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Huntington's Disease Assessment Using Tri Axis Accelerometers

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Abstract

Huntington's disease (HD) is a progressive inherited neurodegenerative disorder, causing involuntary movement and cognitive problems, severely affecting the quality of life. Controlling upper limb function is a core feature of daily activity and can prove problematic for people with HD. The Money Box Test (MBT) has been developed with a purpose of quantifying the involuntary movement frequently seen in people with HD. In this research, wearable and highly sensitive accelerometers are used to collect the acceleration of the hands and chest during the performance of the MBT. Using this data, a new approach is proposed to automatically classify the participants into two classes, healthy and HD, on the basis of the time series accelerometer data. A set of 90 time domain features is extracted from the accelerometer data, a feature selection technique is used to analyse the feature significance and to reduce the dimensionality of the dataset, and finally an SVM classifier is used to classify subjects into healthy and HD classes. The data of seven healthy controls and 15 HD patients are used in this study. The highest accuracy with the most significant eight features is 86.36% with the sensitivity and the specificity values being 87.50%, and 83.33% respectively.

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Keywords: Huntington's disease, Money Box Test, Upper limb movement, Triaxial accelerometer.

1. Introduction

Huntington's disease (HD) is a progressive neurodegenerative genetic disorder caused by a cytosine-adenine-guanine (CAG) repeat mutation in the HTT gene [1,2,3]. This results in degeneration of the striatum, the largest component of the basal ganglia. This is a group of nuclei located in the cerebrum highly connected to virtually all regions of the brain.

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One of the symptoms associated with HD is impairment in motor control, categorised by chorea and dystonia. This, combined with the cognitive and behavioural symptoms [1] can affect common daily activities such as multitasking. The onset of disease is diagnosed clinically when motor abnormalities begin, termed "motor manifest" which is typically between 30-50 years of age. However, cognitive and behavioural symptoms [3] can be detected many years (even decades) prior to motor symptoms which progressively impacts the quality of life of people with HD. As there is currently no cure for HD, most of the current research in this area focuses on identifying the deficits at the early stage of the disease, in order to benefit from future medical interventions that may help delaying the progress of the disease [4].

Upper limb dexterity is a core component of hand function and loss of dexterity can impact upon the completion of daily activities such as eating and getting dressed. Many of these tasks are often carried out whilst doing other tasks, such as talking, which for someone without neurological impairment may be considered easy [5]. However, for people with a neurological disorder, such as HD, added cognitive load can result in reduced performance in either one or both tasks being performed [6]. As the basal ganglia is heavily involved in the automaticity of movement [7], it is likely that degeneration of this neural circuitry in people with HD results in decreased automatic control of movement. This may then lead to an increased requirement for cognitive resources to control movements, thus limiting the attentional capacity for any additional, concurrent tasks. In terms of daily activity, this is not only dangerous under certain conditions but can also affect the quality of life of an individual. Many HD studies relentlessly look for ways to slow the progression of disease and improve the quality of life. With this in mind, sensitive, quantitative outcome measures are essential and must be designed and utilised to accurately detect any improvement in disease symptoms, such as upper limb and cognitive function, following an intervention.

The Moneybox test (MBT) is a newly developed multi-task assessment of bilateral, upper motor function aiming to tackle the lack of quantitative functional outcome measures specific to symptoms associated with HD. This relatively simple task is unique as it can be used individually as a single, dual or triple task or as a three test assessment with added difficulty. The MBT is currently being validated in people across all stages of HD, with the aim for it to be used as a sensitive outcome measure for people with HD and potentially other neurological diseases in the future.

Recently, wearable sensors have been used for diagnostic as well as monitoring applications [8,9]. Accelerometers are an example of this kind of sensors, they measure the acceleration of moving objects. With the advances of sensing technology, accelerometers are now capable of collecting and storing acceleration values with high sampling frequency over long periods of time. Therefore many studies have used accelerometers for activity recognition, sleeping patterns and lifestyle monitoring, diagnostic applications, and rehabilitation monitoring [10,11,12]. Effective algorithms are needed to extract the patterns from this data in a meaningful way; machine learning techniques have been shown to be very effective in classifying accelerometer data [13].

