Surface EMG signals compression: comparative analysis with Wavelet-1D and wavelet packet-1D

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ABSTRACT

Electromyogram (EMG) data compression is a subject of great practical importance for the long-term analysis of the neuromuscular systems as well as applications in telemedicine. Compression of biological data remains an important issue, despite the vast increase in storage capacity and transmission speed in communication pathways. Our two proposed methods show the EMG signal compression with significant extracted coefficients respectively. EMG data are compressed by thresholding techniques using Balance Sparsity-norm, selecting different global threshold values for both the wavelet approach. The compression ratio is quite good in case of Wavelet packet 1D as compare to Wavelet 1D where the same 86.96% retained energy is achieved at global threshold '2275' and '2327' respectively. The significant change in the compressed EMG signals at each process is monitored with its attribute i.e. mean, standard deviation and mean abs deviation.

Key words: EMG, Data Compression, Balance Sparsity-norm, Wavelet Packet 1D, Wavelet 1D

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INTRODUCTION TO EMG

Electromyography (EMG) is a study of muscles function through analysis of electrical activity produced from muscles. This electrical activity which is displayed in form of signal is the result of neuromuscular activation associated with muscle contraction. The most common techniques of EMG signal recording are by using surface and needle/wire electrode where the latter is usually used for interest in deep muscle. This paper will focus on surface electromyography (SEMG) signal. During SEMG recording, several problems had to be encountered such as noise, motion artifact and signal instability. Thus, various signal processing techniques had been implemented to produce a reliable signal for analysis. There are also broad applications of SEMG signal particularly in biomedical field. The SEMG signal had been analyzed and studied for various interests such as neuromuscular disease, enhancement of muscular function and human-computer interface.

Representation of electrical potential in form of time varying signal is what we called as EMG signal. By studying the EMG, one is actually looking into the characteristics of body movement due to muscle contraction activity. Obtaining EMG signal from human includes several processes involving recording, data acquisition, signal conditioning and processing. Recording of EMG signal is done by mean of electrodes. Three types of electrodes that are commonly used is wire, needle and surface electrode where the latter being the most widely used since it is non invasive [1]. With different kind of electrode, the EMG signal that obtained might contain different characteristic. That tells why the terms like ‘surface EMG’ and ‘needle EMG’ is used in literature, that is to specify the type of electrode used for recording. Most of the literatures reviewed in this paper either specifically mention the term ‘surface EMG’ or clarify the use of surface electrode in its methodology.

Studies in motion or body movement are probably the area in which SEMG technique is most well suited. A simple bipolar or monopolar electrode is already sufficient for this purpose. The challenge is perhaps to deal with anomaly in signals due to noises or motion artifact. Application of SEMG in motion study is quite huge. It is possible to say that it can be used in almost all type of works concerning muscle movement, not only on limbs but also face [2,3], not limited to human but also on animals [3]. In sports science, movement and motion are always been a subject of study. Data from SEMG is used to obtain statistical analysis result for various purposes which include study in possibilities of injury [4], effect of different skills of sports on neuromuscular activity [5], effect of detraining [6], examination on rapid muscle force characteristics after high level match play [7], quantification of muscle activation pattern of certain activities involving movement [8], just to name a few.

COMPRESSION OF EMG SIGNAL

The majority of compression research has focused on encoding medical images, electrocardiograms, and electroencephalograms. Although long-term myoelectric signal (MES) acquisition is important for Neuro-muscular system analysis and telemedicine applications, very few studies have been published on MES compression. This research investigates static and dynamic MES compression using the wavelet packet thresholding compression method and compares its performance to a standard wavelet compression technique. Data compression processes are of great interest to biosignal analysis, especially when data transmission (e.g. in telemedicine applications) or long-term recordings (e.g. in sleep laboratories, intensive care) are involved. With appropriate processing of biosignals, the redundant data stream could be reduced to the most significant parameters that could efficiently contribute to medical decision making. In this way, high density storage could be achieved. In the same vein, reduction of the number of bits required to describe a biosignal could facilitate the data transmission, but it must be done with great care if it results in a loss of information.[10][12]

DATA COMPRESSION

Data compression minimizes the number of bits required to represent information by reducing the redundancy present in the original signal. The reduction in storage requirement is usually expressed as a percentage using a figure of merit called the compression factor (CF).

$$CF(\%)=U_s-C_s/U_s\times 100 \text{-----} (1)$$

In (1) Us is the original data size and Cs is the compressed data size. Lossless compression techniques attain low CFs and produce decompressed signals that are identical to the original data. Conversely, lossy compression techniques attain significantly higher CFs and produce decompressed signals that differ from the original signal. The reconstruction error is often expressed using a distortion metric called the percent residual difference (PRD).[14][15]

