate research that requires monitoring of human movement and has now been adopted for assessing healthcare needs [8], [10]. Unfortunately, although much is documented in the literature on human activity recognition using accelerometers, there is little agreement on the aspects that include the number of measured axes in each accelerometer sensor, the number and placement of individual sensors, the sampling rate, the number of participants, the type and number of activities, the computed features, and the filter window type (sliding or non-sliding), design and size [10]. These differences, along with the lack of good benchmark dataset, make it difficult to compare the new approaches to existing methods.

The purpose of this paper is to propose an approach for human activity recognition, apply it to a dataset collected from a small cohort of individuals with Parkinson's disease and to compare the proposed approach with a dataset collected from unimpaired individuals [10].

2 Background

The SPHERE research project (<http://irc-sphere.ac.uk>) aims to deploy, collect and analyse data from a range of sensors in 100 residential homes in the Bristol area. A key aspect of this research is to consider the data analysis and data mining tech-

niques that will enable this data to be used by the individual, their carers, and researchers to monitor healthcare related problems [9], [11]. The project is nonspecific to specific healthcare needs but could include COPD (chronic obstructive pulmonary disease), Parkinson's disease, stroke, frailty, depression, sleep disorders, and obesity [9].

Data collection will include body-worn sensors that can operate for up to a month without recharging while transmitting key information to the house infrastructure for data storage and analysis [11]. A key hypothesis is that changes in the data characteristics over time will be indicative of health-related concerns [9], [11]. Thus, short-term change may be an indication of a medical emergency such as a fall [9], [11]. Long-term changes in the data would be indicative of an ongoing chronic medical problem that may require a change in management, for example, a change in the gait pattern of an individual with Parkinson's disease may indicate a change in drug treatment is needed [9], [11].

This paper aims to recognise different postures and ambulation for individual using the angle between the gravity vector and the posture of the individual's body and using the dot product of successive acceleration vectors. This data can be considered in the context of a sphere with a radius equal to the earth gravitational acceleration. The successful classification models could help in detection of activities of daily life (ADL) in real-time.

2.1 Related work

There is a considerable body of work in the literature on human activity recognition using inertial sensors. Most publications are based on their own dataset which is collected using a variety of different methods. Some of this literature is summarised in Table 1 which shows for each method, the conditions of collecting data, the number of participant subjects, the number of performed activities, the features and the algorithms used to classify the collected data. Due to the different approaches in the literature, it is difficult to make direct comparisons between different studies. However, the recent availability of movement datasets allows us the opportunity for limited comparison of our method across a wider set of experimental data.

Key questions are the number of sensors that should be used and type of classification algorithm. The study done by [12] showed that using one sensor placed on the human trunk can be efficient in detecting various types of fall event, with results showing up to 96.7% accuracy. However, using more than one sensor improve accuracy in recognising a number of activities of daily life [13]. In addition, [10] explained that every classification algorithm can obtain substantial accuracy for specific activities and consequently, for one method, a number of classifiers can be exploited for different activity groups' recognition.

Table 1. Summary of previous work for activity recognition.

Authors	No. Of Sensors	Sensor Placement	Sampling Rate (Hz)/ No. Of Subject/ No. Of Activities	Window Size	Extracted Features	Used Classifier
[10]	4 triaxial accelerometer & gyroscope	right wrist, chest, right hip and left ankle.	204.8/19/13	5 s with 50% overlap	minimum amplitude, maximum amplitude, mean amplitude, variance of amplitude, spectral centroid, bandwidth, energy and gravitational component of the acceleration signal.	Hierarchical classification using ADA, kNN and SVM.
[14]	5 biaxial accelerometer	right hip, dominant wrist, non-dominant upper arm, dominant ankle and non-dominant thigh.	76.25/20/20	6.7 s with 50% overlap	mean, energy, frequency domain entropy, correlation of the acceleration signals.	Decision Tree.
[15]	3 triaxial accelerometer	waist, thigh and ankle.	64/20/8	2 s with 50% overlap	magnitude of first five components of FFT analysis.	kNN.
[12]	1 triaxial accelerometer, gyroscope & tilt	chest.	-3/5	50 & 100 s	raw data and mean.	Bespoke Algorithm for real-time fall detection.
[16]	1 iPhone triaxial accelerometer & Nike+iPod Sport kit	thigh & foot.	200/8/4	1 s	magnitude, mean, standard deviation, minimum value, maximum value, min minus max, max minus min and energy.	Naive Bayesian Network.
[17]	1 triaxial accelerometer	waist.	45/6/12	1 s	median filtering and low pass filtering.	Bespoke Algorithm.