This paper introduces a new approach to automatically classify the subjects into healthy and HD using accelerometers during the MBT. To achieve this purpose, the proposed algorithm employs signal processing techniques, feature selection methods and automatic classification techniques. The data of seven healthy controls and 15 people across all stages of HD were used in this study. The highest accuracy with the most significant eight features is 86.36% with the sensitivity and the specificity values being 87.50%, and 83.33% respectively.

2. The Money Box Test (MBT)

The MBT is an assessment test that focusses on bilateral, upper motor function recently developed at Cardiff University. It has been developed in accordance with translational neuroscience and physiological principles, aiming to tackle the lack of quantitative and functional outcome measures available for the broad disease manifestation witnessed in people with HD, figure 1 to show Moneybox test contents. During the test subject is asked to sit in a hard backed chair with the moneybox positioned in front of him/her. Eight tokens are set in decreasing order of size from the top to the bottom. The subject is asked to take each token using the non-dominant hand, pass it to the dominant hand and put it in the box; he/she is asked to do that as quickly as possible. The subject is asked to stay as still as possible throughout the test. During the baseline MBT, the subject is asked to transfer the tokens in order of size only, while during the dual task MBT the subject is asked to transfer the tokens in order of their value, starting with the highest value to the lowest value as quickly as they can. During the triple task MBT, the subject is asked to transfer the tokens in order of their value whilst simultaneously reciting the alphabet as fast as they can. In this paper only the data from the baseline MBT is used.

Fig. 1: The Moneybox test enclosed in the case when not in use (left) and open ready for testing (right)

3. Experimental setup

This section introduces the proposed approach to analysis and classification of the acceleration data, describes the main stages of this approach in detail: data collection, data analysis. Finally, it presents the produced results.

3.1 Data collection

Three GENEActiv triaxle accelerometers (Activinsights Ltd, Cambridgeshire, UK) have been used to capture the movement of the subjects during the MBT. The number of subjects recruited for the test was 22, out of which 15 were HD patients and 7 were healthy controls. The average age of each group is 48.5 and 25.6 respectively. For the MBT tests, every participant wore one accelerometer on their right wrist, one on their left wrist and one in the center of the chest. A sampling frequency of 100 Hz is used to collect the data, uploaded accelerometer data is converted to 15s epoch .csv files using GENEActiv PC software. The data is a time stamped stream of the acceleration in three dimensions (X, Y, and Z). Figure 2 shows a sample of the

accelerometer data; Figures 1 a, b, and c show healthy subject's left hand, right hand, and chest acceleration signals, while Figures 1 d, e, and f show the HD patient's data.

3.2 Data analysis

This section explains the main stages of the system and the main purpose of each stage. Figure 3 shows the system diagram consisting of three main stages: feature extraction, feature selection and classification stages. The process starts by extracting from the raw acceleration data a set of features that can represent the movement signature of a patient. In previous research, a variety of features have been used to represent the nonlinear signals such as motion acceleration. Based on an extensive literature review, a set of 90 time domain features is extracted for each subject; ten features foreach of three axis of the three accelerometers.

