

Survey of Different EMG Signal Analysis Techniques

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ABSTRACT: Electromyographic (EMG) signals are significant in numerous biomedical and neurological applications. However, noisy EMG signal has always been an obstacle to achieve the desired results. To optimize the performance and reduce the noise in EMG signal, the signal has to undergo pre-processing, detection and processing. Analysis of EMG signal is not an easy task as it is a composite signal mixed with noises. These noises are acquired by the EMG signal while travelling through different body tissues. Surface EMG signal may contain noises due to interference of different motor signals present around the motor units of interest. The processing of EMG signal is performed in several different ways. Time-frequency approaches, different transforms and few algorithms to analyse EMG data are discussed. The paper provides the application- oriented approach for the selection of analysis methods.

KEYWORDS: EMG signals, time- frequency approaches, wavelet analysis, artificial intelligence, transforms.

I. INTRODUCTION

EMG is a biomedical signal collected from skeletal muscles in human body. The main reason behind the EMG signal analysis lies in its importance for clinical and biomedical applications. Orofacial EMG signals can be used in speech therapies for the patients of idiopathic Parkinson's disease [1]. The EMG signal recording and processing is comparatively a newer field and there are still many difficulties in detection and decomposition of the EMG signal. Since EMG is a low frequency and low amplitude signal, even low quality of noise can affect the quality of signal and distort the required EMG signal. Improving detection techniques to reduce noise and better algorithms for detecting the EMG signal have been researched extensively.

EMG is presented as a function of time and can be described in terms of its amplitude, frequency and phase. It is a signal which measures electrical currents generated during the contraction of the muscle which represents the neuromuscular activity of that muscle. Out of three types of muscles in human body, EMG signals are collected from skeletal muscles. The skeletal muscle tissues are attached to the bones. The contraction of these muscles is responsible for supporting and moving the human skeleton. When an impulse is generated by the neuron, the contraction of the skeletal muscle is initiated which is usually voluntary. Skeletal muscles are studied in order to obtain the EMG data. Skeletal muscle fibers have abundant neurons for its contraction. This type of neuron which produces contraction are called motor neurons and are placed closer to muscle tissue but not actually connected to it. One motor neuron can provide stimulation to many muscle fibers. The human body is considered electrically neutral as a whole as it has the same number of positive and negative charges. But while in the resting state, the nerve cell membrane is polarized due to differences in the concentrations and ionic composition across the plasma membrane. A potential difference exists between the intracellular and extracellular fluids of the cell in human body. The EMG signal is controlled by the nervous system and depends upon various factors such as type of body tissue, anatomical and physiological properties of the muscle and type of motor units present in the muscle. The MUAPs (Motor Unit Action Potentials) play an

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important role in diagnosis of neuromuscular disorder. The shapes and firing rates of the MUAPs provide important information to detect various neuromuscular disorders and hence are of special interest to generate EMG data.

When a stimulus is generated from the neuron, as a response, a muscle fiber depolarizes as the signal propagates along its surface and the fiber twitches. This depolarization along with a movement of ions in the cell generates an electric field near each muscle fiber. An EMG signal is the train of such Motor Unit Action Potential (MUAP) showing the muscle response to neural stimulation. The EMG signal appears random in nature and is generally modeled as a filtered impulse process where the MUAP is the filter and the impulse process stands for the neuron pulses, often modeled as a Poisson process [2]. Figure 1 shows the process of acquiring EMG signal and its decomposition to achieve the individual MUAPs.

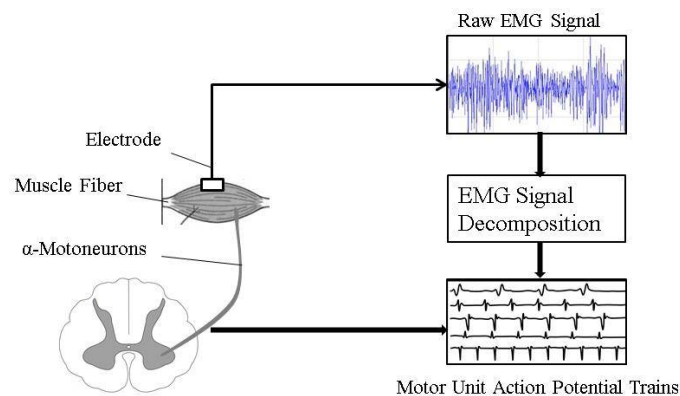


Fig 1. EMG signal and its decomposition [3]

