IOSR Journal of Electronics and Communication Engineering (IOSR-JECE)
e-ISSN: 2278-2834,p- ISSN: 2278-8735.Volume 14, Issue 1, Ser. II (Jan.-Feb. 2019), PP 48-54
www.iosrjournals.org

A Study of Various Methods for Detection and Analysis of EMG Signal and Its Application

Prashant S Wankhade[1], Richa Rajani[2]
Assistant Professor[1], Student[2] AlamuriRatnamala Institute of Engineering and technology, Shahapur, Thane, Maharashtra, *India*
Corresponding Author: Prashant S Wankhade

***Abstract**: Electromyography signal is most important signal for analysis of any muscle and can be used for biomedical applications. The techniques of EMG signal analysis such as Surface Electromyography Signal Processing, Wavelet transforms, Independent Component Analysis (ICA)is discussed in this paper in depth. This paper provides researchers a goodunderstanding of EMG signal and its analysis procedures. This knowledge will help to develop more flexibleand efficient applications.*

***Keywords**: EMG, wavelet transform, ICA, SEMG*

Date of Submission: 01-03-2019 Date of acceptance: 18-03-2019

I. Introduction

EMG (electromyography) is a study of muscles function using electrical signal generated by any type of muscle. The detection, processing and analysis of EMG signal has become a major research area in biomedical field involving wide range of expertise from physician, engineer to computer scientist. Study of EMG is said to begin as early as 17th century. Nevertheless, not until the last couple of decades, the EMG study had been intense due to the use of modern electronic devices and equipment along with new techniques in signal processing [1].

Representation of electrical potential in form of timevarying 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 [2]. With different kind of electrode, the EMG signal that obtained might contain different characteristic.

EMG is also used in many types of research laboratories, including those involved in biomechanics, motor control, neuromuscular physiology, movement disorders, postural control, and physical therapy. EMG is controlled by nervous system and depends on anatomical and psychological properties of muscles [3].

II. Methods For EMG Signal Processing

EMG signal processing in any method is divide in various steps i.e. data acquisition, data pre-processing, data modelling, data analysis and interpretation. There is various method for processing of EMG signal but in this paper, only three main techniques are discussed.

a) Surface Electromyography Signal Processing
b) Wavelet transforms
c) Independent Component Analysis (ICA)

a) Surface Electromyography Signal Processing

i. Amplification

EMG signal obtained by electrode is relatively small with amplitude range up to 10 mV or ±5 mV [3,4]. This amplitude range might be too small for further processing. In most applications, EMG signal need to be digitized and sent to processor, microcontroller or CPU for feature extraction. Since signal with insufficient amplitude range might not be feasible to be analysed, amplification of the signal is a necessity. Usually this is done with instrumentation amplifier built specifically to amplify bio signal. Prior to amplification, a pre-amplifying stage would also be necessary to provide initial amplification and converts the signal to a low level of impedance before it is fed to the main amplifier [5]. Instrumentation amplifier could be constructed using general purpose op-amp such as LM 741. However, it is also available in form of a special function integrated circuit (IC). Examples of instrumentation amplifier IC used in literatures are the Analog Devices AD 620 [6,7], Burr-Brown INA 102[5] and Texas Instruments INA 128 [8]. The amplification gain varies according to amplifier manufacturer. Some literatures record an overall gain of 70,000 starts from preamplifier stage [5]. Others use smaller gain from 600,1000 to 10,000 [9] and 50,000 [10].

ii. *Noise sources and removal*

A raw EMG signal sometimes contains inevitable noise. With the presence of noise, the data of muscle contraction characteristic would no longer be genuine. Noise in EMG signal might caused by i) inherent noise in electronics equipment, ii) ambient noise from electromagnetic radiation, iii) motion artifact and iv) inherent instability of signal [11].Noise could also originate from the electrode. The metal electrolyte contact of electrode is intrinsically noisy and ithas become an important factor in EMG noise. It is a limiting factor for detection of very small potentials.