3 Data source

In preparation for deployment to residential houses in the Bristol area the Sphere project collected data from a small cohort of individuals with Parkinson's disease [18]. Data was collected in the individual's home over a period of approximately 1-2 hours during which time the individual was asked to continue his or her daily activities [18]. During this data collection period the individuals demonstrated typical activities. A suite of five accelerometers with sampling rate set to 50 Hz was used for data collection, and ground truth captured by video recording the activities. The five accelerometers were worn on the waist at the lower back, left wrist, right wrist, left ankle and right ankle. For the work presented in this paper, only the waist worn accelerometer data was used. The accelerometer data was labeled using the ELAN 4.9.3 package to categories eight key activities [18], [19]. These were sitting in a chair, standing, sit to stand, stand to sit, walking, stair-up, stair-down and turning. For the comparison purpose, the proposed method has also been applied on a data called "Benchmark dataset" that was collected by [10] which is available on (<http://www.activitynet.org>). This dataset was collected from 19 subjects for 13 activities. These activities were sitting, lying, standing, washing dishes, vacuuming, sweeping, walking outside, ascending stairs, descending stairs, treadmill running (8.3 km/h), bicycling (50 watt), bicycling (100 watt) and rope jumping.

4 Data Analysis

The data analysis recognizes that the principal measured component from accelerometer data is the omnipresent 1g field. Thus features relating to angle and magnitude with respect to this field dominate, and movement activities are effectively imposed on this data. Data from waist sensor of a single individual with Parkinson's disease was used for preliminary analysis. The data was initially processed by considering the principal movements of the individual to be in the 'sagittal plane' (i.e. forwards and backwards). The angle between the gravity vector and the pose of the individual's trunk was computed using the arctangent ('atan2' function). The axes that used as arguments for 'atan2' function are the vertical axis and the axis that point to forward or backward direction. For feature extraction, a non-sliding of 24, 48, 72, 96, 144, 192 and 240 sample window sizes with 50% overlap and same sizes sliding windows were used to determine the best window size and window type. Three features were extracted for classification which are mean, standard deviation and energy. The energy is computed by adding together the sum of the squared values for each axis, divided the addition result by three then divided by the number of samples. Classification was performed using DTs (Decision trees) and NB (Naive Bayes) separately, and validated using 10 fold Cross Validation method.

5 Results

The obtained results from both of the classification methods show that the 48 sample sliding window has better classification accuracy than the other windows, with 79% accuracy for DTs and 85% for NB. Table 1 shows that NB outperform DTs in recognition of five activities which are the ambulation acts. While the best results for stationary acts gained by TDs.

Table 2. Classification accuracy (in per cent) for DTs and NB using Parkinson's data set.

Activities	DTs	NB
Sitting	99.63	96.08
Standing	98.35	97.69
Sit to Stand	68.75	75.00
Stand to Sit	66.67	66.67
Walking	90.91	95.04
Stairs-up	87.50	100.00
Stairs-down	66.67	77.78
Turning	50.00	75.00
Overall Accuracy	78.56	85.41

As a result of the success of the 'atan2' function, addition analysis was considered to allow increase the veracity of the data. This was done by considering the projection of the gravity vector onto a sphere radius (g). Thus, static and slow movements will be characterised by points on or near the surface of this sphere, and more dynamic movements will be characterised by signature trajectories above or below the surface of the sphere. Figure (1. a, b & c) shows the projection of three of the labeled activities sitting, standing, and stand-to-sit.