However, analysis of EMG signal is not an easy task as it is a complicated signal mixed with different types of noises. These noises are acquired by the EMG signal while travelling through different body tissues. In case of surface EMG signal, the collected signal may contain noises due to interference of different motor signals present around the motor units of interest. To improve the reliability of the received signal, it is essential to filter different kinds of noise and interference introduced in signal. The instability of EMG signal amplitude plays an important role in introducing the noise making the analysis of EMG a critical task.

Section II describes the brief history of EMG signal and methods of collection of EMG signal. It also describes the simple mathematical model of EMG signal. Section III reviews time-frequency approaches, wavelet transforms and artificial intelligence as tools to analyse the EMG signal. Section IV discusses the advantages and the most suitable application for each method. A conclusion is presented in section V of the paper.

II. RELATED WORK

Though recording and processing of EMG signal is a novice science, discovery of EMG signal is few centuries older. Jan Swammerdam (1637 - 1680) who was a Dutch anatomist and biologist discovered that the stroking of innervating nerve of frogs generates a contraction and evidence show that he also conducted the first electrical stimulation experiments[4]. Francesco Redi was the first to recognize the connection between the muscles and generation of electricity [5]. In 1666, he documented that the electric ray fish used a highly-specialized muscle to generate the electricity. Alessandro Volta developed the very first device that could be used to stimulate the muscles. Luigi Galvani who is credited as the father of neurophysiology showed that “electrical stimulation of muscular tissue produces contraction and force.” Carlo Matteucci showed that bioelectricity is connected with the muscular contraction. In 1842, he demonstrated the existence of action potential accompanying the frog’s muscle. A French neurologist Guillaume Duchenne revived Galvani’s work. He was interested in medical electricity for therapeutic purposes. In 1850, he applied electrical stimulation to intact skeletal muscles and systematically mapped out functions of every skeletal muscles [3][6]. The various findings revealed that the muscles around the eyes are only active during a genuine smile

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and an insincere smile involves only the muscles of the mouth [7]. In 1849, Dubios-Raymond discovered that it was also possible to record electrical activity during a voluntary muscle contraction. The first recording of this activity was made by Marey in 1890, who also introduced the term electromyography. In 1922, Gasser and Erlanger used an oscilloscope to record the electrical signals from muscles. Because of the stochastic nature of the myoelectric signal, only rough information could be obtained from its observation. Clinical use of surface EMG for the treatment of more specific disorders began in the 1960s.

While all these advancements happening for recognizing that contraction and relaxation of the muscles produces an electrical signal which can be of vital importance, several instruments were being developed to measure that electric signal. Forbes et al. used the floating electrodes on the moving body. They recorded the EMG signals in elephants. Forbes also used Cathode Ray Tube (CRT) to amplify action potentials of the signals. Andrian and Bronk developed the concentric needle electrode in 1929 [5]. They used it for researching motor controls and muscle scheme. These electrodes enabled the detection of EMG signal in individual muscle fibers and the small group of muscles. These electrodes are the hypodermic needle with insulated wire in its barrel [3]. Herbert Jasper created a unipolar needle electrode. He constructed the first electromyograph which was one of the groundbreaking advancement in neurology and dealing with epilepsy. John Basmajian compiled all of the known information about the EMG and created fine-wire electrodes which are better than the needles [8]. His book called 'Muscles Alive' is one of the most invaluable tools to study about EMG signals. He is the founder of International Society of Electrophysiological Kinesiology (ISEK) which worked to create standards for EMG usage and reporting.

