

Different Techniques for the Segmentation of the EMG Signal - A Review

Ashmeet Kaur¹, Navneet Kaur Panag²

¹Pursuing, M.Tech. Student of Baba Banda Singh Bahadur Engineering College, Fathegarh Sahib, INDIA

²Baba Banda Singh Bahadur Engineering College, Fathegarh Sahib, INDIA

ABSTRACT

In this paper, the electromyographic (EMG) signals of a patient and the normal person are considered. In order to decompose both the signals, different segmentation techniques are used. The two segmentation techniques used in this work are: i) Segmentation using daubechies wavelet transform (DWT), ii) by identifying the peaks of the MUAPs. The MUAPs (motor unit action potentials) are the important source of the EMG signal to provide information about any kind of disorder in the muscles or any disturbance in the functioning of the muscle cells. In this paper, the electromyographic (EMG) signals of a patient and the normal person are considered. In order to decompose both the signals, different segmentation techniques are used. The two segmentation techniques used in this work are: i) Segmentation using daubechies wavelet transform (DWT), ii) by identifying the peaks of the MUAPs. The MUAPs (motor unit action potentials) are the important source of the EMG signal to provide information about any kind of disorder in the muscles or any disturbance in the functioning of the muscle cells.

Keywords— Segmentation, MUAPs, Wavelet Transform.

I. INTRODUCTION

Electromyography (EMG) is a technique of recording the activity of muscles. It records the electrical current generated by the muscles. EMG of the muscle is measured by using an instrument called an electromyograph. It produces electrical record of muscles which is known as electromyogram. The EMG signal is the biomedical signal that consists of a train of motor unit action potentials called the MUAPs. The electrical currents generated in the muscles are measured during its contraction. The contraction and relaxation of the muscles is controlled by the nervous system. Thus EMG signal is the complicated signal and it depends upon the properties of the muscles. Muscles get stimulated by the signals from nerve cells called motor

neurons. The stimulation of muscles thus causes electrical activity, which in turn results into contraction of muscles. This electrical activity of muscles is measured with the help of needle electrode which is inserted into the muscle and the same electrode is connected to a recorder which records the activity of that particular muscle. The electrode and the recorder together are known as the electromyography machine. EMG signal provide an important source of information for the diagnosis of neuromuscular disorders. It helps to identify the abnormalities of nerves or spinal nerve roots that may be associated with pain or numbness. There are many symptoms for which EMG may be useful which include numbness, stiffness, cramps, deformity, etc. EMG results provide the information that whether the symptoms are due to muscle disease or a neurological disorder [8].

II. REVIEW

Gutet al. used a sliding time window for segmentation. In the sliding time window, a certain threshold is considered. When the mean slope within the sliding time window is seen to be increasing the considered threshold value, it is assumed that the active segment begins. When the variation of the EMG signal falls below another threshold value, it is assumed to be the end of this segment [1]. Chauvetet al. used an amplitude detection scheme. In this scheme threshold value is set at all iterations. For a particular iteration, the threshold value is determined by lowering its previous value. This amplitude detection scheme allows the detection of a reduced number of MUAPs, also allowing the identification of a MUAPT [2]. Chauvetet al. later on, detected MUAP peaks when their amplitudes were greater than a detection threshold value. At the first iteration, the threshold value was started only at the highest peak of the signal. After threshold, the number of detected peaks was counted. If the number of peaks reaches at least 5 peaks per second then they are observed and kept. And if the peaks do not reach the