An EMG recording system with wire that connects surface electrode with the adjacent amplifying equipment could be vulnerable to pick up main hums and other electrical interference [12]. Therefore, to solve the noise problem which might results from using lengthy wire, Johnson et al.(1977) had proposed a pair of surface electrode combined with differential amplifier in a single module [12]. The preamplifier circuit built for this module has operational characteristics which allow surface EMG signals to berecorded with effective suppression of extraneous electrical interference. This device which is called miniature skin mounted preamplifier had been used in several literatures. Motion artifact is another source of noise. It could be caused by electrode moving on skin surface and electrode wire movement. Noise produced by motion artifact is in the range of 0 to 20 Hz and the easiest way to deal with this noise is to filter it out with high-pass filter [13]. Regardless of motion artifact noises, SEMG signal in 0 to 20 Hz rangedo provide significant information on firing rates of active motor units [14]. However, in most works, information contained in signal of this range is not of interest.

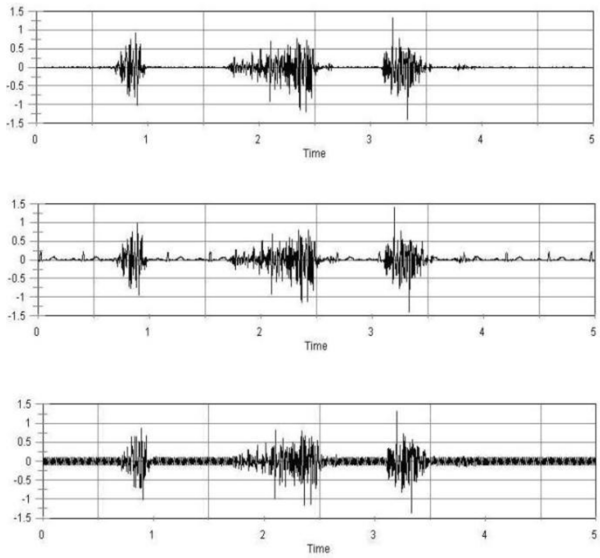

Fig.1. Three figures showing a raw SEMG signal (above), SEMG signal with presence of small ECG artifacts (centre) and SEMG signal with power line interference (below).

There are cases where artifact noise is unavoidable due to natural and intentional causes. For example, Fratini et al. [15]

works on removing motion artifact from surface EMG recording in Whole Body Vibration. Vibration training is used in sport medicine to enhance athletic performance. Surface EMG recording is done on subject undergoing vibration training for muscle activity evaluation. The vibration would produce motion artifact and creates noise. Fratini et al. [15] used adaptive filtering to abolish such noise. Accelerometers are placed onto platform or directly on muscles providing error signal shape to be cancelled from the raw SEMG signal. The results obtained shows effective cancellations of the vibration frequency. In general, surface electrode is used to pick up any biosignal. Obviously, interference from other biosignal is very likely during surface EMG recoding. Electrocardiography (ECG) is the most common source of interference and often known as ECG artifact. A number of literatures had studied location of surface EMG recording that affected by ECG artifact. Among the muscle location that is vulnerable to ECG interference are trunk muscles [16,17], back muscles [18,19] and chest. Various methods had been studied for ECG artefact removal from SEMG signal. High-pass filtering using

Butterworth filter is probably the most simple and straightforward idea. Value of cut-off frequency must be chosen in the way that it would not affect the real SEMG signal. The optimal value of cut-off frequency as proposed in some literatures would be around 30 Hz [20,21].

b) Wavelet transform

One of the main properties of wavelet transform is that it can be implemented by means of a discrete time filter bank. The WT represents a very suitable method for the classification of EMG signals [27]. It is an alternative to other time frequency representations with the advantage of being linear, yielding a multiresolution representation and not being affected by crossterms [18,20,21,22,23,24]. Under certain conditions, the EMG signal will be considered as the sum of scaled delayed versions of a single prototype. The WT is described by Eqn.1 [25,26]:

$$C(s,p) = f(t).\psi(s,p,t)dt \qquad \text{(i)}$$

where:
C (scale, position) – wavelet coefficient,
f(t) – signal,
ψ(scale, position) – wavelet function.