EMG is the study of electric signals produced by the muscles and in Greek, prefix 'myo-' means muscle. Hence, it is also referred as myoelectric activity. Nerves as well as muscle tissue conduct electrical potential. The electrical potential conducted by the muscle tissue is called as the muscle action potential. To collect the EMG information present in the muscle action potentials, Surface EMG is used. There are two main concerns regarding the detection and recording of the EMG signal which affect the reliability of the collected data. The first is the signal-to-noise ratio (SNR) which is defined as the ratio of the energy in the EMG signals to the energy in the noise signal. The noise in EMG signal is defined as electrical signals that are not part of the desired EMG signal. The other issue is the distortion of the signal. It refers to the relative contribution of any frequency component in the desired EMG signal should not be altered by other factors such as instrument or type of the electrodes used.

Two types of electrodes are used to acquire muscle signals. They are invasive electrode and non-invasive electrode. When EMG signal is acquired from non-invasive electrodes mounted directly on the skin, the signal is a composite. It consists of all the muscle fiber action potentials, occurring in the muscles underlying the skin. These action potentials occur at random intervals. So at any one moment, the EMG signal may be either positive or negative voltage. If individual muscle fiber action potentials are desired, then they are acquired using wire or needle electrodes placed directly in the muscle i. e. invasive needles are used to collect the data. The combination of the muscle fiber action potentials from all the muscle fibers of a single motor unit is the motor unit action potential (MUAP) which can be detected by a skin surface electrode (non-invasive) located near this field, or by a needle electrode (invasive) inserted in the muscle [9].

A simple mathematical model of the EMG signal is given by,

$$x(n) = \sum_{r=0}^{N-1} h(r)e(n-r) + w(n)$$

where, $x(n)$ is a modeled EMG signal, $e(n)$ is a point of processed EMG signal represents the firing impulse $h(r)$ represents the MUAP, $w(n)$ is a zero mean additive white Gaussian noise and N is the number of motor unit firings.

The signal is collected at the electrode and then amplified by a differential amplifier. First stage amplifier is used. If necessary, additional amplifier stages can be added as the EMG signal is of very low order and needs to be amplified to study the various characteristics. EMG signal undergoes different processing stages to eliminate very high or low frequency components which act as noise and also to remove any kind of distortion. The most common variable of interest in EMG signal is its amplitude. Hence, to obtain the amplitude, the signal is rectified and normalized to obtain the EMG amplitude. The next section describes various techniques to analyse EMG signal.

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III. EMG ANALYSING TECHNIQUES

After the initial detection and pre-processing of the EMG signal, the EMG signals are analysed. For the analysis, various methods are available. The selection of the method primarily depends upon the application. Some of the EMG analysing techniques are described in this section.

Time-frequency approach for EMG signal analysis

EMG signal can be represented as a function of time. To gain the quantitative information from EMG signal various time-frequency approaches have been used which include Wigner- Ville distribution (WVD), Cohen class transformation, and Choi- Williams distribution.

During a sustained muscle contraction, the spectral components of the surface myoelectric signal are compressed towards the lower frequencies [10]. This occurs when surface EMG signal is recorded with non-invasive electrodes under dynamic contraction of the muscle, the frequency of the signal changes continuously over the time. Those changes in the frequency are termed as nonstationarities [11]. Nonstationarities of the surface myoelectric signal can be classified as slow or fast. Slow nonstationarities are mostly due to the accumulation of metabolites that causes the electrical manifestations of muscle fatigue. Fast nonstationarities are mainly related to the biomechanics of the task. Variations in muscle force cause a modification of the frequency content of the signal. To deal with these non-stationary signals different time-frequency approaches were devised.

1. Cohen- class time- frequency analysis: To study the frequency content of such a non-stationary signal Cohen time-frequency transform found to be useful. This approach modelled the EMG signal obtained from dynamic contraction as realizations of nonstationary stochastic processes [12]. Previous works by Martin and Flandrin [13], Amin [14] and Syeed and Jones [15] demonstrated that any Cohen class time-frequency spectrum $S(t, f)$ may be written as following equation:

$$S(t, f) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} E \left\{ x \left(t' + \frac{\tau}{2} \right) x^* \left(t' - \frac{\tau}{2} \right) \right\} g(\theta, \tau) \cdot e^{-j2\pi\theta(t'-t)} e^{-j2\pi f\tau} d\theta dt' d\tau$$

where, $E\{\}$ – Expectation operator; $x(t)$ – Realization of the stochastic process under consideration; $x^*(t)$ – Complex conjugate; t – Time; f – Frequency; τ – Time- lag; θ – Frequency- lag; t' – Auxiliary variable; $g(\theta, \tau)$ – Kernel of the transform.

