Physical Activity Recognition of Elderly People and People with Parkinson's (PwP) during Standard Mobility Tests using Wearable Sensors

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***Abstract*—Physical activity recognition plays a vital role in the application of wearable sensors in healthcare. This paper explores the capability of machine learning algorithms to recognise activities of healthy elderly adults and people with Parkinson's (PwP) using wearable sensor data. We examined the potential of triaxial accelerometer alone and with gyroscope for activity recognition. We employed a comprehensive study of several features and classifiers for recognising different activities. The random forest algorithm identified physical activities among elderly people and PwP with an accuracy of 92.29% when both accelerometer and gyroscope sensors used at the same time.**

***Index Terms*—Activity recognition, Parkinson's, wearable sensors**

I. INTRODUCTION

Physical activity recognition using machine learning algorithms trained on data from wearable sensors has a crucial role in several applications such as fall detection. If we can monitor people using unobtrusive sensors, we may soon be able to review and check their activities over a long period of time. We also may be able to understand more about changes in their health state such as deteriorating mobility and balance. Movement parameters obtained from wearable sensors might also reveal subtle changes which are harder to identify clinically in the early stage of neurodegenerative diseases such as stroke or Parkinson's and thus assist in diagnosis.

The aim of this study was to examine whether machine learning algorithms trained on data of tri-axial accelerometer alone or with Gyroscope could identify human physical activities. In this study, we developed our algorithms using a cohort of healthy older adults participants and Parkinson's (PwP) performing validated clinical tests. We chose this cohort of people because they have very different movement patterns while performing physical activities in comparison to young participants.

II. RELATED WORKS

In this section, we reviewed prior work of activity recognition using wearable sensors; and explain the difference between our method and the current works in the literature. Among a large body of work on activity recognition these studies [1], [2], [3] and [4] concentrated on activity recognition for PwP. Most of the studies evaluated their systems using data from young and healthy participants. But, our algorithms have been developed using a cohort of older participants and a disease-specific, PwP.

III. METHODS

In this study, we explored the use of wearable sensors for automatic identification of activities performed by participants in the laboratory. The flowchart in Figure 1 presents an overview of proposed activity recognition study, which includes four main levels: data collection, pre-processing, activity recognition and evaluation.

A. Data collection

10 healthy elderly volunteers (mean age 75 years) and two PwP (mean age 76 years) participated in our study. They performed six various mobility tests in the laboratory including Tandem walk [1], stand to sit, sit to stand, standing, backwards walking test and 3m walk. Each activity was performed three times. We collected participants movement by a video camera and a wearable sensor (includes an accelerometer and a gyroscope, set to capture three axes at 50 Hz) attached to participant's lumbar spine as shown in Figure 2. This sensor's position is near to the centre of mass of the body thus can considerably indicate various human activities.

B. Pre-processing

We segmented the recorded video and sensor data using ELAN annotation software[2] according to activities. Each activity was then further segmented to sliding windows of 2s (100 samples) as most studies used 2-3 s window size in order to drive their features. We obtained several features, time

[1]During Tandem walk participants were asked to walk 10 steps while at each step the toes of one foot touching the heel of the other foot [5].

[2]https://tla.mpi.nl/tools/tla-tools/elan/

978-1-5386-2524-8/17/$31.00

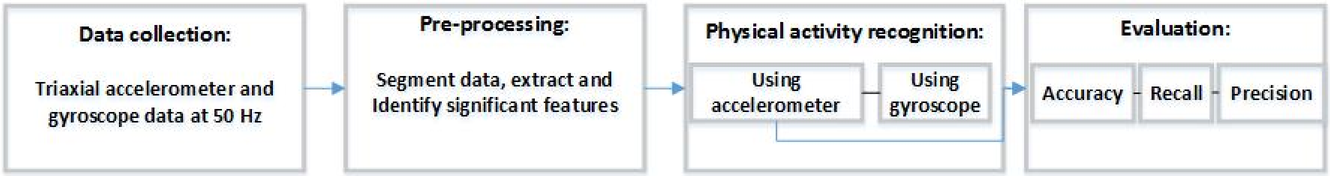

Fig. 1. Physical activity recognition framework.

Fig. 2. An example of an elderly participant wearing a wearable sensor while performing physical activities in the laboratory.