METHODOLOGY

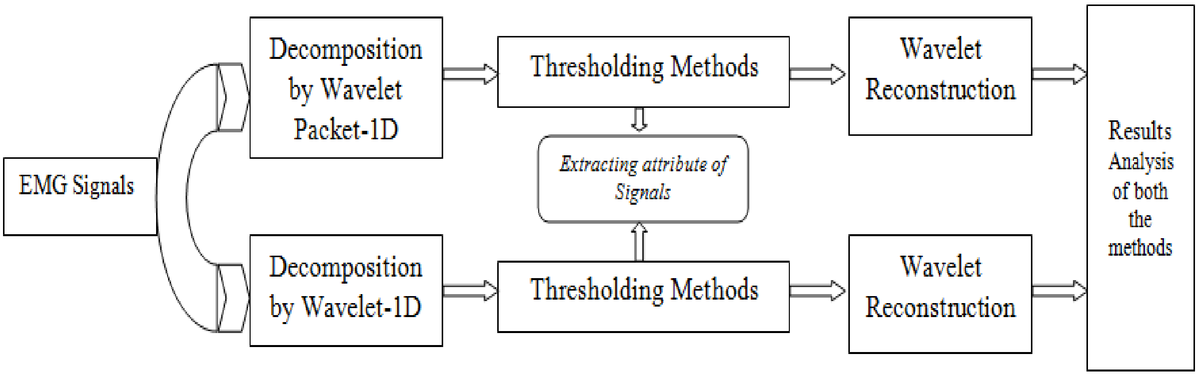

Fig.1.Block Diagram of our propose model.

The EMG is collected from PhysioBank ATM having 4000 samples of a healthy subject and the length of the recorded signals was 10 seconds. The simulation part is carried out in Matlab platform. The compressed EMG signals attribute is tabulated in Table-1 and significant parameters are extracted.

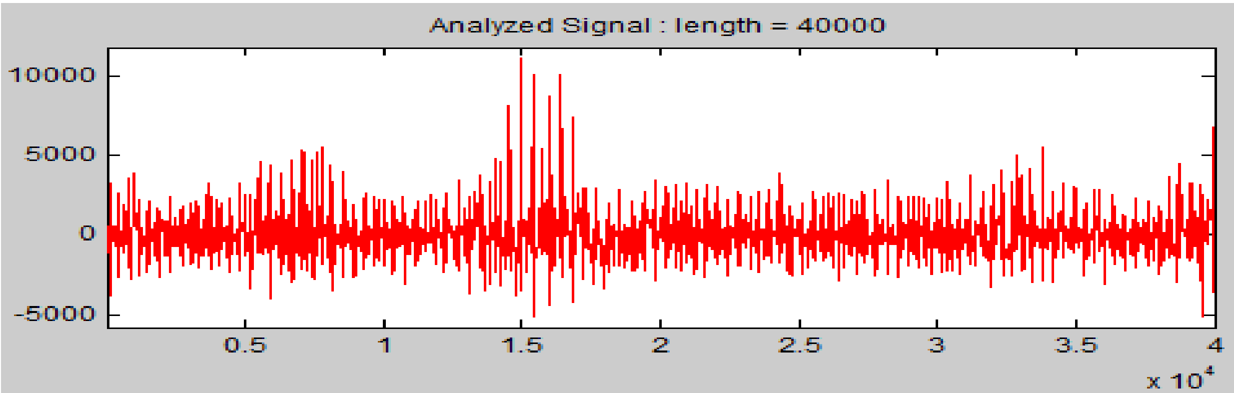

Fig.2 .Input EMG Signal having length 40000 samples.

We have analyzed the input signal by applying wavelet 'haar' with level-3 & the selected entropy is Shannon for both the methods. The decomposed tree showed in length type Node level.

A. Wavelet Packet Decomposition

Originally known as Optimal Subband Tree Structuring (SB-TS) also called Wavelet Packet Decomposition (WPD) (sometimes known as just Wavelet Packets or Subband Tree) is a wavelet transform where the discrete-time (sampled) signal is passed through more filters than the discrete wavelet transform (DWT).In the DWT, each level is calculated by passing only the previous wavelet approximation coefficients (cA_j) through discrete-time low and high pass quadrature mirror filters. However in the WPD, both the detail (cD_j (in the 1-D case), cH_j, cV_j, cD_j (in the 2-D case) and approximation coefficients are decomposed to create the full binary tree.