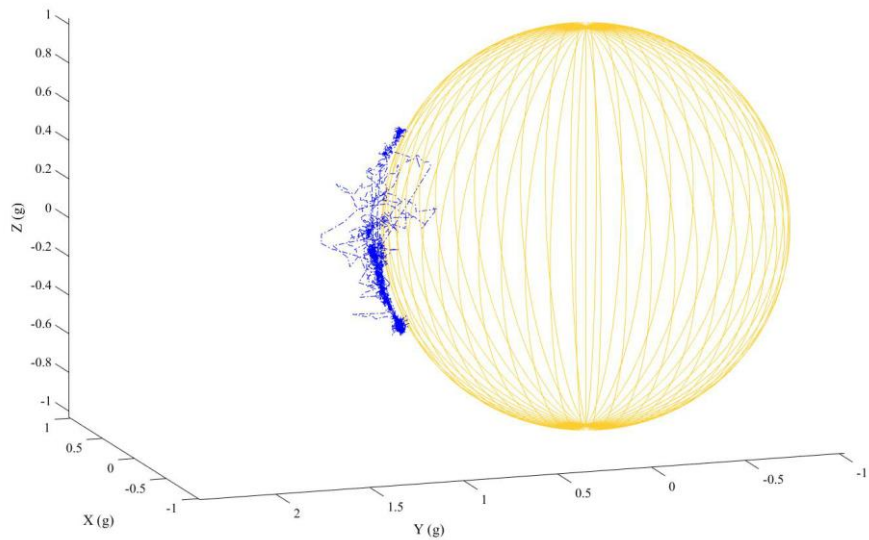


Figure 1.a projection of the waist accelerometer sensor data for sitting activity onto the sphere.

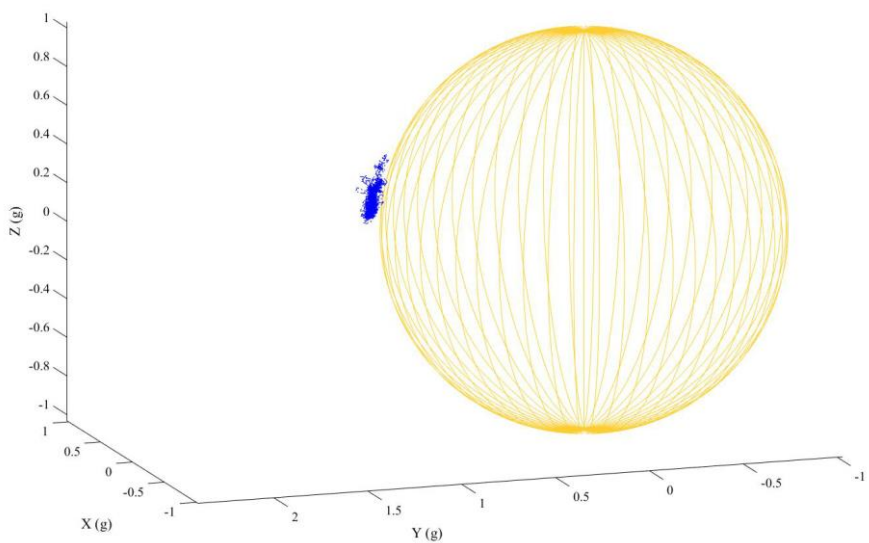


Figure 1.b projection of the waist accelerometer sensor data for standing activity onto the sphere.

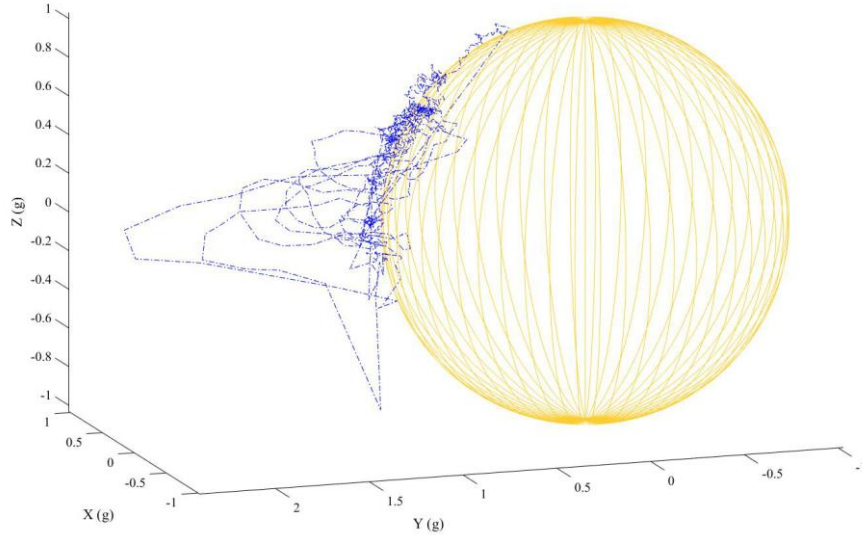


Figure 1.c projection of the waist accelerometer sensor data for stand-to-sit activity onto the sphere. Data points away from the sphere represent the accelerations needed during movement.

