The Comparison of Neurodegenerative Diseases and Healthy Subjects Using Discrete Wavelet Transform in Gait Dynamics

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***Abstract*—The main objective of the study is to obtain the comparison of the frequency band energies in gait signals ALS (Amyotrophic Lateral Sclerosis), PD (Parkinson Disease), HD (Huntington Disease) and healthy subjects. The gait signals are decomposed into approximation and details by using DWT and the energy values of them are calculated. The D3, D4, D5 details are determined as critical features according to energy percentages. Consequently, the study demonstrates that proposed method makes easily ALS discrimination of other neurodegenerative diseases and control subjects possible.**

***Index Terms*—neurodegenerative disease, discrete wavelet transform, gait dynamics**

I. Introduction

Some researches in the literature have been claimed that degenerative diseases might make fluctuations in the gait dynamics [1]-[5]. There are many studies for investigation of gait dynamics in the literature [6] and [7]. The studies are generally centered upon Wavelet and Multi Scale Entropy (MSE) based studies on gait analysis lately [8]-[10].Researches on non-stationary analysis using Time-Frequency (TF) and statistical based methods are also available in the literature [11] and [12]. Hausdorff et al. have proposed Detrended Fluctuation Analysis (DFA) method to investigate stride to stride interval time series in PD, HD and ALS[3], [4].Liao et al. have shown that PD, HD and especially ALS diseases alter the gait symmetry in stance time using MSE based method [13].Baratin et al. have proposed unbiased cross validation that is a method for linear and nonlinear classification of ALS and control subjects [14].Wu, Y. et al. have used signal turn count based method for discrimination of control and ALS groups [15]-[17]. Lee, Sang-Hong et al. have used DWT for feature extraction from gait signal for discriminating of PD [18].Sugavaneswaran L, et al. have proposed a Time Frequency (TF) based method for classification control and ALS [12]. Similarly, Zheng H. et al. have classified control and HD using statistical methods [11]. Sarbaz et al. have achieved control and HD discrimination using spectral analysis [19]. Consequently, the researches in the literature explain that the gait signals are altered according to in control and other neurological diseases till now [11], [12], [14]-[17], [20], [21]. Researchers have usually focused on stride interval time series in their studies. Likewise, this study is focused on the Compound Force Signal (CFS) analysis.

The fundamental purpose of the study is to determine the distinctive features of neurodegenerative diseases on the CFS signal using DWT. Discrete Wavelet Transform (DWT) is an efficient tool as TF signal processing method used in engineering and biomedical applications. The one of the most important specifications of wavelet transform is the capability to analyze gait signals with low frequencies.

During the study, firstly, the raw gait signals recorded from left and right feet are added respectively. And then, these signals are decomposed into approximation and details components for feature extraction using DWT. The features are evaluated in groups consists of ALS, PD, HD and controls at the end of the study.

II. Material and Method

A. Database Description

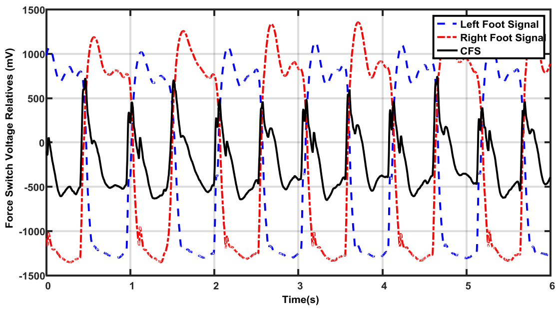

Figure 1. Force signal for left foot, right foot and CFS (summation of left & right signals).

