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Literatre Review

Oropesa et al.(1999) use discrete wavelet transform (DWT) to extract energy from seven EEG subbands as featuresand use them in their classification algorithm along with an additional six more features based on total energy and the relative energy of subbands.To train their artificial neural network (ANN) algorithm, Oropesa et al. use 30-second epochs of two separate EEG channels. They reach an accuracy of 77.6%. Zoubek et al. (2007) apply both DWT and fast fourier transform (FFT) to extract features. To train their algorithm, they use 20-second epochs of four EEG channels (C3-A2, P3-A2, C4-A1, and P4-A1) from 47 night sleep recordings of healthy adults. Using relative wavelet energy of five EEG subbands, Zoubek et al. obtain an accuracy of 71%. By including the features extracted from EOG and EMG channels, Zoubek et al. improve the accuracy of the same classification algorithm to around 80%. Doroshenkov et al.(2007) use the classification approach based on ~~H~~idden Markov ~~M~~odel (HMM). They use FFT to extract four features of subbands. They use the recordings of two EEG channels (Fpz-Cz and Pz-Oz) of eight subjects (without using any medications) from physionet online dataset. They achieve best result of accuracy for sleep stage four (91.54%) and the worst one for sleep stage one (4.84%). Sinha (2008) classifies three stages of sleep: awake (AWA), rapid eye movement (REM) and sleep spindles (SS). Sinha uses DWT method to extract features for two-second epochs of 64 EEG data. Applying ANN as a classifier ~~achieves~~ 95.55% rate of accuracy. Ebrahimi et al.(2008) use seven EEG recordings from physionet online dataset of Pz-Oz channel. Ebrahimi et al. apply DWT to extract features of 30-second epochs and use energy, total energy, ratio of different energy values of six subbands accordingly as well as mean of the absolute values of the coefficients and standard deviation of the coefficients in each sub band. ANN is applied as a classifier. The authors have achieved an accuracy rate of 93% in the classification of five sleep stages. Gunes et al. (2009) propose a novel data pre-processing called K-means clustering based on feature weighting (KMCFW) and use Welch method to extract the features. They used three night sleep recording. They used C4.5 decision tree to classify five sleep stages. Gunes et al. achieve the success rate of 92.4% by using this method. Jo et el. (2010) design the fuzzy classifier based on the genetic algorithm (GA) for a single channel EEG signal (C3-A2). They use FFT for 30-second long epochs to obtain relative power spectra of five EEG subbands as features. Finally, they obtained the accuracy rate of 84.6% in classifying of four sleep stages. Tagluk et al.(2010) use a multi-layer neural network (NN) which simultaneously apply EEG, EMG and EOG. Tagluk et al. obtain the dataset from seven hours sleep recording of 21 subjects which including an EEG channel (C3A2), EMG and EOG. Tagluk et al. obtained the accuracy rate of 74.7%. Fraiwan et al. (2011) use three different methods of time-frequency analysis to extract the features: ChoiWilliams distribution (CWD), Continuous wavelet transform (CWT)and HilbertHuang Transform (HHT). Fraiwan et al. extract seven features by computing Renyis entropy of sub bands. They use the recordings of a single EEG channel (C3-A1) for an entire night of sleep (68 h) of sixteen subjects. Random forest (RF) is applied as a classifier. They obtain the accuracy rate of 83%, 78% and 75% for CWT, CWD and HHT , respectively. Ozsen et al. (2012) use ANN to classify five sleep stages. By using five sleep recordings of EEG, EMG and EOG, Ozsen et al. obtain the total accuracy rate of 90.93% . Koley and Dey (2012) extract 39 features including time domain, frequency domain and non-linear analysis (21 features finally selected). They use single channel EEG (C4-A1) recordings of 28 subjects (having sleep apnea) during one night sleep. They use support vector machine (SVM) as a classifier and achieve the accuracy rate of 91.1%. Liang et al. (2012) apply a linear classifier to classify the features of multiscale entropy (MSE) and auto regressive (AR). They use the recordings of 20 healthy subjects of single EEG channel(C3-A2). They obtain the total accuracy rate of 85.38%.Hsu et al. (2013) apply FFT to extract energy features of sub bands and NN to classify sleep stages. The data set consists of recordings from single EEG channel (Fpz-Cz)of eight subjects during 24 hour of daily life (physionet online dataset). They achieve the accuracy rate of 87.2%.

Wavelet Transform

Wavelet transform (WT) is a powerful technique in signal processing for solving various real-life problems. This method analyzes non-stationary signals which frequency responses varies in time in both time and frequency [1,2]. Wavelet is a small wave which its energy is concentrated in time to analyze EEG signal as a non-stationary signal.

