Assessment of Severity of Huntington's Disease Using Discrete Wavelet Transform

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Abstract*—Neurodegenerative diseases affect Central Nervous System resulting in gradual reduction of cognitive abilities and personality changes. Huntington's disease (HD) is one of the neurodegenerative disease which results in abnormal body movements known as chorea and decreased muscle coordination. In this paper, Discrete Wavelet Transform is used for the analysis of patients with HD to determine the severity of disease. Gait data has been used for the analysis of disease. Two separate data sets have been used; one with healthy control subjects and another with HD. Using data of control subjects, a threshold value have been obtained. Based on this threshold, range of values has been identified for the classification of severity of disease.

***Keywords*—Gait Assessment, Huntington's Disease, Neuro Degenerative Diseases, Severity, Signal Processing**

I. INTRODUCTION

Huntington's disease is one of the progressive neurodegenerative disorders that typically affect a person in his age of 35 to 45 years [5]. It causes involuntary muscle movements and loss of cognitive abilities. This affects the person's ability to handle day to day activities [7]. As the disease progresses, patients gradually loose the automatic control of movements and they become completely dependent on care givers. HD is an inherited disease and early diagnosis of this disease is very important so as to reduce its rate of progress [14].This disease is incurable [10] but, rate of progress may be reduced by using proper medication. Computer aided analysis may help in automatic analysis of biomedical signals and reduces variations of results across medical practioner [11]. In this paper an attempt is made to automatically classify pathological subjects into various categories depending on the level of severity of disease.

II.METHODOLOGY

The present study uses gait database for the analysis and determination of severity of Huntington's disease. Gait data is chosen as it is non invasive method and does not cause any discomfort to the patient. Another advantage of this data acquisition is patient can record the data as and when it is required. The collection of gait data was contributed by Hausdorff et al. [1] and it is downloaded from the web page of Physionet [8]. This data set consists of 5 minutes of recording of gait signals consisting of 45,000 samples of both normal control subjects and pathological subjects suffering from Huntington's disease. Out of these 45000 samples, first four thousand and last five thousand samples are discarded due to beginning and ending time of walking. The remaining 36,000 samples are normalized and considered for analysis. The data set consists of gait signals of both left leg and right leg. Analysis may be carried out by considering gait signals of either of the legs. In this work, gait signals of left leg are considered for analysis. Discrete Wavelet Transform (DWT) is very well suited for the analysis of slowly varying signals like biomedical signals. Since present work aims to determine the start points of the gait data for the determination of severity, DWT is used for the analysis.

For every control subject, a total of 36,000 gait signal samples considered are divided into six blocks of six thousand samples each. For each block, db1 wavelet is applied and coefficients are determined. These coefficients are plotted to determine the start time of each step. The plot of wavelet coefficients by using db1 and db2 wavelets is indicated in Fig. 1 and wavelet coefficients by using db3 and db4 wavelets is indicated in Fig. 2.