decided value, the threshold value was decreased to 90% of its precedent value [3]. Katsis et al. used a window of a constant length and a certain threshold T to identify the MUAP spikes [4], [5], [6]. Pattichis et al. used a sliding window of length 3ms and width $\pm 40\mu V$ for the EMG signal to identify the beginning extraction point (BEP) and the ending extraction point (EEP) of the MUAPs [7]. Reaz et al. described that muscles are made up of a large number of cells that have the ability to contract and relax the muscles. They are also helpful for producing motion in the muscles, for the movement of the material and other substances within the body, for generation of heat and for the stabilization of the body. There are three types of muscle tissues which can be identified on the basis of structure, properties and mechanism: a) skeletal muscle, b) smooth muscle and c) cardiac muscle [8]. Sornmo et al. explained that the skeletal muscle facilitates the movement and the posture of the body. This skeletal muscle is attached to the skeleton. The cardiac is responsible for creating the heartbeat. The smooth muscle is there within the intestines and position of the body. EMG signal is taken from the skeletal muscle [9]. Bida et al. showed that the motor unit gets stimulated when the electrodes are placed on the muscle and the stimulation is applied. When the motor unit is stimulated, its pulse is recorded by the electrode and is displayed in the form of action potential which is known as motor unit action potential (MUAP). An EMG is the train of Motor Unit Action Potential (MUAP) showing the muscle response to the neural stimulation. The EMG signal is the superposition of MUAPs and can be treated as stochastic process [10]. Oskoei et al. proposed that there are two methods of EMG segmentation. These are disjoint segmentation and overlapped segmentation. In disjoint segmentation, different segments are used which have predefined length and these segments are used for feature extraction. In case of overlapped segmentation, a new segment is placed over the present segment with an increment. Thus the disjoint segmentation deals only with the segment length while the overlapped segmentation deals with segment length and increment [11]. Oskoei et al. also compared the disjoint and overlapped segmentation by comparing their segmentation performance. In disjoint segment, segment length of 200ms is taken and in overlapped segment, the segment length of 200ms is taken with an increment of 50ms. Their results indicated that the disjoint segmentation of 200ms length provided high performance in EMG segmentation [11]. Christodoulou et al. calculated the threshold which depends upon the maximum value and the mean absolute value of the EMG signal. The threshold value can be calculated using a window of constant length and an algorithm for segmentation of EMG signal. The peaks obtained over the calculated threshold value are observed and considered as the active segment [12]. Fang et al. used a horizontal cursor to separate the EMG signal from the noise. The cursor is set to a level where the spike potential can be distinguished from the background noise. When the spike waveform is detected, the segment

of spike waveform is observed and collected having the peak at the centre [13]. Guglielminotti et al. came up with the theory that in the time-scale plane, if the wavelet analysis is taken to match the shape of the MUAP, then the WT gives the best energy localization [14]. Laterza et al. used wavelet analysis to match the shape of the MUAP. They summed up that wavelet transform is the best useful technique for the detection of MUAP when white noise is present in the signal [15]. Ismaïl et al. theorized that, the fast and short term Fourier transforms are the most common method for determining the frequency domain features of the EMG signal. But they also came up with the point that the main disadvantage of using these transformations is that they assume the signal to be stationary [16]. Pattichis et al. found out if the signals are required to be analysed at different resolution levels, the wavelet transform can also be used. The wavelet transform algorithm includes the decomposition of the signal and then the reconstruction of the signal. They briefly discussed how coefficients of the WT obtained from each stage can be used to construct the functional approximation to the original signal [17]. Fang et al. introduced that during a strong muscle contraction there will be more than one single motor unit (SMU) potential that will be registered overlapped with each other. In 1997, they introduced a technique for the segmentation of the EMG signal and for classification of their SMU potentials. The main advantage of this technique is that it measures the waveform similarity of SMU potentials in wavelet domain. This method was based on spectrum matching in wavelet domain. Sometimes the spectrum matching technique is really considered to be more effective than waveform matching techniques. There is a technique for the segmentation of multi-unit EMG signal which has four different procedures: signal de-noising procedure, spike detection, spike classification and spike separation procedure [18]. Zennaro et al. proposed that for the differentiation of the action potential (AP), the low level frequency wavelet coefficients are more important than the higher band wavelet coefficients [19]. Yamada et al. in 2003 showed that for the classification of MUAPs, the high frequency information is also important. Another method was proposed using the principle components analysis (PCA) for wavelet coefficients to solve the problem of subjective criteria of feature selection. The segmentation algorithm composed of four stages: segmentation, decomposition using wavelet transform, PCA, and gathering the signal. The benefit of this technique is that manually selection of coefficients is not needed. It stores all the frequency data in the account [20]. Plevin et al. in 2002 proposed that the decomposition of EMG signal uses higher order non-linear least mean square optimization. The segmentation of the signal is based on the third-order cumulants whose values enter as coefficients of equations of the nonlinear system. Nonlinear LMS optimization is used to solve the system. A multiple-input multiple-output model was used for this technique as it can give a detailed account of several MUAP impositions of EMG signal [21]. Gut et al.