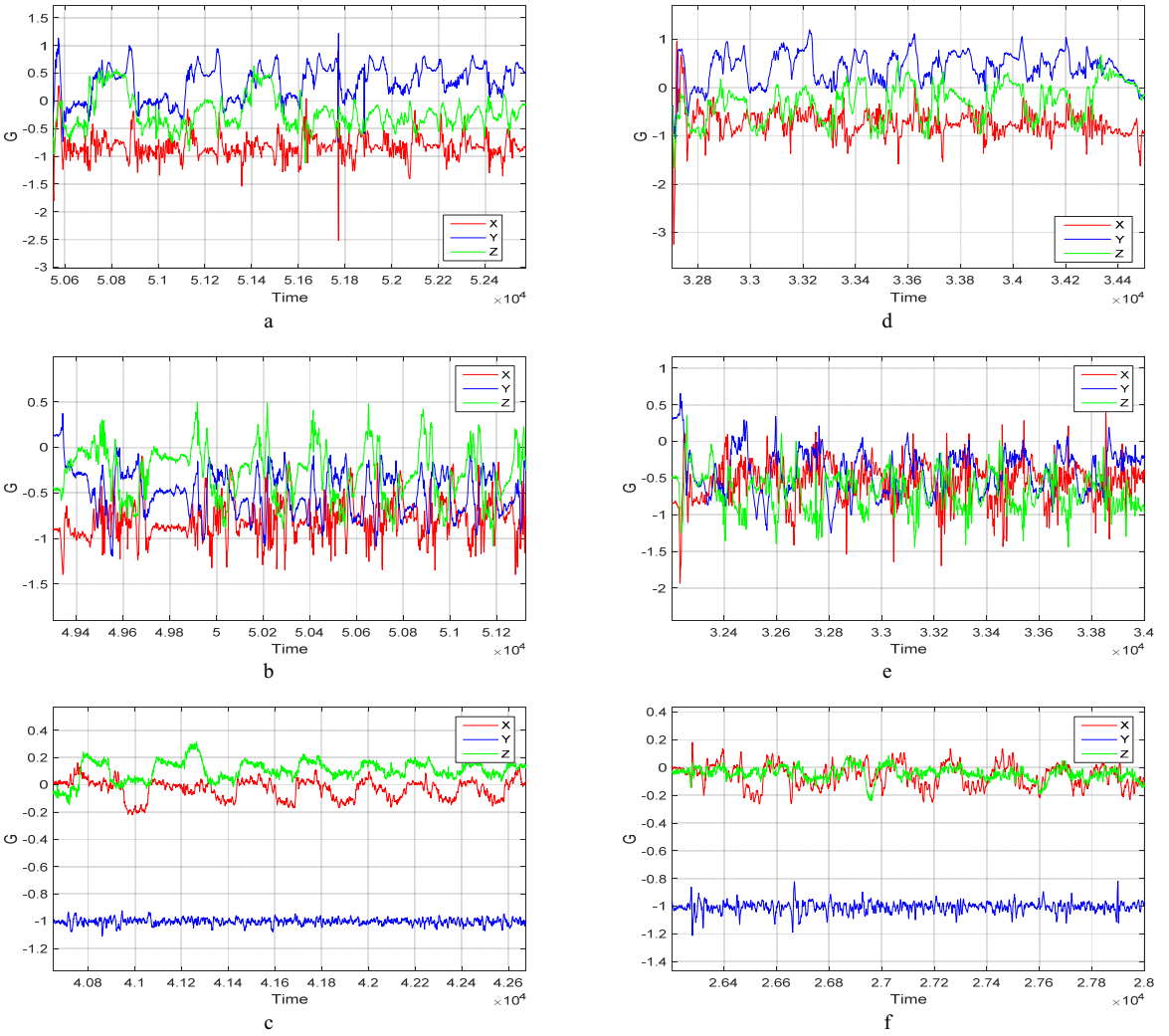

Fig. 2. a, b, and c show healthy subject's left hand, right hand, and chest acceleration signals, d, e, and f show the HD patient's data.

Employing nonlinear analysis techniques to acceleration data exhibiting complex behaviour, may provide insight about the movement signature. Recurrence Quantification Analysis (RQA) [14] can provide useful information regarding the pattern and structure of the signals even for the non-stationary data. Four features can be extracted based on RQA: Recurrence rate in the signal, recurrence structure complexity, ratio of recurrence points, and average time that signal segments remain the same. Another nonlinear parameter is used to quantify the chaotic behaviour of the signals; Lyapunov exponent (LE) [15] is a typical measure of the chaos. Finally, two features measure the complexity of the signal; Sample entropy [16], and Permutation entropy [17]. Table 1 shows the list of the extracted time domain features.

Feature selection is a technique used to analyse the significance of features for classification tasks. It is an important tool for reducing the dimensionality of a dataset and improving the performance of automatic classification algorithms by selecting the features with high discriminative ability, consequently rejecting insignificant or redundant features [18].