WT will be also used to analyze signals atdifferent resolution levels. It will be analyzed therelationship between wavelet coefficients and the time frequency plane. The DWT is a transformation of theoriginal temporal signal into a wavelet basis space. Thetime-frequency wavelet representation is performed byrepeatedly filtering the signal with a pair of filters that cutthe frequency domain in the middle. Specifically, the DWTdecomposes a signal into an approximation signal and adetail signal. The approximation signal is subsequentlydivided into new approximation and detail signals. Thisprocess is carried out iteratively producing a set ofapproximation signals at different detail levels (scales) anda final gross approximation of the signal. This can beexpressed as follows (Fig.2-3):

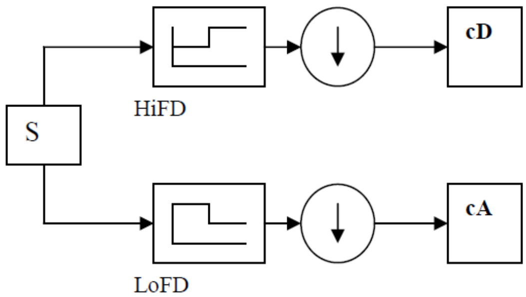

Fig. 2. Discrete wavelet transform: S – signal; HiFD – high pass filter; LoFD – low pass filter; cA – wavelet coefficients for high scale; cD – wavelet coefficients for low scale

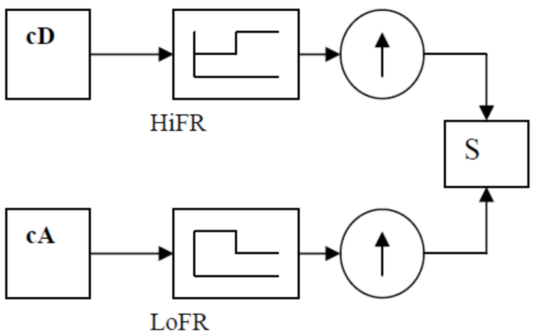

Fig.3. Inverse discrete wavelet transform: S – signal; HiFR – high pass filter; LoFR – low pass filter; cD – wavelet coefficients for low scale; cA – wavelet coefficients for high scale.

The *A* and *D* sequences obtained as the result ofIDWT are still massive in terms of the number of samples, which contributes to large dimensionality of feature space. Besides, the sequences have a high noise component inherited from the original EMG signal (Fig.4-5).

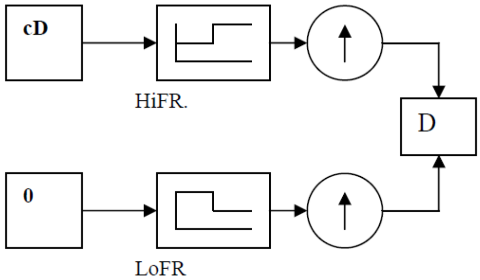

Fig. 4. The reconstruction of detailed sequence; 0 – the signal is equal 0; HiFR – high pass filter; LoFR – low pass filter; cD – wavelet coefficients for low scale; D- detailed sequence.

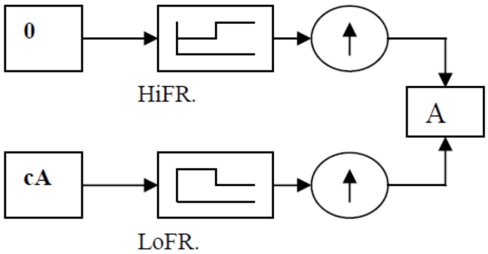

Fig. 5. The reconstruction of approximation sequence; 0 – the signal is equal 0; HiFR – high pass filter; LoFR – low pass filter; cA – wavelet coefficients for high scale; A- approximation sequence.