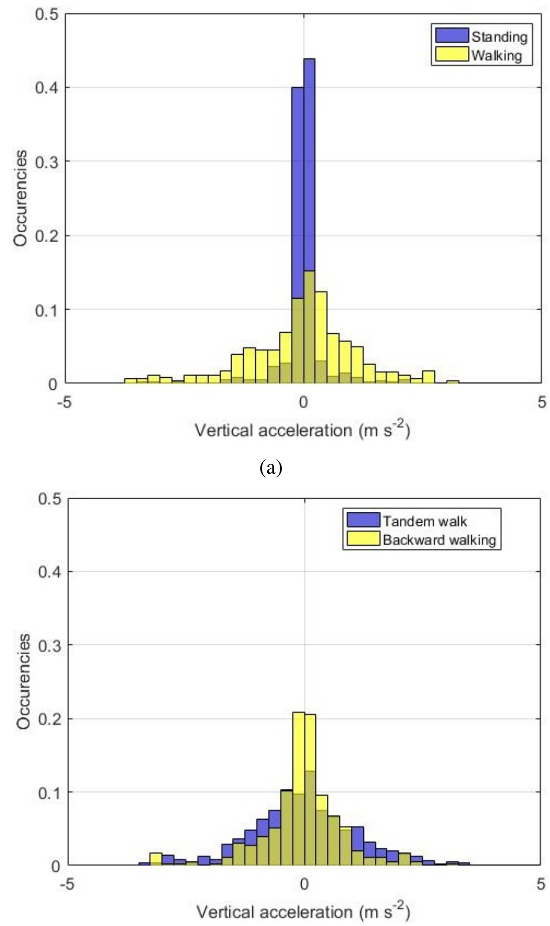

Fig. 3. Normalised histograms of (a) 3m walk and standing activities and (b) Backward walking and Tandem walk, presenting RMS feature can be used for recognising standing and walking activities in (a).

and frequency-domains from each window generating a feature vector. These features are summarised in Table I. This feature vector was then used to train the classifiers.

For instance, mean and Root Mean Square (RMS) value of acceleration could be used as simple statistical features. The RMS value can be used to classify walking from standing activities as shown in Figure 3(a). However, backward walking test and Tandem walk may have very similar features that cannot be separated easily using these statistical features, see Figure 3(b).

To investigate the importance of each sensor (accelerometer and gyroscope), we extracted features from the accelerometer and gyroscope data and utilised them to identify activities in two cases: individually and concurrently. Various feature selections methods were tested to eliminate redundant features such as correlation based feature selection, forward and backwards features selection methods and a wrapper feature selection method based on random forest algorithm. We utilised the WEKA toolkit [26] [3] for implementing these feature selection methods. By using feature selection methods, we were able to identify specific features which were unique to each activity performed in this study, these features were less correlated between activities and therefore less likely to confuse recognition of one activity from another.

[3]http://www.cs.waikato.ac.nz/ml/weka/

C. Activity recognition

We examined several machine learning algorithms and feature sets to identify the most reliable activity recognition technique. These machine learning algorithms include Naive Bayes [27], LogitBoost [28], random forest [29] and Support Vector Machine (SVM) [30]. For training and testing of these machine learning algorithms, a 10-fold cross-validation was utilised. The precision, recall and accuracy were used to find the algorithm that performers the best for activity recognition.

TABLE I
EXTRACTED FEATURES FROM THE DATA FOR PHYSICAL ACTIVITY RECOGNITION. THE THREE AXES OF THE ACCELEROMETER AND/OR GYROSCOPE WERE CONSIDERED INDEPENDENTLY AS A FEATURE. FOR POWER SPECTRAL DENSITY, LOCATIONS AND POWER LEVELS OF HIGHEST SIX PEAKS WERE EXTRACTED AS FEATURES. TOTAL POWER IN FIVE PREDEFINED FREQUENCY BANDS (0.5-20) WERE UTILISED AS SPECTRAL POWER FEATURES.

Feature	Method 1	Method 2	Studies
Mean (μ)	μ_{Acc}	μ_{Acc} & μ_{Gyro}	[6]
Autocorrelation (r)	r_{Acc}		[7]
Power spectral density (P)	P_{Acc}	P_{Gyro}	[8]
Spectral power (s)		s_{Acc}	[9], [10]
Entropy (En)	En_{Acc}	En_{Acc} & En_{Gyro}	[11], [12]
SumPowerDetCoeff ($SPDC$)	$SPDC_{Acc}$		[13], [14]
InterQuartile range (IQ)		IQ_{Gyro}	[14], [6], [15], [16]
Spectral variance (Sv)		Sv_{Gyro}	[17]
Main frequency (Mf)	Mf_{Acc}	Mf_{Acc} & Mf_{Gyro}	[18]
Intensity (Int)	Int_{Acc}	Int_{Acc}	[19]
Zero-crossing rate (Zcr)	Zcr_{Acc}	Zcr_{Acc}	[20], [6]
Skewness (Sk)		Sk_{Gyro}	[10], [21], [22]
Correlation coefficient (CC)	CC_{Acc}	CC_{Acc} & CC_{Gyro}	[23], [24], [25]

TABLE II
THE PERFORMANCES OF THE ACTIVITY RECOGNITION USING DIFFERENT CLASSIFICATION METHODS.