For n levels of decomposition the WPD produces 2^n different sets of coefficients (or nodes) as opposed to (3n + 1) sets for the DWT. However, due to the down sampling process the overall number of coefficients is still the same and there is no redundancy.

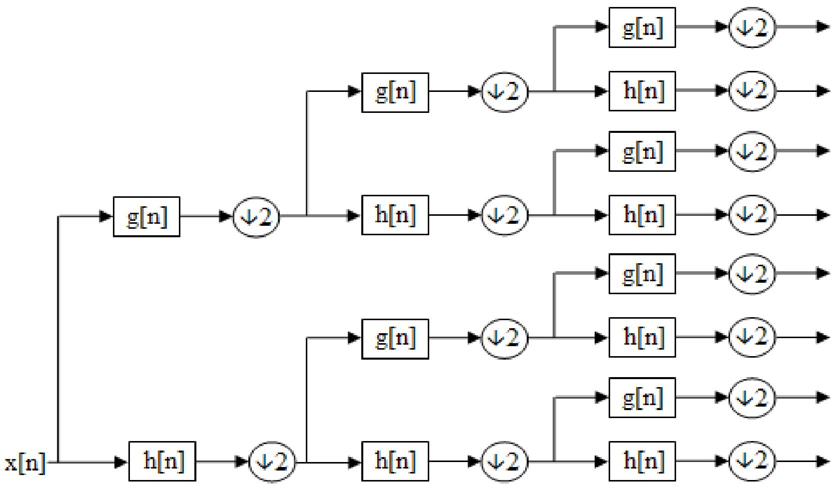

Fig3. Wavelet Packet decomposition over 3 levels. g[n] is the low-pass approximation coefficients, h[n] is the high-pass detail coefficients

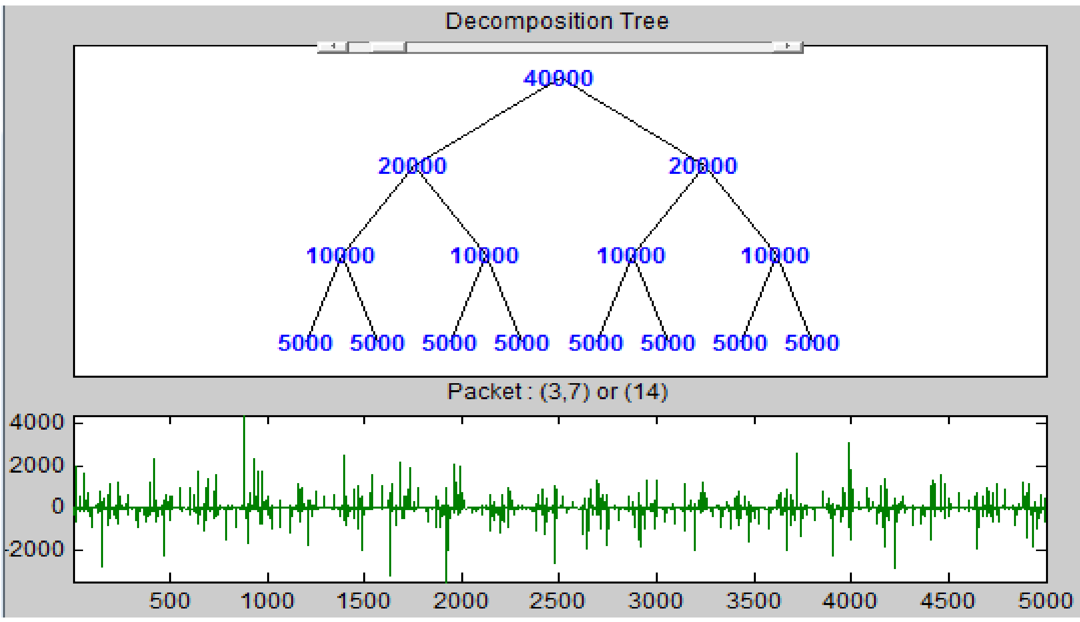

Fig4.Wavelet Packet Decomposition of length 4000 samples & the decomposed packet (3, 7) of EMG Signal