The scales *c* were chosen in conjunction with thesampling rate to give wavelets with a period in the 3-20 ms range. This range was reported for single human muscle action potentials. The magnitude of *C(a,d)* was a measure of the matching of the original with the *'db4'* scaled and translated wavelet. Results of the decomposition are shown in figure 6. Analysis was performed using the Matlab 6 Wavelet Toolbox. The level of decomposition is described by numbers close the signals. The sequences have different value of level and frequency. The signal $a_5$has high scaleand low frequency. The detailed sequences *(d1- d5)* have the lower scale than *a5*. The biggest scale has signal *d5,* and the lowest scale has signal *d1*. Those are the signals with the highest frequency.

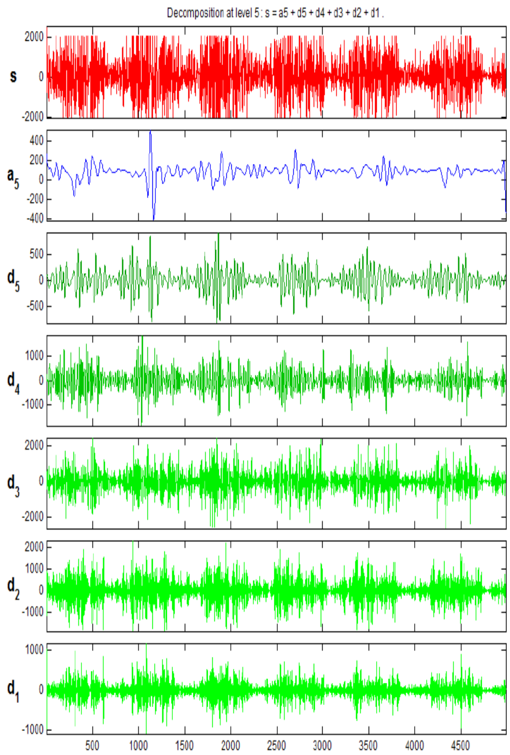

Fig.6. Wavelet decomposition

c) *Independent Component Analysis (ICA)*

The ICA algorithm has rapidly become one of the most prominent signal processing techniques. The ICA is a statistical method, which can assume the original signal from the mixture signal.P. Common first proposed this method [28] and it is used for transforming an experimental multivariate
random vector into components that are statistically independent from each other. In ICA there is noorder of magnitude associated with each component, and the extracted components are invariant to the
sign of the sources. Using this vector-matrix notation, the above mixing model is written as:

x=As (ii)

Equation (ii) represents an ICA model. Where $X = [x1, x2 \ldots xm]^T$is an m vector of linear mixtures, $S = [s1, s2,\ldots,sn]^T$is an n-dimensional random vector of independent source signals, and A is full-rankm × n scalar linearly mixing matrix (n × m). Without knowing the source signals and the mixingmatrix, a signal copy of the statistically independent sources s will be estimated from observedmixtures x. Figure 6 shows that the block diagram of the blind source separation technique.

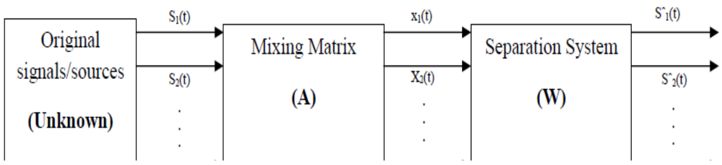

Fig.7 Blind source separation (BSS) block diagram

In figure [7], s (t) are the sources. X (t) are the recordings sˆ(t) are the estimated sources, A is the mixing matrix, and W is the un-mixing matrix. Without non-Gaussianity, the estimation of the ICA model is not possible. ICA yields improvements above Principal Component Analysis (PCA), when signals do not display a Gaussian distribution [29]. It is suitable to separate the EMG signals from
different sources when the assumptions below are fulfilled:

(i) Sources are independent at each time instant
(ii) Mixing matrix is linear and propagation delays of it are negligible
(iii) The sources are stationary and do not change with time
(iv) The signals are non-Gaussian
(v) The electromyographic (EMG) artifacts are statistically and mutually independent.

Consequently, ICA is a feasible method for source separation and decomposition of an EMG signal.