determined the beginning point and the end point of the segment using a sliding time window. In the sliding time window, a certain threshold is considered. When the mean slope within the sliding time window is seen to be increasing the considered threshold value, it is assumed that the active segment begins. When the variation of the EMG signal falls below another threshold value, it is assumed to be the end of this segment [22]. Kauret al. examined different techniques for EMG segmentation. The three techniques analysed were: analysed three EMG segmentation techniques: 1) by identifying the peaks of the MUAPs, 2) by finding the beginning extraction point (BEP) and ending extraction point (EEP) of MUAPs, and 3) by applying the discrete wavelet transform (DWT). In the first decomposition method, the EMG signal was decomposed by using an algorithm that distinguished the parts of low activity and the individual MUAPs; the second technique identified the BEPs and EEPs by using a sliding time window through the whole signal and identified the BEPs and EEPs of the possible MUAPs; and in the third technique, MUAPs were detected from the EMG signal by decomposing the signal using the daubechies4 (db4) wavelet. The workings of the three techniques were observed. The first technique had the best performance with a total success rate of 95.90%, in comparison with second technique having the total success rates of 75.39% and 66.64% for the third techniques [23].

III. TECHNIQUES USED FOR SEGMENTATION

1. Segmentation done by Daubechies Wavelet Transform:-

There are many Daubechies transforms, they all are very similar. The technique used for the segmentation of the EMG signal in this work is the db4 wavelet transform. The db4 wavelet is the easiest wavelet transform. In db4 wavelet transform, considering a signal f , having an even number of values N , then the first level of db4 waveform is called the mapping and it is given as $f \rightarrow (a^1 | d^1)$. The mapping goes from the signal f to its first trend sub signal a^1 and to its first fluctuation sub signal d^1 where each value a_m of $a^1 = (a_1, a_2, \dots, a_{N/2})$ is equal to a scalar product which is given as

$$a_m = f \cdot V_m^1 \quad (1.1)$$

Here V_m^1 is the scaling signal.

Similarly each value d_m of $d^1 = (d_1, d_2, \dots, d_{N/2})$ is equal to the scalar product

$$d_m = f \cdot W_m^1 \quad (1.2)$$

Here W_m^1 is the wavelet.

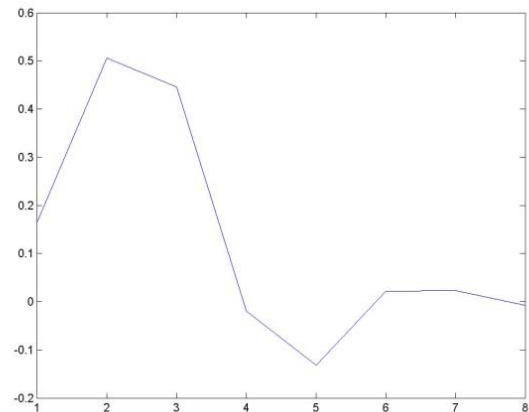


Figure 1: Segmentation of EMG Signal using DWT for Normal subject

The Figure shows the decomposition of the EMG signal with the Daubechies wavelet transform. In this case a portion of MUAPs is shown which is extracted using the db4 wavelet transforms [23].