Observation of these activities indicates that the use of the dot product of successive acceleration vectors should be significantly useful in increasing the accuracy of classification algorithm. To examine the features gained using both ‘atan2’ function and dot product operation and for comparison purpose, a benchmark dataset collected by [10] was used.

The benchmark dataset was collected using four sensors with 204.8 Hz accelerometer and gyroscope from 19 subjects achieved 13 activities. These sensors were placed on right wrist, right hip, left ankle and chest. A sliding window of 5 second size with 50% overlap was used for analysis of the data collected by [10]. For each window, the total number of features extracted and used by [10] was 152 features for dynamic activities and 12 features for static activities.

All of the four sensors from the benchmark dataset were used in our analysis. Both of ‘atan2’ function and dot product operation were used to compute features from these four accelerometer sensors. Because those sensors placed on limbs tend to have greater range of movement, the atan2 function was computed for each pair of axes on each of the 4 sensors. This result in three values for every accelerometer. For feature extraction, a sliding windows of size 204, 408, 612, 816, 1020 and 1224 sample was used. This nearly correspond to 1, 2, 3, 4, 5 & 6 seconds respectively, with 50% overlap. For classification, three features where extracted for each accelerometer which are mean, standard deviation and energy; and mean for every gyroscope axis and energy for each gyroscope. The total number of features used in this work for all the four sensors is 52 features. Classification was performed using DTs

(Decision trees) and NB (Naïve Bayes) separately, and validated using 10 fold Cross Validation method.

The results obtained from both DTs and NB algorithms with the results of [10] approach are shown in Table 3. The results show that for DTs the 612 sample (nearly 3s) and for NB the 1020 sample (nearly 5s) sliding windows have better classification accuracy than the other windows, with overall accuracy 91.05% for DTs and 79.26% for NB. The results shown in this table and in Table 2 will be discussed in section 6.

Table 3. Classification accuracy for 13 activities and overall accuracy for DTs, NB and [10], using the benchmark dataset.

Activities	Proposed DTs	Proposed NB	Results from [10]
Sitting	95.26	13.19	88.9
Lying	97.65	95.43	100.0
Standing	95.10	90.11	89.8
Washing Dishes	96.88	97.02	98.1
Vacuuming	77.72	90.61	85.4
Sweeping	81.80	69.35	89.9
Walking	97.13	94.38	99.0
Ascending Stairs	87.59	93.75	95.5
Descending Stairs	86.30	88.09	95.2
Treadmill Running	98.62	98.03	100.0
Bicycling on Ergometer (50 W)	86.51	7.35	69.1
Bicycling on Ergometer (100 W)	87.36	95.37	53.5
Rope Jumping	95.69	97.71	100.0
Overall Accuracy	91.05	79.26	89.6

6 Discussion

In this work, two classification algorithms (Decision Trees (DTs) and Naïve Bayes (NB)) were applied separately to examine the usefulness of our proposed method to extract meaningful features of movement (dot product of acceleration and atan2). These features were used to classify activities for an individual with Parkinson's disease; and also as a direct comparison to published benchmark data from [10]. The application of DTs and NB on the waist sensor data of a single individual with Parkinson's disease has shown the advantage of the NB algorithm over the DTs algorithm for these features, with 85.41% and 78.56% overall accuracy respectively. As outlined in Table 2, from the eight activities in the dataset, DTs had the best classification accuracy when compared to NB for sitting and standing activities.

Whereas, NB outperformed DTs in recognition of success for the five dynamic activities. However, performing these two classification algorithms on a benchmark dataset using four sensors (placed on the right wrist, right hip, left ankle and chest) for 19 individuals result in outperforming of DTs algorithm over NB algorithm. As shown in Table 3, the failure of the NB algorithm was in recognition of sitting, sweeping and bicycling ergometer (50) activities, with classification accuracy 13.19%, 69.35% and 7.35% for each of them respectively. The reason for these poor results is that the misclassification particularly of SI (sitting), SW (sweeping), and BC50 (bicycle ergometer at 50 W resistance level) by the NB algorithm as shown in Table 4. The uncertainty of NB appears to be between two stationary acts, [sitting and standing] and between the matched repetitive higher-speed acts, [vacuuming and sweeping, bicycling ergometer (50 W) and bicycling ergometer (100 W)].