Nowadays it is widely used to separate and remove noise sources from EMG and to decompose EMG signals into a maximum number of independent components. There are different types of ICA algorithms; some of them are used for processing the EMG signal, such as the Fast ICA algorithm, the

Joint Approximate Diagonalization of Eigen-matrices (JADE), and the Infomax Estimation or maximum likelihood algorithm. The Fast ICA algorithm is a very popular method due to its simplicity, fast convergence and satisfactory results.

Hyvarinen introduced new contrast (or objective) functions for ICA based on the minimization of mutual information first [30]. There are two types of fast ICA algorithms: Fixed-point algorithm for one unit, and Fixed-point algorithm for several units. The Fast ICA algorithm could be performed at the beginning of each iteration, in order to solve overlaps and cancellations between MUAPs. It solves the low signal-to-noise ratio, which is the main complication in surface EMG signal decomposition [31].

Nakamura *et al*. reported that ICA is a very useful technique for decomposing sEMG signals into Motor-Unit Action Potentials (MUAPs) originating from different muscle sources. Fast ICA could provide much better discrimination of the properties of Motor-Unit Action Potential Trains (MUAPTs) for sEMG signal decomposition (*i.e.*, waveforms, discharge intervals, *etc*.) than PCA [32]. Fast ICA is

a type of algorithm that successfully isolates power-line components from EMG signals. However, the performance of Fast ICA fluctuates quickly and few components obtained by ICA decomposition are inverted—a major problem when automatically decomposing EMG signals. Cardoso firstly proposed the JADE algorithm [33], which is more effective than Fast ICA for decomposing sEMG signals [33].

The JADE algorithm is based on the principle of computing several cumulant tensors, which are a generalization of matrices [34]. Firstly, Zhou *et al*. examined the feasibility of ICA based on an Information maximization (Infomax) algorithm for obtaining more information of the active motor units. Infomax ICA was unable to isolate all the MUAP trains due to time delays and the variances in shape between the surface action potentials detected at the different electrode locations. Furthermore, blind source separation techniques addressing a more complex convoluted mixing model are required for obtaining accurate firing rate information [35]. Bell and Sejnowski first introduced the Maximum Likelihood (ML) algorithm by using the stochastic gradient method [36]. The estimation of this algorithm is based on the fact that no prior information is available.

Furthermore, Garcia *et al*. demonstrated that the JADE ICA could be used successfully for solving overlaps of MUAPs. In each iteration of the algorithm, the action potentials of one motor unit (MU) could generally be separated from the others. They showed that the JADE algorithm is more efficient than Fast ICA. JADE's performance is not strongly affected by added noise. However, inter-channel delay is the main drawback of this method [37].

In this section, the authors have reviewed some of the more prevalent approaches to ICA along with their potential benefits when applying them to EMG signals. The author has concluded that the ICA-based filtering procedure provides successful results in removing ECG artifacts and power-line noise (PLI), due to its largely independent signal-to-noise ratio, and because of its subtle effects on frequency content.

III. Conclusion

EMG (Electromyography) is one of the efficient techniques used for analysis of muscle activity.EMG carries important information regarding the nerve system which gives a reliable results. There are number of techniques used for analysis of this generated signal but in this, mainly three techniques are discussed. The aim of this paper to provide study of these techniques and accordingly it will help to analyse the EMG signal in different environment. This comparison ofmethodologies will help researchers encounter the perfect method for analyzing EMG signals, which isrequired in medical and physiological applications, such as diagnosis of neurological problems,biomedical and biochemical research, prosthetic arm control and end-user applications.

Reference

[1]. A. N. Norali, M.H. Mat Som ," Surface Electromyography Signal Processing and Application: A Review" , Proceedings of the International Conference on Man-Machine Systems (ICoMMS), October 2009, BatuFerringhi, Penang, MALAYSIA.

[2]. B. Gerdle, S. Karlsson, S. Day, and M. Djupsjöbacka, "Acquisition, Processing and Analysis of the Surface Electromyogram," in Modern Techniques in Neuroscience, U. Windhorst and H. Johansson, Eds. Berlin: Springer Verlag, 1999, pp. 705-755

[3]. J. Pauk, "Different techniques for EMG signal processing", Journal of Vibroengineering10(4):571-576, December 2008

[4]. Sundaraj, K., "Cheap In-House Setup for EMG Acquisition," IFMBE Proceedings BIOMED, pp. 146-148, 2008.