Naive Bayes	**Accelerometer**	**Accelerometer & Gyroscope**
Precision	0.98	1.00
Recall	0.98	0.97
Average accuracy	78.39	81.24
LogitBoost	**Accelerometer**	**Accelerometer & Gyroscope**
Precision	0.98	0.99
Recall	0.90	0.99
Average accuracy	87.63	89.69
Random forest	**Accelerometer**	**Accelerometer & Gyroscope**
Precision	0.99	0.99
Recall	1.00	0.99
Average accuracy	89.91	92.29
SVM	**Accelerometer**	**Accelerometer & Gyroscope**
Precision	0.91	0.95
Recall	1.00	1.00
Average accuracy	82.17	84.17

IV. RESULTS

As shown in Table II, random forest algorithm best identified the physical activity of elderly people and PwP during standard mobility tests with an accuracy of 89.84% using accelerometer data and 92.29% using both accelerometer and gyroscope data. The LogitBoost gives the best results after random forest with an accuracy of 87.63% (using accelerometer) and 89.69% (using accelerometer and gyroscope) respectively. The Naive Bayes algorithm shows the lowest accuracy with 78.39% using the accelerometer and 81.24% using both accelerometer and gyroscope data which is consistent with the result reported by Safi et. al [31]. As can be seen in Table II, using both accelerometer and gyroscope data in the feature vector can improve the accuracy of classification algorithms.

When we used both accelerometer and gyroscope data, the most informative feature sets were obtained equally from both acceleration and angular velocity. For acceleration data, the features derived along the vertical axis were the most informative features. However, for angular velocity, features were mostly along the horizontal posterior-anterior direction.

The confusion matrix (presenting the true activity class vs. the predicted class) of the random forest classifier is illustrated in Tables III and IV. The backwards walking test was confused with the Tandem walk test as it included a component of walking. If we are going to monitor people for a long period of time at their home, it is very rare that people perform Tandem walk activity.

V. CONCLUSION

We evaluated machine learning algorithms for identifying activities of elderly people and PwP based on data obtained using low-cost wearable sensors. We assessed the power of accelerometer alone or in conjunction with gyroscope for physical activity identification. Results show that the use of both sensors concurrently can improve the accuracy. The performance of activity recognition methods using decision tree algorithm showed the best accuracy. We would like to test the proposed system when people perform activities at home for a longer period of time and on a larger study.

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TABLE III
CONFUSION MATRIX OF RANDOM FOREST FOR PHYSICAL ACTIVITY RECOGNITION USING ACCELEROMETER DATA.

Random forest	Standing	3m Walk	Tandem walk	Backwards	Sit to stand	Stand to sit
Standing	1.00	0.00	0.00	0.00	0.00	0.00
3m Walk	0.00	0.67	0.28	0.04	0.00	0.00
Tandem walk	0.02	0.03	0.90	0.05	0.01	0.00
Backwards	0.05	0.00	0.56	0.38	0.02	0.00
Sit to stand	0.00	0.03	0.13	0.00	0.70	0.13
Stand to sit	0.00	0.03	0.23	0.00	0.03	0.70

TABLE IV
CONFUSION MATRIX OF RANDOM FOREST FOR PHYSICAL ACTIVITY RECOGNITION USING ACCELEROMETER AND GYROSCOPE DATA.

Random forest	Standing	3m Walk	Tandem walk	Backwards	Sit to stand	Stand to sit
Standing	0.99	0.00	0.00	0.00	0.00	0.00
3m Walk	0.00	0.84	0.15	0.01	0.00	0.00
Tandem walk	0.00	0.02	0.94	0.04	0.01	0.00
Backwards	0.05	0.00	0.52	0.41	0.02	0.00
Sit to stand	0.00	0.03	0.17	0.00	0.80	0.00
Stand to sit	0.00	0.00	0.17	0.07	0.00	0.77

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