Filter feature selection methods are common methods because of their simplicity and computational efficiency, and in addition they are classifier-independent techniques. Many measures are used to analyse the feature significance such as Mutual Information [19] which is widely used measure; it measures the amount of information the feature shares with the class label.

The proposed approach employs a recently developed feature selection method, Joint Mutual Information Maximisation (JMIM) method [20]. This is a nonlinear filter technique that employs the joint mutual information and maximum of the minimum criteria. The method has been reported to outperform the state of the art methods. The method selects the features that maximise the following formula:

$$f_{JMIM} = \arg\ max_{f_i \in F-S}(min_{f_s \in S}(I(f_i, f_s; C))) \quad (1)$$

Where F is the original feature set, S is the selected subset feature, f_i is the candidate feature, f_s the selected feature.

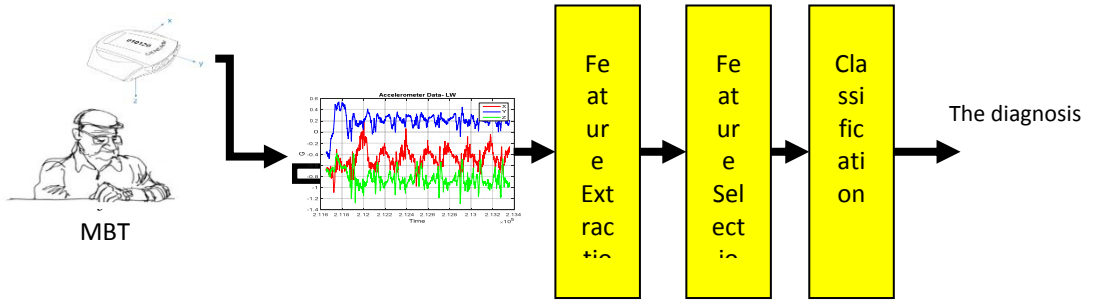

Fig. 3. The proposed automatic classification system

The selected features are used to train an SVM classifier with linear kernel from the Matlab Statistics Toolbox. Classification accuracy, sensitivity, and specificity are used as the performance measures of the proposed approach. The classification accuracy is tested using leave one out cross-validation; training and testing are performed after adding each feature to the subset. Therefore, the produced classification accuracy, sensitivity, and specificity reflect the discriminative power of the whole subset after adding the new selected feature and is not based on the newly selected feature only.

Table 1. The list of the extracted time domain features

Feature	No. of attributes per subject	Feature description	
Recurrence rate	9	It is the Recurrence rate in the signal, the probability that any state will recur again.	Recurrence Quantification Analysis (RQA)
R_ Entropy	9	Measure the recurrence structure complexity	
Determinism	9	It is the ratio of recurrence points	
Average Diagonal line	9	Average time that signal segments remain the same.	
LE	9	Lypaunov exponents, it measures the level of chaos in the time series signal	
Sample entropy	9	Assesses the complexity of the time series signal	
Permutation entropy	9	Assesses the complexity of the time series signal	
Standard deviation	9	The standard deviation of the time series signal	
Mean	9	The mean of acceleration signal	
Correlation between axis	9	Correlation between each two axis for each accelerometer	

3.3 Results

The most 10 significant time domain features are shown in Table 2. Sample entropy and Lypaunov exponent are shown as the most important measures for the discrimination between healthy control and HD subject. The result shows that the level of chaos for right and left hands is a powerful measure. For the chest accelerometer, the complexity level of the chest sensor signals is important, the correlation between the chest Y axis and Z axis is shown to be significant as well as the mean of chest X axis. Due to the chorea and dystonia, HD patient are likely to make uncontrollable limb movements, this type of movements are reflected as a chaos in the accelerations signals. The chest accelerometer showed that the HD patients tend to lean forward during the test.