[5]. V. Gupta, N.P. Reddy, and E.P. Canilang, "Surface EMG Measurements at the Throat during Dry and Wet Swallowing," Dysphagia, vol. 11, pp. 173-179, 1996.

[6]. W. Peasgood, T. Whitlock, A. Bateman, M.E. Fry, R.S. Jones, and A. Davis-Smith, "EMG-controlled closed loop electrical stimulation using a digital signal processor," Electronics Letters, vol. 36, pp.1832-1833, 26th October 2000.

[7]. N.M.L Celani, C.M. Soria, E.C. Orosco1, F.A. di Sciascio, and M.E. Valentinuzzi, "Two-Dimensional Myoelectric Control of a Robotic Arm for Upper Limb Amputees," Journal of Physics: Conference Series, vol. 90, pp. 1-8, 2007.

[8]. A. Bhaskar, E. Tharion and, S.R. Devasahayam, "Computer-based inexpensive surface electromyography recording for a student laboratory," American Journal of Physiology - Advances in Physiology Education, vol. 31, pp. 242-243, 2007.

[9]. A. Rainoldi, C. Cescon, A. Bottin, R. Casale, and I. Caruso, "Surface EMG alterations induced by underwater recording," Journal of Electromyography and Kinesiology, vol. 14, pp. 325-331, 2004.

[10]. P. Zhou and W.Z. Rymer, "Motor Unit Action Potential Number Estimation in the Surface Electromyogram: Wavelet Matching Method and Its Performance Boundary," First International IEEE EMBS Conference on Neural Engineering, pp. 336-339, 2003.

[11]. "Surface Electromyography: Detection and Recording," DelSys Incorporated, 1996.

[12]. S.W. Johnson, P.A. Lynn, J.S.G. Miller, and G.A.L. Reed, "Miniature skin-mounted preamplifier for measurement of surface electromyographic potentials," Medical and Biological Engineering and Computing, vol. 15, pp. 710-711, 1977.

[13]. K. Najarian and R. Splinter, "Chapter 11: Electromyogram" in Biomedical signal and image processing, CRC Press, 2006, pp. 237-256.

[14]. R. Merletti and H.J. Hermens, "Detection and conditioning of surface the EMG signal," in Electromyography: physiology, engineering, and noninvasive applications, R. Merletti, and P.A. Parker, Eds. Wiley- IEEE, 2004, pp. 107-132.

[15]. A. Fratini, M. Cesarelli, P. Bifulco, A. La Gatta, M. Romano, and G. Pasquariello, "Acceleration driven adaptive filter to remove motion artifact from EMG recordings in Whole Body Vibration," IFMBE Proceedings MEDICON, pp. 990-993, 2007.

[16]. G.T. Allison, "Trunk muscle onset detection technique for EMG signals with ECG artifact," Journal of Electromyography and Kinesiology, vol. 13, pp. 209-216, 2003.

[17]. Y. Hu, X.H. Li, X.B. Xie, L.Y. Pang, Y. Cao, and K.D.K. Luk, "Applying independent component analysis on ECG cancellation technique for the surface recording of trunk electromyography," IEEEEMBS 27th Annual International Conference of the Engineering in Medicine and Biology Society, pp. 3647-3649, 2005.

[18]. Y. Hu, J.N.F. Mak, and K.D.K. Luk, "Effect of electrocardiographic contamination on surface electromyography assessment of back muscles," Journal of Electromyography and Kinesiology, vol. 19, pp. 145-156, 2009.

[19]. C. Marque, C. Bisch, R. Dantas, S. Elayoubi, V. Brosse, and C. Pe´rot, "Adaptive filtering for ECG rejection from surface EMG recordings," Journal of Electromyography and Kinesiology, vol. 15, pp. 310-315, 2005.