There was a high classification accuracy of DTs so the confusion matrix has not been shown. It is possible that this classification accuracy may be due to the correlations in features values that are picked up by the rule-based activity recognition of DTs. For instance, the DTs classified sitting and standing as activities having different angles between individual's trunk and gravity vector at the hip and low velocity at the hip, wrist and ankle sensors. It distinguishes bicycling (50 W) activity from bicycling (100 W) activity because each one of them involves different levels of velocity (moderate and high) at the ankle sensor. Also, it differentiates between sweeping and vacuuming, even though both activities show high energy in wrist acceleration because the two activity are characterised by different gravitational angles in wrist sensor. The weaker performance of NB approach may be due to its inability to adequately model such rules.

Comparing these results with the approach of [10] it can be noted that although the DTs method had an overall classification accuracy that is higher than the results shown in [10], the latter outperform the DTs method in specific recognition of nine of the thirteen activities. The better individual recognition results of [10] are probably due to the hierarchical approach used. This approach divided the thirteen activities into groups and use a SVM for the initial group classification and different algorithms to do the subgroup classification. However, for this dataset, this approach had a low classification accuracy for sitting, standing, bicycling (50 revolutions per minute) and bicycling (100 revolutions per minute). In addition, this approach used 152 features for each sliding window of dynamic activities. While our proposed method uses just 52 features for each sliding window. The high number of features could result in more computational complexity in real-time systems.

Table 4. Confusion matrix for NB algorithm of the proposed method. Boxed numbers highlight the misclassification of key activities.

	SI	LY	ST	WD	VC	SW	WK	AS	DS	RU	BC 50	BC 100	RJ
Sitting (SI)	60	7	6	0	1	2	0	0	0	0	2	0	2
Lying (LY)	45	439	2	0	0	0	0	0	0	0	0	0	0
Standing (ST)	316	14	410	7	6	0	0	0	0	0	0	0	0
Washing-Dishes (WD)	7	0	27	912	5	3	0	0	0	0	0	0	0
Vacuuming (VC)	2	0	7	10	415	196	6	0	0	0	2	0	0
Sweeping(SW)	3	0	3	11	28	516	18	0	0	1	5	8	0
Walking (WK)	0	0	0	0	0	1	1933	16	3	2	3	1	0
Ascending Stairs (AS)	0	0	0	0	1	10	32	300	26	0	4	1	0
Descending Stairs (DS)	0	0	0	0	2	15	57	4	244	9	1	0	0
Treadmill Running (RU)	0	0	0	0	0	0	2	0	1	897	25	0	0
Bicycling 50 (BC 50)	0	0	0	0	0	0	0	0	0	0	68	33	3
Bicycling 100 (BC 100)	0	0	0	0	0	1	0	0	0	0	814	886	1
Rope Jumping (RJ)	22	0	0	0	0	0	0	0	3	6	1	0	256

Nevertheless, this method has been applied on two different datasets, one acquired from an individual with Parkinson's disease and the other from 19 young healthy individuals. The results show that the use of a number of sensor with both accelerometer and gyroscope have a substantial impact on the classification accuracy for all activities rather than the use of single accelerometer sensor. An improvement on the proposed method might be achieved by exploiting a number of classification algorithms. The use of the combination of different classification algorithms applied on the proposed features with different window sizes may result in higher classification accuracy as well as real-time recognition system for activities of daily live (ADL). There is a difference between window sizes of the DTs and NB to achieve the best results from both the Parkinson's and the benchmark datasets. There are many possible causes but it should be noted that the Parkinson's data set was collected in a home environment while the benchmark data collected in a purpose built laboratory.

7 Conclusion

This paper considers the recognition of a small set of activities based on accelerometer data from an individual with Parkinson's disease. A novel feature set is considered and a benchmark dataset of daily household activities is used to provide a comparison. Since accelerometers are primarily in a 1g environment it is relatively easy to compute the angle between a sensor worn on the individual's trunk and the gravity trajectory, and this together with the dot product of successive acceleration vectors provide significant features for recognising a person's activities using accelerometry. A decision tree classification method with sliding window of size nearly 3 second was shown to be significantly better than a Naïve Bayes approach. This study shows that the inclusion of data from additional sensors placed on the person's wrist and ankle improves the classification process and will lead to enhancing the results, particularly for classification of walking activities. A multi-level classification system that exploits several algorithm with different window sizes, will be exploited in future work to increase recognition accuracy.

It is clear that better knowledge of the underlying cause of the data will lead to the higher veracity of information transmitted at a lower rate. This is particularly important in the case of long term ambulatory wearable sensors where data must be transmitted from the individual to a base station through a low energy channel at a low bit rate.

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