The EMG signal of a myopathy patient is also segmented in order to know the mechanism of the muscles of the patient clearly. This segmentation of the myopathy signal will help to diagnose the part of the muscle where the disorder is detected. Basically segmentation is done so that the signal could be decomposed into simpler form. Thus the signal could be easier to read when used clinically. Similar to the EMG of a normal person, the EMG signal of the patient will be decomposed in the same manner [24]

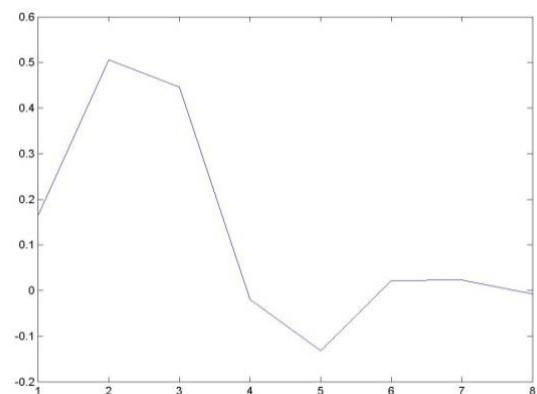


Figure 2: Segmentation of EMG signal using DWT for Myopathy subject

Advantages of using DWT technique are:-

- The Daubechies wavelet transforms have proved to be the efficient tools for the signal segmentation and signal processing.
- These can be used for compression of the signal, for the classification of the signal and also in image analysis, compression and noise removal for audio signals and images, and include image enhancement and recognition.

2. Segmentation by Identifying the Peaks of MUAPs :-

In order to detect the MUAPs comprising the EMG, the signal is segmented to generate the possible MUAP waveforms. Regions of low activity are removed using a threshold T which depends upon $\max_i \{x_i\}$ and the mean absolute value $(1/L) \sum_{i=1}^L |x_i|$ where x_i are the discrete values of the EMG signal and L is the number of samples. The threshold T is calculated as below:

$$\text{If } \max_i \{x_i\} > \frac{30}{L} \sum_{i=1}^L |x_i|, \text{ then } T = \frac{5}{L} \sum_{i=1}^L |x_i| \text{ else } T = \max_i \{x_i\} / 5 \quad (1.3)$$

This threshold is used to identify the peaks of MUAPs of the EMG signal. Peaks that are above the mentioned threshold are considered as individual MUAPs. Also a window of 60 samples is placed over the identified peak. If there is any greater peak found then it is also considered in the window otherwise the 60 points is considered as MUAP waveform [3].

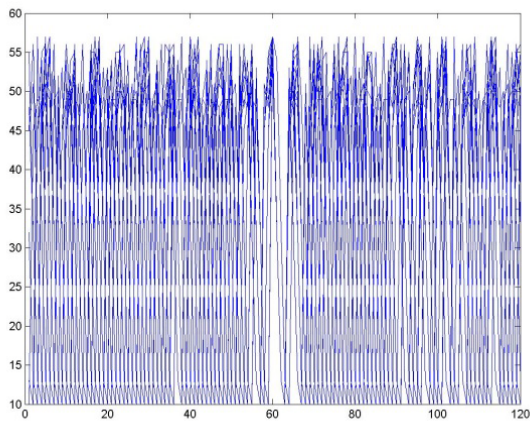


Figure 3: Segmentation of EMG Signal by Identifying the Peaks of MUAPs for Normal Subject

Similarly the peaks of the MUAPs of a myopathy patient are also identified so that a small and simpler part of the signal could be obtained and studied properly [23].