This database consists of 64 left and right leg gait dynamics records. These datasets occur from 4 groups which are 13 subjects with Amyotrophic Lateral Sclerosis (ALS) aged between 36 and 70 years, 15 subjects with Parkinson's disease (PD) aged between 44 and 79 years, 20 subjects Huntington's disease (HD) aged between 29 and 71 years and 16 healthy control subjects aged between 20 and 74 years obtained from

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www.physionet.org [3], [22], [23]. The data obtained with force-sensitive resistors denotes the force fluctuation under right and left foot [23]-[25]. The overall data occurred from addition of force fluctuation under right and left foot is called as Compound Force Signal (CFS) in this study. CFS signal is used as one minute length data in the study. It is shown in Fig. 1 that is only 6 seconds time episode of this data which is sampled 300 Hz sampling frequency.

B. *Discrete Wavelet Transform (DWT)*

Time-Frequency analysis is important for analyzing of a signal. Especially, DWT is used as TF analysis at low frequency signals. DWT decompose into sub bands components of a signal using filter banks. In this study, CFS signals are decomposed into approximation (Low Pass Filtered) and detail (High Pass Filtered) coefficients during DWT analysis. The wavelet and scaling functions in DWT are calculated mathematically as

$$\phi_{i+1,j}(k)=\frac{1}{\sqrt{2}}\sum_n c_n\phi_{i,2j+n}(k) \tag{1}$$

$$\psi_{i+1,j}(k)=\frac{1}{\sqrt{2}}\sum_n b_n\phi_{i,2j+n}(k) \tag{2}$$

where, *i* and *j* denote dilation and translation parameters of the scaling function $\phi_{i,j}(k)$ and wavelet function $\psi_{i,j}(k)$. And also, c_n values are called as scaling coefficients while b_n values are wavelet coefficients. Thus, $S_{i+1,j}$ approximation coefficients and $T_{i+1,j}$ detail coefficients are determined theoretically as

$$S_{i+1,j}=\frac{1}{\sqrt{2}}\sum_n c_n S_{i,2j+n} \tag{3}$$

$$T_{i+1,j}=\frac{1}{\sqrt{2}}\sum_n b_n S_{i,2j+n} \tag{4}$$

After reconstruction processing of DWT approximation (A) and details (D) components of the CFS signal are calculated as [26].

$$A_I(k)=S_{I,j}\phi_{I,j}(k) \tag{5}$$

$$D_i(k)=\sum_{j=0}^{2^{I-i}-1}T_{i,j}\psi_{i,j}(k) \tag{6}$$

where, *I* is the decomposition level of DWT. Finally, the CFS signal *X* can be reconstructed as

$$X=A_I(k)+\sum_{i=0}^{I}D_i(k),\quad i=1,2,...,I \tag{7}$$

The number of different decomposition level is compared in according to distinctive attribute in the CFS signalsexperimentally. The best decomposition level is obtained as 6 levels in DWT. If decomposition level is smaller, it is not good in the frequency bands and so, it is not distinctive. Otherwise, the bigger decomposition level splits distinctive frequency bands and the scale gets smaller. Consequently, the best decomposition is obtained in 6 levels. The filter coefficients are calculated according to main wavelet function which is determined experimentally as db3 wavelet in Daubechies family in the study [27].

Evaluation of the study is made according to percentage of ratio the energy of details and Approximation components to the total energy of the signal. It is explained mathematically as

$$E_P=\frac{E_C}{E_T}\times 100 \tag{8}$$

where, E_C is the energy that denotes the summation of squares of the detail and approximation reconstruction components. E_T explains the energy of CFS signal *X*. E_P refers to the percentage of energy ratio.

The DWT structure is shown in Fig. 2. According to the figure, the frequency banks from A1 to A6 refer to approximation reconstruction signals and the frequency banks from D1 to D6 denote the detail reconstruction signals. The feature extraction is determined with Energy percentages that obtained from the rate of the signal energy values each approximation and details reconstruction signals to total CFS signal energy, respectively.

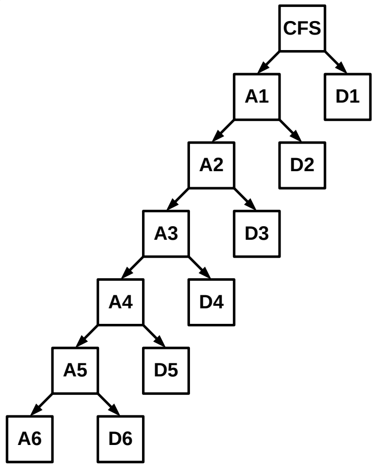

Figure 2. The DWT structure.