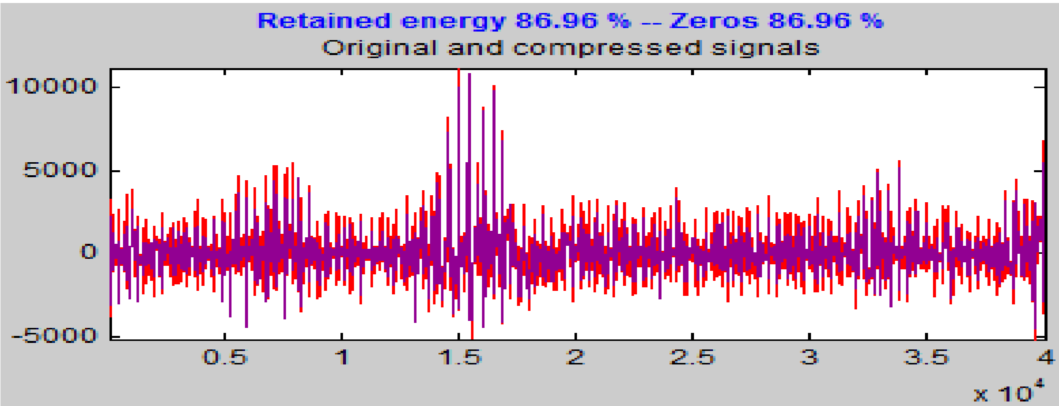

Fig5. Compression at Global threshold '2275'

B. Wavelet Transform 1D

The wavelet transform is a time-scale decomposition with basis functions that are translations and dilations of a prototype function called mother wavelet. The CWT has one serious problem: it is highly redundant (In its continuous form, it is actually infinitely redundant). The CWT provides an oversampling of the original waveform: many more coefficients are generated than are actually needed to uniquely specify the signal. This redundancy is usually not a problem in analysis applications such as described above, but will be costly if the application calls for recovery of the original signal. For recovery, all of the coefficients will be required and the computational effort could be excessive. In applications that require bilateral transformations, we would prefer a transform that produces the minimum number of coefficients required to recover accurately the original signal. The *discrete wavelet transform* (DWT) achieves this parsimony by restricting the variation in translation and scale, usually to powers of 2. The basic analytical expressions for the DWT will be presented here; however, the transform is easier to understand, and easier to implement using filter banks. In the DWT, a new concept is introduced termed the *scaling function*, a function that facilitates computation of the DWT. To implement the DWT efficiently, the finest resolution is computed first. The computation then proceeds to coarser resolutions, but rather than start over on the original waveform, the computation uses a smoothed version of the fine resolution waveform. This smoothed version is obtained with the help of the scaling function. In fact, the scaling function is sometimes referred to as the *smoothing function*.