Wavelet analysis measures the frequency similarity between the signal and the original wavelet(mother wavelet). In WT, computations are done for different frequency components (scale) by shifting the time window until the wavelet reaches at the end of the signal[3].WT has a precise time resolution at high frequencies and good frequency resolution at low frequencies. With this feature, WT helps the analysis of non-stationary signals[4].

The continuous wavelet transform (CWT) of a signal, x(t), is defined as follows,
$CWT(a,b) = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{|a|}}\psi(\frac{(t-b)}{a})dt$

The coefficients of CWT are computed within this formula by the integral of the original signal which is multiplied by a mother wavelet w. The scaling parameter(a) is related to frequency. High scales correspond to low frequencies which give information of the entire signal whereas low scales (high frequencies) give detailed information in the signal. The parameter b corresponds to the location of time window which is shifted over the length of the signal. In fact, CWT measures the similarity of the frequency in the original signal and the mother wavelet. The CWT has a weak point for calculating coefficients at each scale. Because it requires expensive computational task as the matter of redundancy. The Discrete Wavelet Transform (DWT)solves this problem by operating filtering tasks.In this procedure, the signal is passed through a half band low pass filter which results removing some samples from signal. Therefore, the scales and time window shifts are chosen based on powers of two (dyadic). The DWT is defined as,

$DWT(j,k) = \frac{1}{\sqrt{|2^j|}} \int_{-\infty}^{\infty} x(t)\psi(\frac{(t-2^jk)}{2^j})dt$

where a and b in the CWT are replaced by 2^j and 2^jk, respectively. At every level of the DWT, the signal is passed through a low pass (LP) and high pass (HP) filters which results in half number of samples and half the frequency. The outputs of LP and HP at each level i are called approximation (Ai) and detail (Di) coefficients , respectively. Fig. 1 shows the wavelet decomposition of a signal through 3 levels of filtering. In this figure, the coefficients A1, D1, A2, D2, A3 and D3 are the DWT coefficients which includes the frequency content of the original signal within the bands $0 - \frac{fs}{2}, \frac{fs}{2} - fs, 0 - \frac{fs}{4}, \frac{fs}{4} - \frac{fs}{2}, 0 - \frac{fs}{8}$ and $\frac{fs}{8} - \frac{fs}{4}$, respectively where fs is the sampling rate(frequency) of the original signal x[n].

In the figure, the discrete x(n) signal crosses has the sampling rate of (100Hz) which passes iteratively through HP to generate detail coefficients (Di[n]) and crosses through LP to obtain approximation coefficients (Ai[n]). In analysis of EEG signals, the number of levels of decomposition is chosen based on the sampling rate of the original signal and the range of frequency components which are desired to be extracted from the signal.Since the range of the useful frequency information of EEG signals falls between 060 Hz, usually decomposition level is set at 5. Selecting inappropriate number of decomposition levels causes loss of desired information. The five level of DWT decomposition of EEG data (100