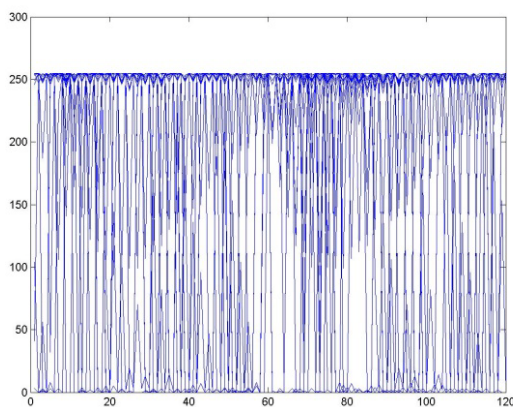


Figure 4: Segmentation of EMG signal by Identifying the Peaks of MUAPs for Myopathy Subject

Advantages of using the Segmentation Technique by Identifying the Peaks of the MUAPs:-

- It is easy to use. Also, it is a good technique for the identification of the highest peaks of MUAPs.
- This is the technique that has the capability to adapt different EMG signals.
- The important matter of concern in this case was choosing a proper window length in order to cover the main duration of MUAP spikes whenever the disease cases are to be considered. If the window length considered will be shorter then it will not be possible to contain the main MUAP spikes. This happens especially in case of motor neuron diseases because in those cases the MUAPs have longer duration [3].

IV. CONCLUSIONS

In conclusion, the segmentation done by extracting the peaks of MUAPs using a certain threshold value and the daubechies wavelet transform are seen to be showing the exact results with proper extraction of the peaks. These techniques are considered as the simple, accurate, fast and reliable methods for the decomposition of the signal. It was found that both the methods are good for the processing of the non-stationary signals such as bio-medical signals where both time and frequency information is required. The advantages and disadvantages of both the techniques are discussed.

V. ACKNOWLEDGEMENT

I thank Dr.Gursewak Singh Brar (H.O.D of Electrical Department) and Prof.Navneet Kaur Panag (Assistant Professor of Electrical Department).

REFERENCES

- [1] R. Gut and G. S. Moschytz, "High Precision EMG Signal Decomposition Using Communication Techniques", IEEE Transactions on Signal Processing, Vol. 48, No.9, 2000, pp. 2487-2494.
- [2] E. Chauvet, O. Fokapu, J. Y. Hogrel, D. Gamet and J. Duchene, "Automatic identification of motor unit action potential trains from electromyographic signals using fuzzy techniques", Medical and Biology Engineering and Computing Vol. 41, No.6, 2003, pp. 646-653.
- [3] E. Chauvet, O. Fokapu, J. Y. Hogrel, D. Gamet and J. Duchene, "A method of EMG decomposition based on fuzzy logic", Proceedings of the 23rd Annual EMBS International Conference, Vol. 2, 2001, pp. 1948-1950.
- [4] C.D. Katsis, D.I. Fotiadis, A. Likas and I. Sarmas, "Automatic discovery of the number of MUAP clusters and superimposed MUAP decomposition in electromyograms", Proceedings of the 4th Annual IEEE Conf. on Information Technology Applications in Biomedicine, 2003, pp. 177-180.