III. Results

The percentages of energy values are calculated separately in database. These values are compared within four patterns including ALS, PD, HD, control. The comparison of the patterns is shown in Fig. 3 according to each level component. According to Fig. 3, A6 denotes approximation components in the sixth level and D1, D2,…, D6 refer to detail components in each levels. The distinctive features are shown between ALS andcontrol groups as D3 (ranging from 18.75 Hz to 37.5 Hz), D4 (between 9.375 Hz and 18.75 Hz in frequency band), D5 (frequency range within 4.6875 Hz and 9.375 Hz) details and A6 (ranging from DC to 2.3437 Hz) approximation. Besides, D4 and D5 details also ensure slight distinction between ALS vs. PD and HD groups. Conversely, it is difficult the discrimination of PD vs. HD in this method. So, the best features are D3, D4, D5 details and A6 approximation according to this study.

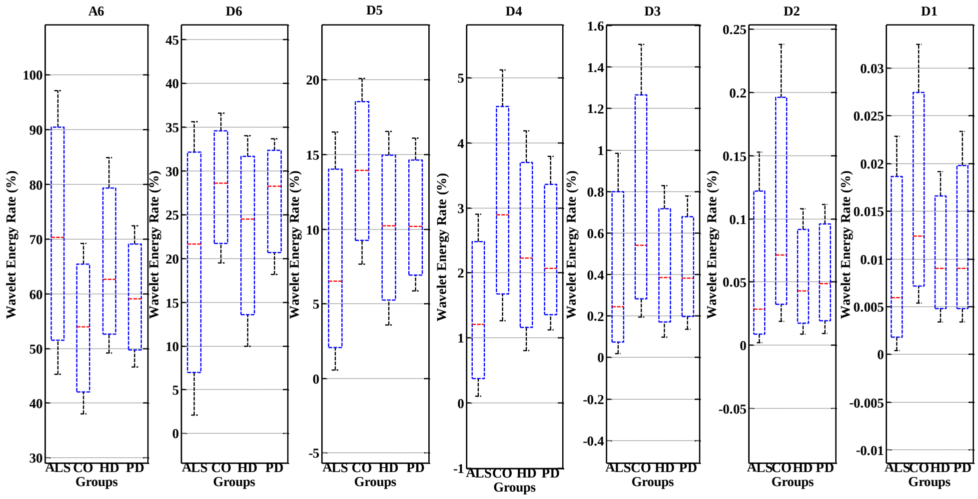

Figure 3. The percentage energy comparison of details and approximations.

IV. Conclusion and Discussion

The studies in the literature have generally focused on the cycle time, stride length and speed of gait signals [2], [7] and [8]. In this study, CFS signals as different from in the literature are analyzed with 300 Hz sampling frequency. Thus, DWT transform can be easily applied and also one minute signal approximately 18000 samples length is enough to decomposition. DWT is an efficient tool for decomposition into frequency bands [9], [14] and [20]. The energy percentages of D3, D4, D5 details and A6 approximation are determined as critical bands for ALS and control distinction. D4 and D5 details are crucial bands for discrimination of ALS vs. HD and PD groups. Contrarily, the study results point out that D1, D2 and D6 components can't be used for discrimination in neurodegenerative diseases. Therefore,it is clear that this method is not useful for classification between PD and HD. As a conclusion, proposed method brings out critical parameters for distinction of ALS vs. control, PD and HD. In the future works, these parameters can be used in ALS diagnostic devices using the clustering methods, artificial intelligent, linear classification methods etc. algorithms. And also, these parameters are obtained from the resulting of only one minute gait record. Thus, this algorithm is so fast and practical for diagnostic of ALS.

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