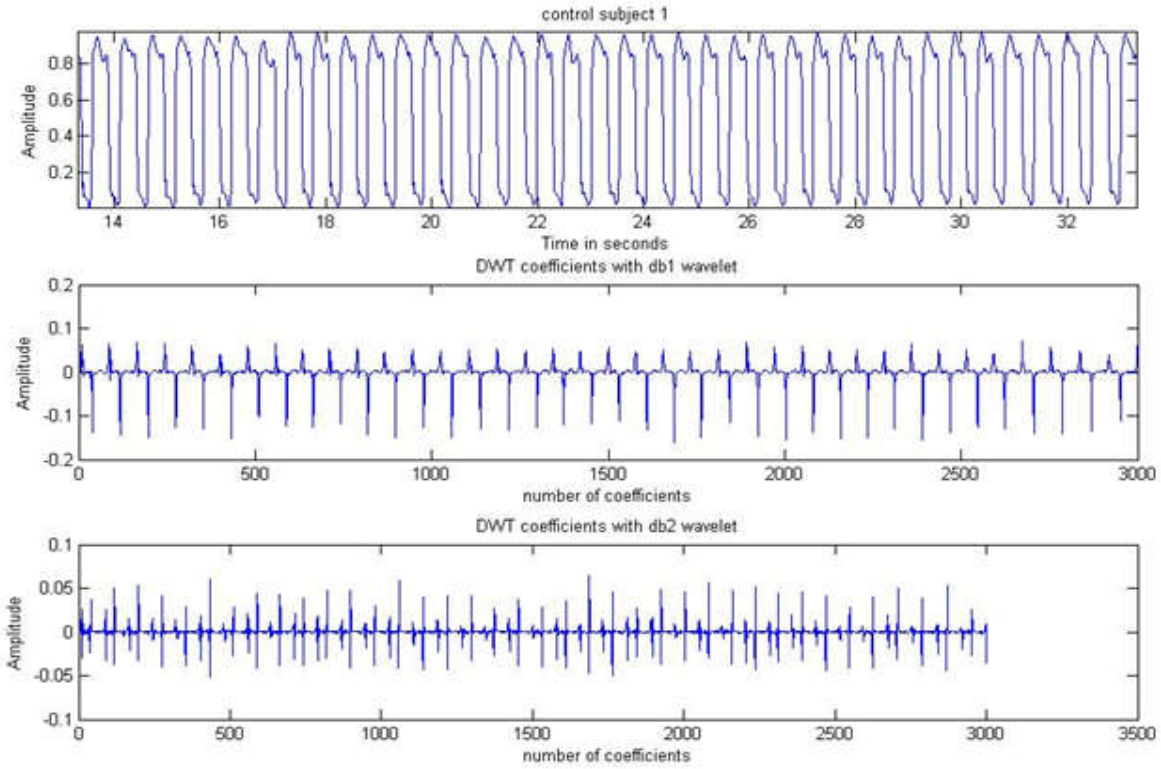

Fig. 1 Plot of wavelet coefficients with db1 and db2 wavelet

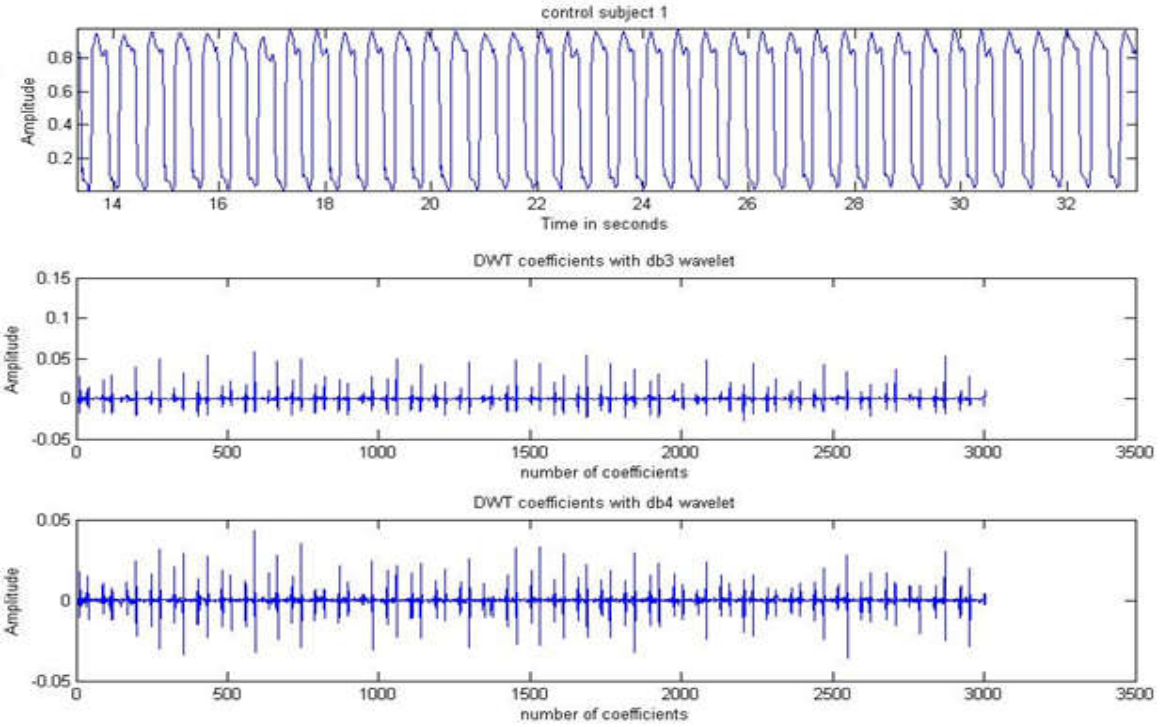

Fig. 2 Plot of wavelet coefficients with db3 and db4 wavelet

By observing figure 1 and 2, it may be concluded that db1 wavelet is better suited for determination of transitions of waveform and hence used for analysis. Next a threshold value of -0.3 is considered and values below the threshold are considered as zero and above the threshold are equated to -1.The modified wavelet coefficients are plotted in Fig.3.

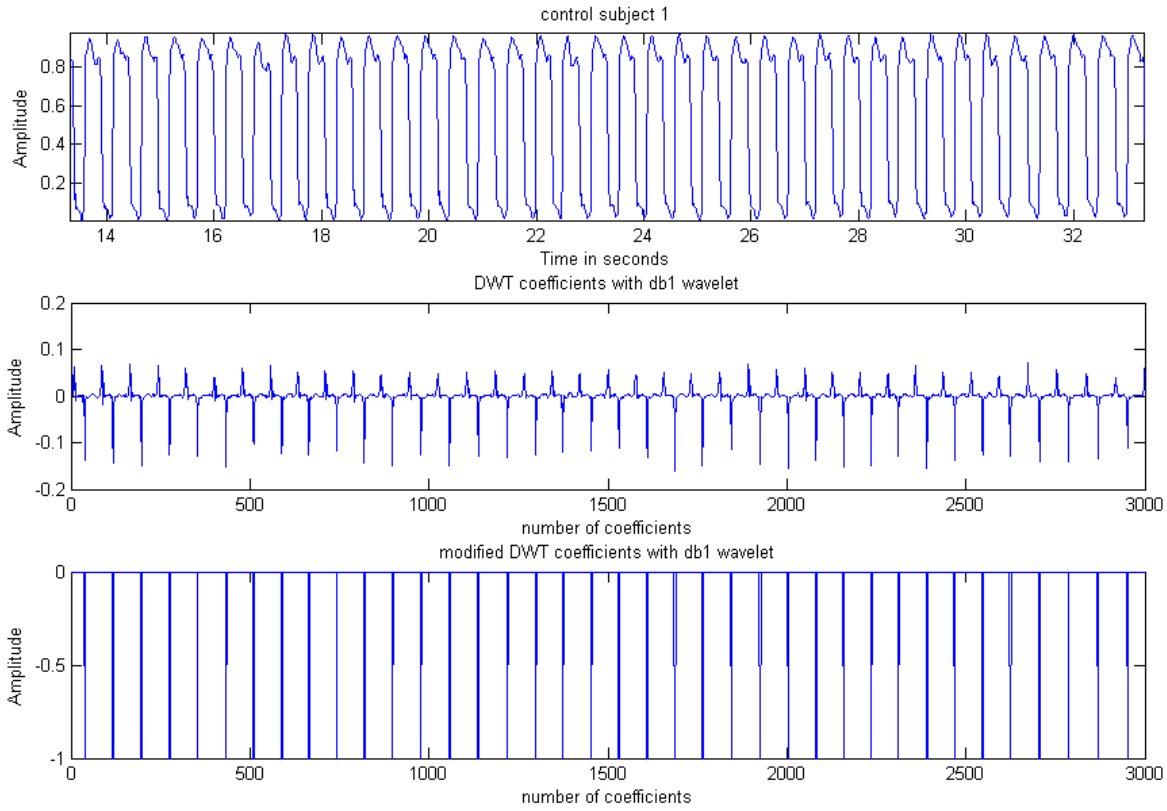

Fig. 3 Plot of input signal with original and modified wavelet coefficients

As observed from the Fig. 3, even the modified filter coefficients indicate the presence of multiple start points at each step. To correctly determine the start point for each step, these multiple start points must be eliminated. To do this, starting from the beginning, two successive values are considered and checked whether the first one is zero and next one is -1. If this condition is satisfied, then the count is incremented and next twenty points are skipped so as to eliminate immediate next start point which is duplicated. If the condition is not satisfied, then count is held at the current value and algorithm selects next two points to check the condition. In this way, the algorithm determines total number of start points in a block of six thousand samples and is repeated for all the six blocks to determine the number of start points in each block.