$x(t)$ indicates the analytic process obtained from the real recording of EMG signal. The kernel $g(\theta, \tau)$ does not depend on time as well as frequency lag, hence the resulting distribution is time and frequency shift invariant [16]. This characteristic holds chief importance when correlating the time-frequency representation with physical or physiological phenomena and makes Cohen class distributions suitable to study dynamic muscle contraction. This work demonstrated that the formulation presented in this equation might also be utilized when a single realization of the analysed stochastic process is available, as is the case when processing surface myoelectric signals recorded dynamic contractions [15].

2. Wigner- Ville Distribution (WVD): In 1995, Cohen inferred that when the kernel of the transform from is chosen to be equal to 1 i.e. $g(\theta, \tau) = 1$, the resulting distribution is referred as the Wigner-Ville distribution [16]. The equation for WVD can be given as follows:

$$W_x(t, \omega) = \int_{-\infty}^{\infty} x \left(t + \frac{\tau}{2} \right) x^* \left(t - \frac{\tau}{2} \right) e^{-j\omega\tau} d\tau$$

where $x(t)$ and $x^*(t)$ are EMG signal and its complex conjugate respectively.

The WVD displays frequency as function of time and hence a complete information contained in an EMG signal can be represented using WVD. This method is optimal to analyze signals constituted by a single component. In 1992,

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Ricamato [17] discovered that this distribution can be used to display the frequency ranges of the motor units. However, WVD is not well suited for application to multicomponent signals, since the bilinearity of the transform induces the presence of interference terms [16]. To reduce that interference, several different kernels have been studied.

According to Amin [17], the Wigner-Ville distribution displays very good localization properties, and it is generally concentrated around the instantaneous frequency of the signal. However, when the signal evaluated is a multi-component signal, it displays the components of the individual frequencies, but it also displays the cross terms which are spurious. The joint density spectrum produced by the Wigner-Ville distribution is very noisy [18]. When the original signal is the sum of two or more signals, cross terms are produced.

3. Fourier Transform: When WVD is implemented in digital form, fast Fourier transform (FFT) is used which is discrete representation of signal in both time and frequency domain. A common type of time-frequency distribution is the Short-Time Fourier Transform (STFT). This technique utilizes the basic definition of time-frequency. If time-frequency distributions look at the frequencies that exist during a certain time section of a signal, then one way to generate this distribution is to take a short time portion of the signal, apply the Fourier transform to it, and proceed to the next time section. At each time a different spectrum is obtained and the totality of these spectra is a time frequency distribution [17]. The equation representing STFT spectrum is given by,

$$S_t(f) = \int_{-\infty}^{\infty} e^{-j2\pi ft} s(\tau) d\tau$$

where, $s(\tau)$ represents the given EMG signal.

The STFT distribution works well unless there are very rapid fluctuations in the original signal. It displays the compression of the spectrum for muscle contraction very well. The major difficulty with the STFT distribution is that it does not satisfy four important properties that are desired for time-frequency distributions. The first two are the time and frequency marginal [18]. They are not met because the windowing of the STFT changes the characteristics of the original signal. Narrowing the window in time yields a poor frequency resolution, while a high frequency resolution is accompanied by a poor time resolution. The other two properties not satisfied are time and frequency support.

The Short Time Fourier Transform appears to most clearly show the compression of the spectrum as the muscle fatigues. However, the STFT does not satisfy the marginal, properties. This factor implies that when a time slice of the STFT distribution is taken, it does not equal the power density spectrum at that point in time. The same is true for a frequency slice of the distribution. The time support property is not satisfied because the distribution is not necessarily zero before the signal begins or after it ends. Furthermore, if the original signal is bandlimited, the STFT distribution may not be zero outside the band; therefore, the frequency support property is not satisfied.