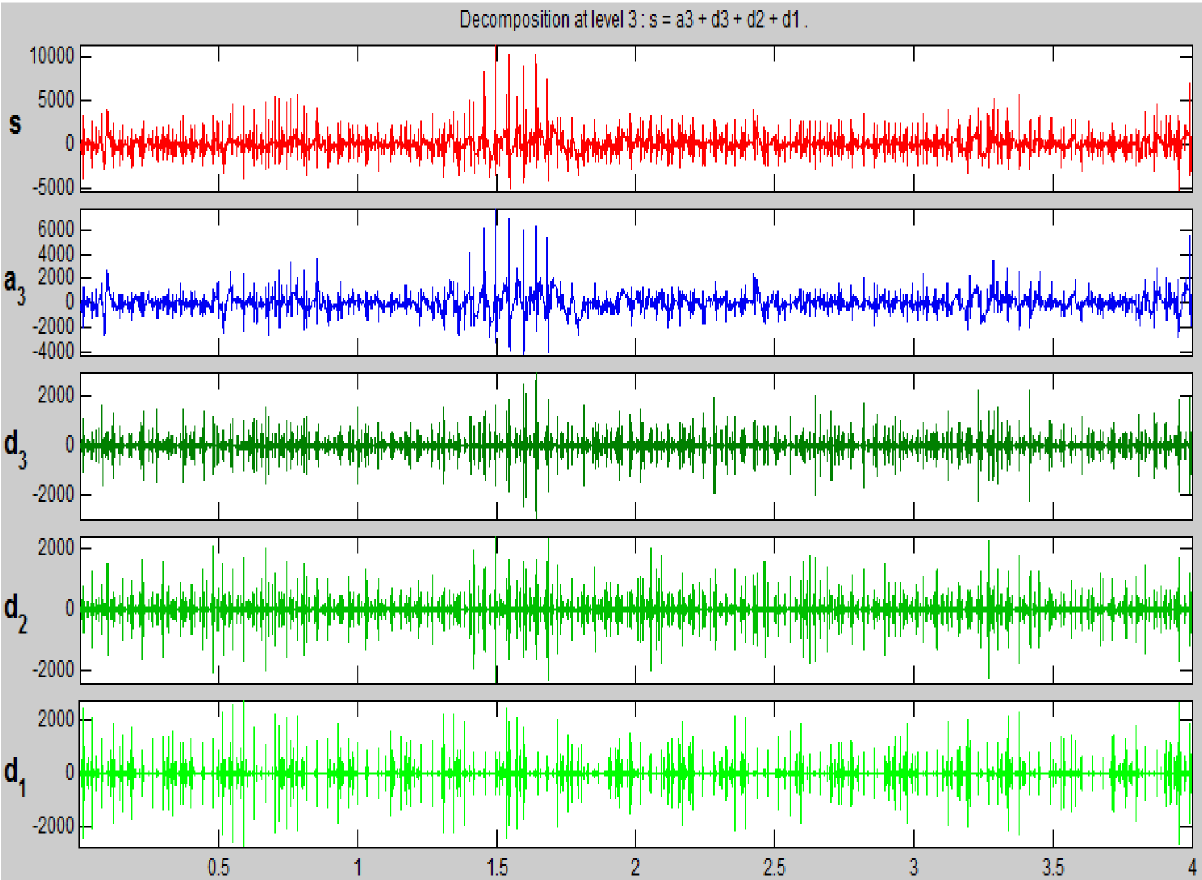

Fig6. Decomposition of EMG signal at level 3 with' haar' wavelet

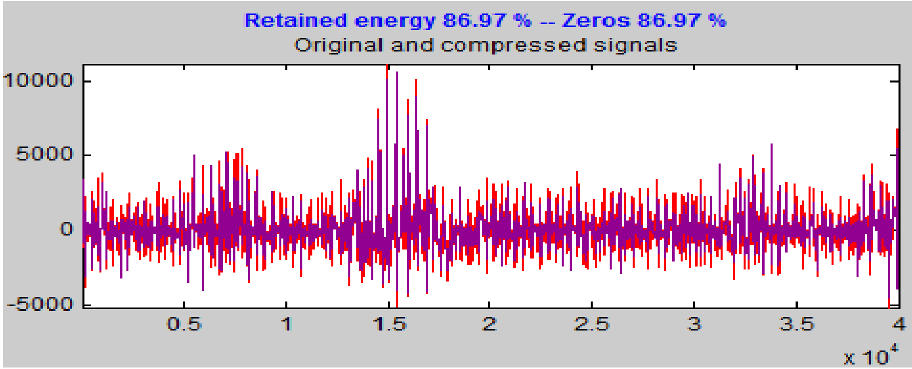

Fig7. Compression at Global threshold '2327'

Table.1. Comparative tabulation of Mean, Standard Dev. & Mean abs Dev for Wavelet packet 1D & Wavelet 1D

Balance Sparsity-norm		*Wavelet packet 1D*				*Wavelet 1D*		
Global thld limit	*Retained Energy in %*	*Mean*	*Standard Dev.*	*Mean abs Dev.*	*Retained Energy in %*	*Mean*	*Standard Dev.*	*Mean abs Dev.*
0	100.00	-2.30e-015	3.6e-01	0	100.00	-2.60e-015	3.5e-01	0
100	99.87	-1.49e-015	29.34	21.55	99.86	-1.92e-015	31.18	22.21
5044	79.89	-8.88e-016	367.8	171.3	79.73	-9.79e-016	369.2	171.6
6117	79.11	-1.04e-016	374.4	172.8	78.95	-1.13e-015	376.2	173.2
6765	78.64	-1.18e-015	379	173.7	78.64	-1.18e-015	379	173.7
8067	78.20	-1.002e-015	382.9	174.4	78.20	-1.002e-015	382.9	174.4

From the above tabulation we can conclude that the retained energy is higher at each level in case of wavelet packet 1D. The mean, standard deviation & mean abs deviation is less in wavelet packet 1D as compared to wavelet 1D. The compression performance is better in wavelet packet 1D for our EMG signal.

CONCLUSION

SEMG should be utilized especially for clinical diagnosis since its non-invasive approach makes it much more comfortable for subjects. Compression processes are of great interest to biosignal analysis, especially when data transmission (e.g. in telemedicine applications) or long-term recordings. The results of this investigation indicate the choice of an appropriate Wavelet compression algorithm is highly dependent on the application. This research investigated Wavelet compression using wavelet 1D and Wavelet packet 1D using thresholding methods and compared its performance to a standard wavelet compression algorithm. However we are approaching towards accuracy and precision in wavelet packet 1D at lower threshold level whereas the same result can be achieved with wavelet 1D at higher threshold value. The important parameter to keep in mind is that to monitor the percentage of retained energy of the EMG signals during different threshold levels.

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