Once start points for each block are determined for a single control subject, an array of 1 X 6 elements is generated which contains one entry for each block of 6000 samples. The total number of start points is found by adding all these start points. This is repeated for all the ten control subjects and average value is found out. The values for ten control subjects are as follows: [226,220,231,234,227,225,238,240,235,218]. The control subject whose total number of start points closely matches with the average value is considered as a reference subject. In this work, average value of start points found is 229 and the subject with 231 start points closely matching with average is considered as reference subject. The range of start points i.e. 220 to 240 is considered as normal.

Once again, array of 1 X 6 elements is considered for the control subjects, whose total number of start points is 220 and 240. Variation of values is calculated by the formula $(N_2-N_1)/N_2$, Where N_1 and N_2 are adjacent elements in the array. This calculation results in 1 X 5 array for each control subject. In every array, minimum value and maximum value is found out. The least value among the minimum values and maximum value among maximum values is found and used as threshold for classification of severity. The threshold found in this study is [-0.0541 to 0.0263].

The wavelet coefficients are also found for mild, moderate and severe pathological subjects in the similar way. The mild pathological subject related block of samples where the deviations from normal are visible graphically is shown in Fig.4, moderate in Fig. 5 and severe pathological subject related samples in Fig.6 respectively. Even though sometimes graphically looking into the sample nature and prediction of the severity of the disease may be possible, most of the times our human eyes may fail to distinguish or

discriminate the mild and moderate levels of severity. Due to this, mild may be read as moderate or vice versa. Similarly, middle level of moderate severity level may be interpreted as severe pathological and lower level of severe pathological may be diagnosed as moderate. To overcome these ambiguities, in the visual based judgment, analytical method is proposed.