The results of the classifiers with time domain features are shown in the following Figures; Figure 4 shows the classification accuracy of the SVM classifier, with the highest accuracy of 86.36% achieved using the most significant 8 features. Figure 5 shows the corresponding values of sensitivity and the specificity, which are 87.50%, and 83.33% respectively.

Table 2. The ten most significant time domain features

No	Feature
1	Chest Sample entropy X axis
2	Left hand Lypaunov exponents Y axis
3	Right hand Lypaunov exponents X axis
4	Left hand Lypaunov exponents Z axis
5	Left hand Lypaunov exponents X axis
6	Right hand Lypaunov exponents Y axis
7	Chest Y axis and Z axis correlation
8	Right hand Lypaunov exponents Z axis
9	Chest Sample entropy Y axis
10	Chest X axis mean

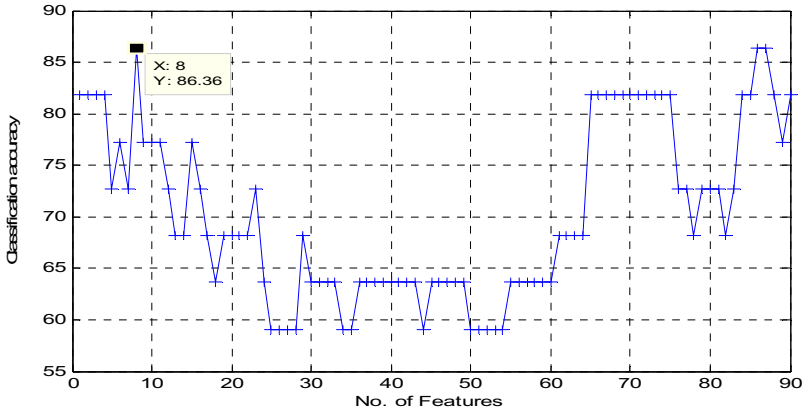

Fig. 4. Classification accuracy

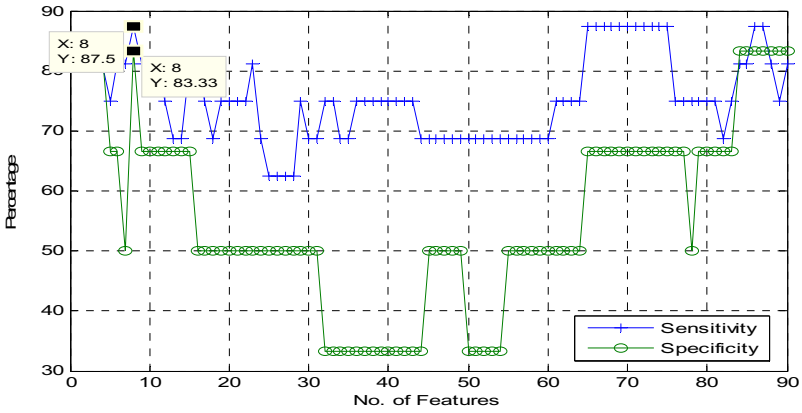

Fig. 5. Sensitivity and specificity

4. Conclusion and future work

This paper presents the results of research aimed at using accelerometers to assess the severity of some of the functional symptoms associated HD patients. A set of 90 time domain features has been extracted for each subject from the data collected using three accelerometers, which were used to describe the movement signature of each of the assessed subjects. State of the art feature selection method was used to identify the most important features for the purpose of discriminating between healthy and HD cases. The results of the experiments with 22 participants indicate that the most important features, which provide high level of classification accuracy are: the features measuring the level of chaos in the raw accelerometer data (Lyapunov exponent) for the right and left hand accelerometers, the features measuring the complexity of chest accelerometer signals (sample entropy) as well as the correlation between the axis of chest accelerometer. The

results also show that the subset of the most significant 8 features produce high accuracy as well as high sensitivity and specificity values.

Future work includes research on extracting frequency domain features, high level features, such as the time of each take and release task, trajectory of the hand movement and orientation of the hands. It is also important that the proposed approach is tested with a larger number of participants and that features and classification are translated into terms that are accessible to patients and clinicians to allow engagement and compliance with a resulting clinical tool.

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