[20]. M.S. Redfern, R.E. Hughes, and D.B. Chaffin, "High-pass filtering to remove electrocardiographic interference from torso EMG recordings," Clinical Biomechanics, vol. 8, pp. 44-48, 1993.

[21]. J.D.M. Drake and J.P. Callaghan, "Elimination of electrocardiogram contamination from electromyogram signals: An evaluation of currently used removal techniques," Journal of Electromyography and Kinesiology, vol. 16, pp. 175-187, 2006.

[22]. P. Zhou, B. Lock, and T.A. Kuiken, "Real time ECG artifact removal for myoelectric prosthesis control," Physiological Measurement, vol. 28, pp. 397-413,2007.

[23]. Martin W, Flandrin P. Wigner–Ville spectral analysis of nonstationary processes. IEEE Trans Acoust Speech Signal Processing. 1985;33:1461–1470.

[24]. Cohen L. Time-frequency analysis. Englewood Cliffs, Prentice-Hall; New Jersey, USA, 1995.

[25]. Kumar D. K., Pah N. D., Bradley A. Wavelet analysis of surface electromyography to determine muscle fatigue. IEEE Trans Neural SystRehabil Eng. 2003;11(4):400–406.

[26]. Ismail A. R., Asfour S. S. Continuous wavelet transform application to EMG signals during human gait. Thirty-Second Asilomar Conference on Signals, Systems &Computers 1998; 1:325-329.

[27]. Laterza F., Olmo G. Analysis of EMG signals by means of the matched wavelet transform. Electronics Letters. 1997; 33(5):357–359.
[28]. Comon, P. Independent component analysis—A new concept? Signal Process. 1994, 36, 287–314.
[29]. Staudenmann, D.; Daffertshofer, A.; Kingma, I.; Stegeman, D.F.; van Dieen, J.H. Independent component analysis of high-density electromyography in muscle force estimation. IEEE Trans. Biomed. Eng. 2007, 54, 751–754.
[30]. Hyverinen, A. Fast and robust fixed- point algorithms for independent component analysis. IEEE Trans. Neural Netw. 1999, 10, 626–634.
[31]. Garcia, G.A.; Maekawa, K.; Akazawa, K. Decomposition of synthetic multi-channel surface-electromyogram using independent component analysis. Lect. Notes Comput. Sci. 2004, 3195, 985–992.
[32]. Nakamura, H.; Yoshida, M.; Kotani, M.; Akazawa, K.; Moritani, T. The application of independent component analysis to the multi-channel surface electromyographic signals for separation of motor unit action potential trains: Part I—Measuring techniques. J. Electromyogr.Kinesiol. 2004, 14, 433–441.
[33]. Cardoso, J.F.; Souloumiaac, A. Blind beam forming for Non-Gaussian signals. IEEE Proc. F 1993, 140, 362–370.
[34]. Acharaya, D.P.; Panda, G. A review of independent component analysis techniques and their applications. IETE Tech. Rev. 2008, 25, 320–332.
[35]. Zhou, P.; Madeleine, M.; Lowery, W; Rymer, Z. Extracting motor unit firing information by independent component analysis of surface electromyogram: A preliminary study using a simulation approach. Int. J. Comput. Syst. Signal. 2006, 7, 19–28.
[36]. Bell, A.J.; Sejnowski, T.J. An information maximization approach to blind separation and blind deconvolution. Neural Comput. 1995, 7, 1129–1159.
[37]. García, G.A.; Okuno, R.; Akazawa, K. A decomposition algorithm for surface electrode-array electromyogram A non-invasive, three-step approach to analyze surface EMG signals. IEEE Eng. Med. Biol. Mag. **2005**, 24, 63–72.

IOSR Journal of Electronics and Communication Engineering (IOSR-JECE) is UGC approved Journal with Sl. No. 5016, Journal no. 49082.

Prashant S Wankhade. "A Study of Various Methods for Detection and Analysis of EMG Signal and Its Application." IOSR Journal of Electronics and Communication Engineering (IOSR-JECE) 14.1 (2019): 48-54.