- [5] C.D. Katsis, Y. Goletsis, A. Likas, D.I. Fotiadis, I. Sarmas, "A novel method for automated EMG decomposition and MUAP classification", *Artificial Intelligence in Medicine*, Vol. 37, No.1, 2006, pp. 55-64.
- [6] C.D. Katsis, T. P. Exarchos, Costas Popaloukas, Yorgos Goletsis, Dimitrios I. Fotiadis, Ioannis Sarmas, "A two stage method for MUAP classification based on EMG decomposition", *Computers in Biology and Medicine*, Vol. 37, No. 9, 2007, pp. 1232-1240.
- [7] C.S. Pattichis, C.N. Schizas and L.T. Middleton, "Neural Network Models in EMG Diagnosis", *IEEE Transactions on Biomedical Engg*, Vol. 42, No. 5, 1995, pp. 486-496.
- [8] M.B.I. Reaz, M.S. Hussain, and F. Mohd-Yasin. "Techniques of EMG signal analysis: detection, processing, classification and applications". *Biological procedures online*, Springer, 8(1):11-35, 2006.
- [9] L. Sornmo and P. Laguna. "Bioelectrical signal processing in cardiac and neurological applications". Elsevier Academic Press, 2005.
- [10] O. Bida. "Influence of electromyogram (EMG) amplitude processing in EMG-torque estimation". PhD thesis, Worcester Polytechnic Institute, 2005.
- [11] M.A. Oskoei and H. Hu. "Support vector machine-based classification scheme for myoelectric control applied to upper limb". *Biomedical Engineering, IEEE Transactions on*, 55(8):1956-1965, 2008.
- [12] C.I. Christodoulou and C.S. Pattichis. "Unsupervised pattern recognition for the classification of EMG signals". *Biomedical Engineering, IEEE Transactions on*, 46(2):169-178, 1999.
- [13] J. Fang, G.C. Agarwal, B.T. Shahani, "Decomposition of EMG signal by wavelet spectrum matching", *Proceedings of the 19th International Conference - IEEE/EMBS*, Vol. 3, 1997, pp. 1253-1256.
- [14] P. Guglielminotti, R. Merletti, "Effect of electrode location on surface myoelectric signal variables: a simulation study", *9th Int. Congress of ISEK*, 1992.
- [15] F. Laterza, G. Olmo, "Analysis of EMG signals by means of the matched wavelet transform". *Electronics Letters*, Vol. 33, No. 5, 1997, pp. 357-359.
- [16] A.R. Ismail, S.S. Asfour, "Continuous wavelet Transform application to EMG signals during human gait", *32nd Asilomar Conference on Signals, Systems & Computers*, 1998, Vol. 1, pp. 325-329.
- [17] C.S. Pattichis, M.S. Pattichis, "Time-scale analysis of motor unit action potentials". *IEEE Transactions on Biomedical Engg*, Vol. 46, No. 11, 1999, pp. 1320-1329.
- [18] J. Fang, G.C. Agarwal, B.T. Shahani. "Decomposition of EMG signals by wavelet spectrum matching". *Proceedings of the 19th Annual International Conference of the IEEE Engineering in Medicine and Biology Society* 1997; Chicago, IL, USA. pp. 1253-1256.
- [19] D. Zennaro, P. Welling, V.M. Koch, G.S. Moschytz, T. Laubli. "A Software Package for the Decomposition of Long-Term Multichannel EMG Signal Using Wavelet Coefficients". *IEEE Trans Biomed Eng* 2003; 50(1):58-69.
- [20] R. Yamada, J. Ushiba, Y. Tomita, Y. Masakado. "Decomposition of Electromyographic Signal by Principal Component Analysis of Wavelet Coefficient". *IEEE EMBS Asian-Pacific Conference on Biomedical Engineering* 2003; Keihanna, Japan. pp. 118-119.
- [21] E. Plevin, D. Zazula, "Decomposition of surface EMG signals using non-linear LMS optimisation of higher order cumulants". *Proceedings of the 15th IEEE Symposium on Computer-Based Medical System* 2002; pp. 149-154.
- [22] R. Gut and G.S. Moschytz. "High-precision EMG signal decomposition using communication techniques". *Signal Processing, IEEE Transactions on*, 48(9):2487-2494, 2000.
- [23] G. Kaur, A.S. Arora and VK Jain. "Comparison of the techniques used for segmentation of EMG signals". In *Proceedings of the 11th WSEAS international conference on Mathematical and computational methods in science and engineering*, pages 124-129. World Scientific and Engineering Academy and Society (WSEAS), 2009.
- [24] A.B.M. Suddulouh and A. Md. Iqbal, "An Approach to Identify Myopathy Disease Using Different Signal Processing Features with Comparison", *IEEE Transactions*, pp. 155-158, 2012.