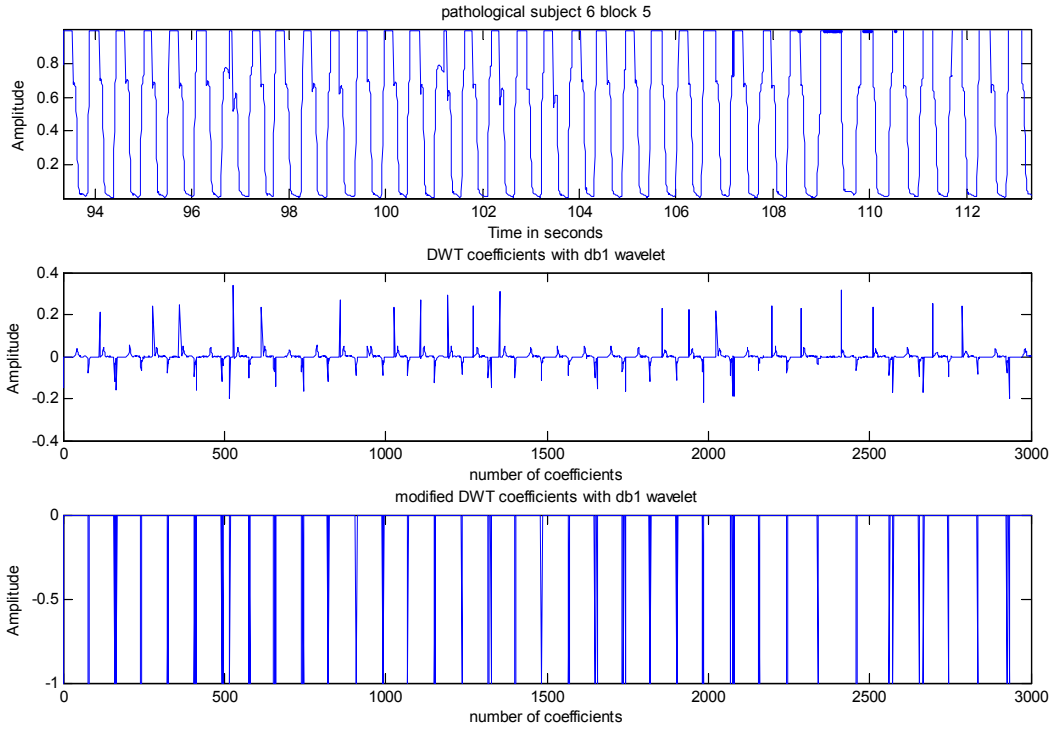

Fig. 4 Plot of input signal with original and modified wavelet coefficients of mild pathological subject 6, block 5

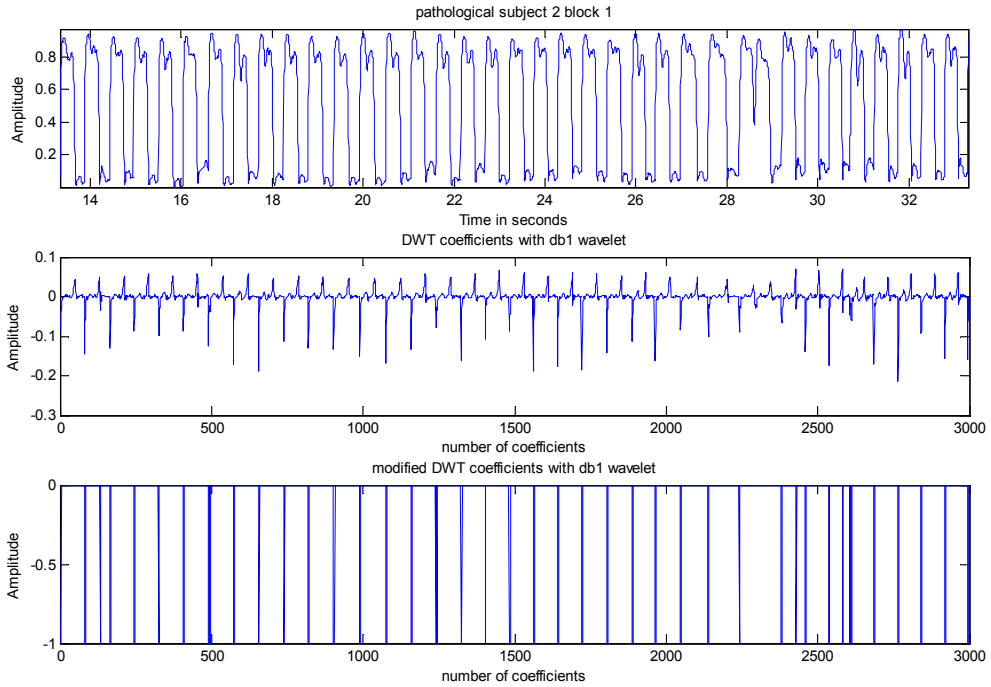

Fig. 5 Plot of input signal with original and modified wavelet coefficients of moderate pathological subject 2, block 1