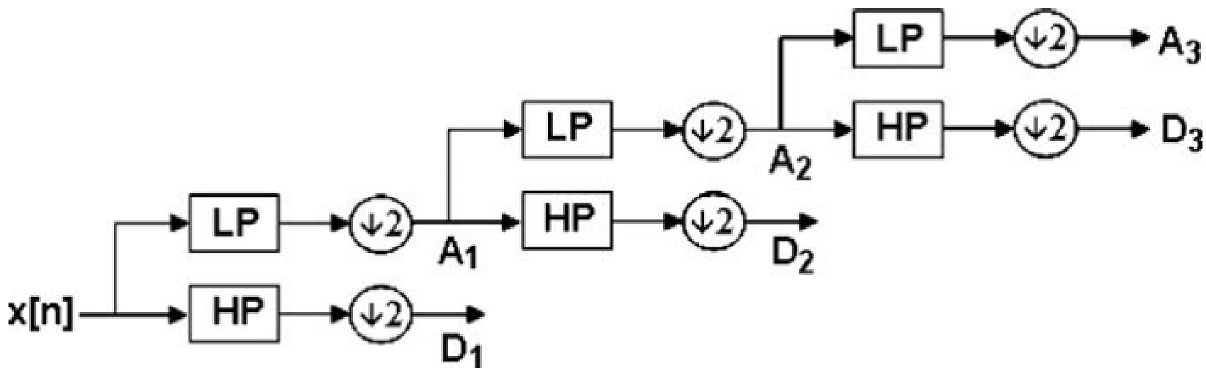

Figure 1: Sub-band decomposition of DWT implementation

Hz) is given in Fig.2. It can be seen from Fig. 2 that the components A5 decomposition is within the delta range (03 Hz), D5 decomposition is within the theta range (36 Hz), D4 decomposition is within the alpha range (612 Hz) , D3 decomposition is within the beta range (12 – 25 Hz) and D2 decomposition is within the gamma range (25 – 50 Hz). Therefore, in order to extract the meaningful features from the EEG signal, D2-D5 detail sub-bands and A5 approximation band are used in this study. Several successful studies related to EEG choose Daubechies wavelet as an appropriate wavelet as well as level 4 and level 5 of this function is preferred[5,6,7]. In this paper, db5 is selected as the mother wavelet for DWT decomposition.

Specifications of Dataset

The EEG dataset is available online at PhysioBank [8]. The polysmnographic (PSG) sleep recordings included signals from EEG (Fpz-Cz and Pz-Oz channels), horizontal EOG, submental chin EMG and an event marker. Well-trained technicians scored manually hypnograms based on the 1968 Rechtschaffen and Kales manual [9]. There are two subsets of data. In the first set, 20 healthy subjects were selected in order to study the effects of age on sleep. Two EEG datasets (about 20 hours) were recorded during two subsequent day-night periods for each subject at their home. In the second dataset, 22 subjects that had difficulty in falling sleep were selected from a study of Temazepam effects on sleep. The PSGs (about 9 hours) were recorded in the hospital during two nights.

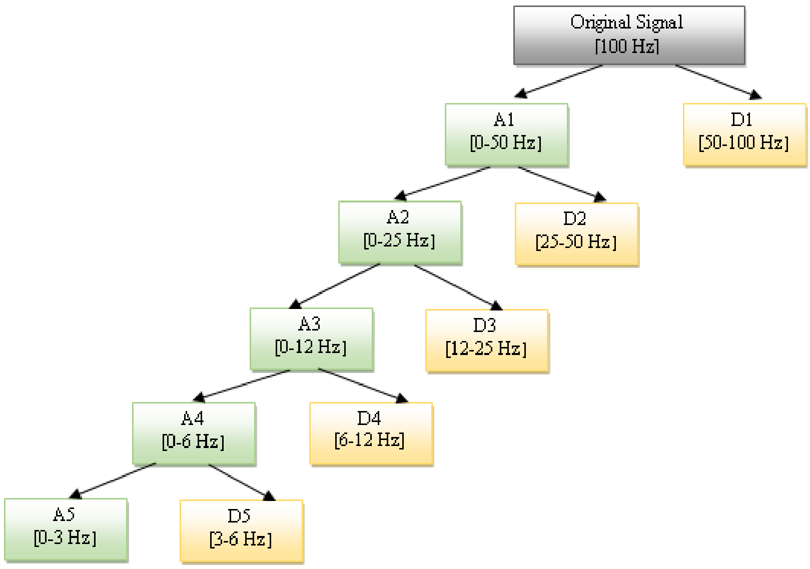

Figure 2: Sub-band decomposition of DWT implementation

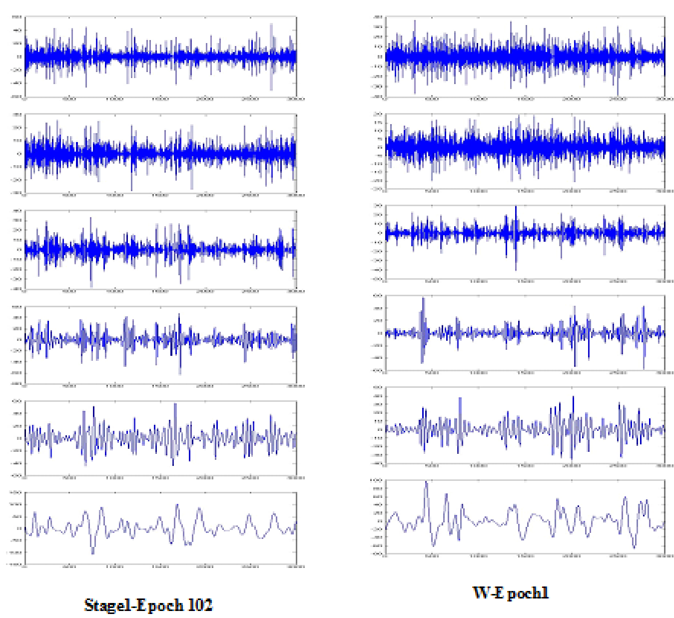

Figure 3: Sleep Decomposition

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