4. Choi-Williams Distribution: The Choi-Williams method was proposed in 1993. This method did not satisfy all the desired properties for the time-frequency analysis of EMG signal, but has a very good accountability for reducing the interference. Since the surface EMG has more interference from adjacent muscle groups this method was beneficial in their analysis. The kernel given by Cohen's distribution is defined as

$$g(\theta, \tau) = e^{-(2\pi\theta\tau)^2/\sigma}$$

In the analysis of surface myoelectric signals recorded during dynamic contractions the parameter σ has been chosen equal to 1 as this value appeared to be satisfactory for processing myoelectric data [12] [19]. When walls appear in the Choi-William distribution, there may be a spike in the original signal. The Choi-Williams distribution may be the only distribution that is sensitive enough to pick this change. The distribution will decide if the walls contain any significant information for the study of muscle fatigue.

Wavelet analysis

This is one of the important methods to study the processing, classification and pattern recognition in EMG signals. Wavelets are particularly useful to study multicomponent EMG signal. Wavelet transform (WT) is a powerful mathematical tool for the analysis of non-stationary and fast transient signals.

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The theory by Guglielminotti and Merletti suggested that if the shape of the wavelet is so chosen that it matches the shape of the MUAP, the reconstructed WT is the best possible energy localization in time domain [20]. Based on this theory, Laterza and Olmo have used wavelet analysis to match the shape of the MUAP [21]. Based on this research, it was concluded that the major advantage of WT is that it is particularly useful for MUAP detection in the presence of additive white noise. In 1999, Pattichis et al. discovered that the WT can also be used to analyse signals at different resolution levels. This method to analyse the signal at different resolution levels is known as multiresolution analysis [22]. The algorithm analysed the relationship between the wavelet coefficients and time- frequency plane. It consists of two phases namely decomposition phase and the reconstruction phase. The wavelet coefficients from each stage of WT are used to reconstruct the approximation of the original signal. Given signal samples x_0, x_1, x_2, \dots , the corresponding continuous time signal is given by following equation [9]:

$$f^o(t) = \sum_k x_k \phi(t - k)$$

where, $\phi(t - k)$ is called a scaling function. This algorithm assumes that the signal samples are weighted averages of the continuous signal.

In 2003, based on this method of analysis, Kumar et al. developed a system in which WT decomposes signal into several multiresolution components according to a basis function called Wavelet Function (WF)[23]. The WF is both dilated and translated in the time undertaking a two-dimensional cross correlation with the time domain surface EMG signal. This method provides a tool to detect and characterize a short time component within a non- stationary signal. It is the technique that provides information related to the time-frequency variation of the signal. Kumar concluded that the Short Fourier Transform (SFT) with the relatively short time windows can attempt to track spectral variation with time, but does not adopt an optimal time or frequency resolution for the non- stationary signal. The time-frequency analysis based on wavelet transform also applied to study the non- stationary EMG signal[23]. However, to improve the accuracy of the reconstructed signal, artificial neural network should be used in combination with the wavelet analysis.

Artificial intelligence

Artificial Intelligence (AI) techniques for EMG signal analysis are mainly based on artificial neural networks. Neural networks provide statistical algorithms and computational models to analyze the information. EMG signal processing is a real time application and hence for modelling EMG signals, AI is found to be useful.

In 1994, Del and Park proposed an application of artificial neural network in recognizing the myoelectric signal (MES) [24]. MES features are first extracted through Fourier analysis and clustered using fuzzy c-means algorithm. Fuzzy c-means is an unsupervised algorithm which allows same data to belong to two or more clusters at the same time and there is no hard partitioning of the data. Data obtained by fuzzy c-means technique are then automatically targeted and presented to a multilayer perceptron type neural network. For real-time operation, a digital signal processor operates over the resulting set of weights and maps the incoming signal to the stimulus control domain.

The research developed a simple yet very robust MES recognition system. This is accomplished by extracting features of the MES by Fourier analysis and clustering within a normal classification space. Fuzzy c-mean algorithm clusters the feature space into nine degrees of muscle contraction providing each MES pattern with a target value. Noise patterns from different sources were added to the classification space with a null target value. The mixed MES and noise patterns become the training data of a particular muscle for a given individual. A multi-layer perceptron based on the error-back propagation algorithm provides the weights that match an incoming MES or noise pattern into a desired output. The neural net output represents a degree of desired muscle stimulation over a synergic but denervated muscle.