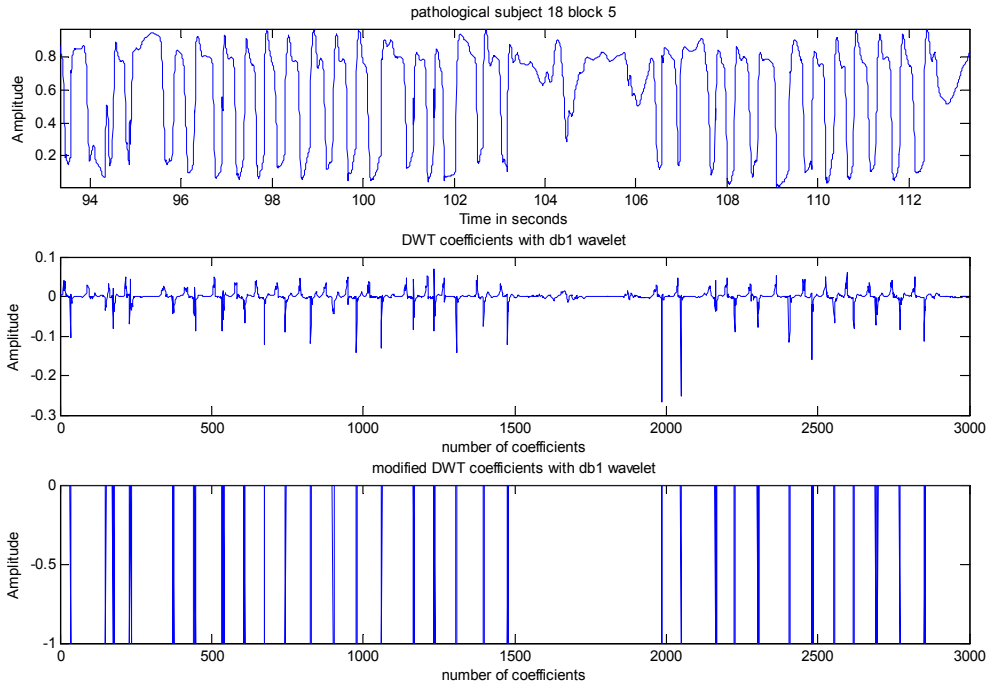

Fig. 6 Plot of input signal with original and modified wavelet coefficients of severe pathological subject 18, block 5

In the analytical method, start points for each block are found for each of the twenty pathological subjects and variation is calculated. Both minimum value and maximum value are found for each pathological subject and tabulated in two separate arrays. The results are indicated in Table I.

TABLE I
MINIMUM AND MAXIMUM VARIATION VALUES

Sl. No.	Type of Values	Values
1	Minimum Values of Pathological subjects	-0.0294 , -0.1190, -0.0513, -0.0571, -0.1316, -0.0976, -0.0444, -0.0263, -0.0541, -0.0588, -0.0526, -0.1250, -0.5000, -0.0270, -0.2500, -0.0909 -0.0357, -0.1842, -0.0857, -0.0244
2	Maximum Values of Pathological subjects	0.1333, 0.0769, 0.0541, 0.0606, 0.0263, 0.1081, 0.0233, 0.0270, 0.0286, 0.0313, 0.0833, 0.1667, 0.0455, 0.0278, 0.3333, 0.2581, 0.0714, 0.2258, 0.0294, 0.0250

Three different ranges of values are fixed for mild, moderate and severe category. While classifying each pathological subject, both minimum and maximum values are taken into consideration. If both values are within mild range, then subject is classified as mild. If one of the values is in mild and another in moderate, then subject is classified as moderate. If one of the values is in mild/moderate and another in severe, then subject is classified as severe. The result of classification along with range of values considered for classification is shown in Table II. By using this method, 18 pathological subjects are correctly classified into different categories. However, two pathological subjects corresponding to 7^{th} and 20^{th} entries in the Table 1 were wrongly classified as normal subjects. The entire analysis procedure was repeated with other wavelets and it is found that along with db1 wavelet, other wavelets like bior1.1, bior1.3, bior1.5 and rbio1.1 wavelets can also be used for analysis without any change in results.

TABLE II CLASSIFICATION OF PATHOLOGICAL SUBJECTS

Sl. No.	Type of Subject	Range for classification	Classification of Pathological Subjects (Subject Number)
1	Normal	[-0.0541 to 0.0263]	
2	Pathological - Mild	[0.026 to 0.066] and [-0.054 to -0.08]	3, 4,6,8,9,10,13,14
3	Pathological- Moderate	[0.067 to 0.106] and [-0.081 to -0.11]	2,11,17,19
4	Pathological- Severe	> 0.106 and < -0.11	1,5,12,15,16,18

III. CONCLUSIONS

In the present work, gait signals of normal subjects are considered and Discrete Wavelet Transform is applied to each of them and based on the results, classification of severity levels is done for the patients suffering from Huntington's disease. This analysis helps to determine the disease at its early stage and this enables the medical practioner to treat the patient in the initial stages of the disease, thus reducing further growth of disease. This can also be used for time to time monitoring of the level of improvement of patient's conditions. This method is very simple and also consumes very less time to generate accurate results.

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