For a different application using EMG signal, a new approach using artificial intelligence to process EMG signal was presented. The objective of the authors was to identify the relationship between the muscle EMG activity and the arm kinematics of human during the drawing of the figure eight using an extended arm and thereby generalizing the ability to draw unlearned movements [25]. The method was based on dynamic recurrent neural networks (DRNN). The neural network consists of fully interconnected neuron-like units with two types of adaptive parameters: classical weights

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between the units and the time constants associated with each neuron. This network identifies some of the complex relationships between the muscle activity EMG and the upper-limb kinematics during complex movements. The network also identified neural constraints such as the covariation between geometrical and kinematics parameters of the movement. From the method proposed by Pearlmutter [26] in 1989, the artificial neural network is a fully connected 20-neuron network; taking this into account, it used the following equation:

$$T_i \frac{dy_i}{dt} = -y_i + F(x_i) + I_i$$

where, y_i – The state or activation level of unit i and $F(\alpha)$ – the squashing function which is given by,

$$F(\alpha) = (1 + e^{-\alpha})^{-1}$$

$$x_i = \sum_j w_{ij} y_j$$

where x_i gives the propagation equation of the network.

The characteristic of DRNN is that the simulated movements are the result of the interaction between raw EMG signals without any theoretical assumptions concerning the type of control. The aptness of the DRNN lies in the adaptive time constants associated to each neuron-like unit. The disadvantage of DRNN is that it needs larger memory to store considerably longer training sequences.

IV. DISCUSSION

Since the EMG signal is a low power signal and is susceptible to noise, there are many important factors which need to be taken into account while processing the EMG. Each method has its own advantages while there could be certain limitations to each of the methods explained in this paper. Compared to the EMG signal processing using time-frequency approaches, wavelet analysis has an advantage as wavelets are not affected by crossterms, are linear and yield a multiresolution representation of an EMG signal. However, the selected wavelets do not match to the MUAP shape every time resulting into errors in pattern recognition using wavelets. Hence, the selection of suitable wavelet is an important criterion for the EMG signal pattern recognition.

Fourier transform is one of the easiest methods to determine the frequency spectrum of the EMG signal. The fast and short Fourier transforms have been used. However, it has a major drawback as it assumes the signal is stationary, for short time intervals, whereas the EMG signals are non-stationary in nature. This results in the loss of signal and the method though easy to use, cannot be applied for large EMG signal trains.

The results of the artificial intelligence using techniques indicated that there is a high accuracy in discriminating the control signal over the interference patterns. Neural networks have many advantages in EMG signal processing as they provide adaptive interfaces, the designing and matching is much simpler as compared to the statistical methods of EMG analysis. It provides cost effective solution and the multilayered feedforward neural network with error-back propagation provides a good learning method for the network for mapping inputs and outputs. Fuzzy logic systems are advantageous in biomedical signal processing and classification. One of the most useful properties of fuzzy logic systems is that contradictions in the data can be tolerated. Using trainable fuzzy systems, it is also possible to discover patterns in data which are not easily detected by other methods. The experience of medical experts can be incorporated in Fuzzy logic systems. It is possible to integrate this incomplete but valuable knowledge into the fuzzy logic system, due to the system's reasoning style, which is similar to that of a human being. Fuzzy logic systems emulate human decision-making more closely than the ANN and hence are more advantageous.

V. CONCLUSION

EMG signals are significant in numerous biomedical and neurological applications. They carry vital information to diagnose and treat various neuromuscular disorders. This paper reviews different methods to process EMG signal. Advantages and disadvantages of each method should be taken into consideration by user when deciding which method to use for the given application.

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EMG signals are non-stationary as well as non-uniform. They are not repeatable and sometimes can even be contradictory. Hence, the processing of such signals becomes a difficult job. The technology to record and analyse the EMG signal is relatively new. Hence, there are many limitations in detection and characterization of existing nonlinearities in the surface electromyography signal, estimation of the phase and acquiring exact information due to derivation from normality. Various traditional algorithms show complex computational methods and higher variance. However, advances in digital signal processing and mathematical models have made it feasible to analyse the EMG signals.

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