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RESEARCH ARTICLE

REVIEW ON EMG SIGNAL ANALYSIS FOR PARALYSED MUSCLES

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ABSTRACT

Biomedical signal is a collective electrical signal acquired from any organ/system that represents a physical variable of interest. This signal is normally a function of time and is describable in terms of its amplitude, frequency and phase. The Electromyogram (EMG) signal is a biomedical signal that measures electrical potentials generated in skeletal muscles during its contraction representing neuromuscular activities. The nervous system always controls the contraction/relaxation. The EMG signal is a complex signal, which is controlled by the nervous system and dependent on the anatomical and physiological properties of muscles. The knowledge of muscle, EMG processing and EMG classification is essential for analysing and understanding the functions of muscle, especially paralysed muscle. Hence this review paper summarizes the information about physiology of normal and paralysed muscle. Work done in EMG processing, EMG analysis and classification methods used for different biomedical applications are mainly discussed in this review paper.

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INTRODUCTION

Muscle is a special kind of tissue that enables human body to move. Muscle is under the control of the nervous system, which processes messages to and from all parts of the body. The chain of nerve cells that runs from the brain through the spinal cord out to the muscle is called the motor pathway. Normal muscle function requires intact connections all along this motor pathway. When the nerve cells, or neurons, that control the muscles, are affected with disease or injury, then the ability to move the muscles voluntarily is lost, resulting in paralysis. Paralysis is the inability to control the movement of the muscles. It can be temporary or permanent. It may affect an individual muscle, or affects an entire body region. The major effect of paralysis is change in muscle tone. Paralyzed muscle may be flaccid, flabby, or it may be spastic and tight. Paralysis accompanies symptoms include numbness, tingling, pain, problems with balance, difficulties with speech, changes in vision and muscle spasticity. That may further leads to deep vein thrombosis, sores, osteoporosis, many more. Successful recovery depends upon routine handling of chronic conditions.
Paralysis can be managed effectively with the appropriate treatment. Treatment options include physical and occupational therapy, medications, surgery, rehabilitation procedures or a combination of these treatments. The goals of treatment are to increase the patient comfort, decrease pain, ease mobility, and prevent or decrease the risk of developing a joint contracture.

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Detection of EMG signals with powerful and advance methodologies is becoming a very important requirement in biomedical engineering. The main reason for the interest in EMG signal analysis is in clinical diagnosis and biomedical applications. 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 the muscle, or by a needle electrode (invasive) inserted in to the muscle. The shapes and firing rates of MUAPs in EMG signals provide an important source of information for the diagnosis of neuromuscular disorders. Once appropriate algorithms and methods for EMG signal analysis are readily available, the nature and characteristics of the signal can be properly understood and hardware implementations can be made for various EMG signal related applications. Extensive efforts are being made in this area by developing better algorithms, upgrading existing methodologies, improving detection techniques to reduce noise, and to acquire accurate EMG signals. Recent advances in technologies of signal processing and mathematical models have made it practical to develop advanced EMG detection and analysis techniques. Various mathematical techniques and artificial intelligence (AI) have received extensive attraction. Signal processing techniques include time-frequency approaches are used for EMG processing. AI approaches towards signal recognition include artificial neural networks (ANN) and dynamic recurrent neural networks (DRNN) are promising methods for biomedical signal classification. Even Wavelet transform is well suited for analysing non-stationary signals like EMG.

The main purpose of this review paper is focussed on the analyse the paralysis in terms of muscle power grading for individuals using EMG signal quantification.

Literature survey

The brief information about physiology of human muscle is tabulated in table 1 and the paralysed muscle information is tabulated in Table 2.

The literature survey has been conducted on Muscular paralysis, Muscle strength and EMG, EMG analysis, EMG quantification and is tabulated in table 3.EMG classifiers and Neural network and wavelet classifiers is tabulated in Table 4. The literature review has shown that the EMG statistical features, time domain features and frequency domain features like mean absolute value, mean absolute value slope, variance, root mean square value, standard deviation, zero crossings,

Table 1. Anatomy and physiology of human muscle

First Author	Description
Jasvinder Chawla [51]	• Muscles are broadly divided into skeletal, cardiac, and smooth muscles. • Most of the skeletal muscular system is arranged into groups of agonists and antagonist muscles that work in concert to provide efficient and controlled motion. • Controlled motion is achieved through the complex interaction of the musculoskeletal system with the pyramidal, extrapyramidal, and sensory components of the nervous system
Henry Gray [52]	• The muscles are connected with the bones, cartilages, ligaments, and skin, either directly, or through the intervention of fibrous structures called tendons or aponeuroses. • Muscle attached to bone or cartilage, the fibers end in blunt extremities upon the periosteum or perichondrium, and do not come into direct relation with the osseous or cartilaginous tissue. • Muscles are connected with its skin, they lie as a flattened layer beneath it, and are connected with its areolar tissue by larger or smaller bundles of fibers, as in the muscles of the face. • The individual muscle cannot always be treated as a single unit, since different parts of the same muscle may have entirely different actions. • Most muscles are mechanical sense units. The muscle fibers constitute the elementary motor elements.

Table 2. Physiology of muscular paralysis

First Author	Description
Heaven Stubblefield [53]	• Paralysis is a loss of muscle function. • Paralysis can be localized or generalized, partial or complete, and temporary or permanent.
Allan H. Ropper [54]	• Paralysis refer to an abolition of function, either sensory or motor. • paralysis means loss of voluntary movement due to interruption of one of the motor pathways at any point from the cerebrum to the muscle fiber

Table 3. Comparison of some research works on EMG Pre processing and methods for EMG analysis

First Author	Case Studies	Pre processing techniques used	Methodology	Conclusion
An-Chih Tsai [7]	EMG acquired from shoulder and elbow movements		STFT-ranking feature projected onto the PCA space	Motion pattern recognition the accuracy of above 90%.
Gonzalo A [9]	8 : normal subjects Age :22–35 years	Filtering using 70Hz-1KHz 1st order Butterworth Bandpass filter, amplified, and rectified.	ICA used for solving overlaps of MUAPs.	Decomposition of the s-EMGs into their constitutive MUAPTs up to 30, 50, and 60% MVC.
FarzanehAkhavanMahdavi [1]	18: Normal Subjects Age: 20 to 30 years	Adjacent and overlapped windowing methods for segmentation.	Wavelet Transform to find MAV of sEMG. RES indices and scatter plots are used for evaluation criteria.	Data Segmentation
L.R. van Bedaf [36]	37: Normal Subjects with long experience in arm forces	Filter: FIR band-pass filter of 28 to 500 Hz. IIR band stop filter of 50.38 Hz	RMS value calculated, and threshold value is used for reliable measurement.	Trials were classified automatically based on the Standard Deviation. Mean of the baseline activity is calculated.
W.S. Marras [37]	120: Normal subjects	High-pass filter of 30 Hz, low-pass filter of 1000 Hz, used for filtering.	Multiple linear regression techniques were used to predict the maximum trunk moments.	Negative coefficients indicate lower strength, positive coefficients indicate greater strength.
Doug Renshaw [38]	12: Normal subjects Age: 18 - 25 years	Acquired EMG signals are rectified and smoothed using the RMS with a 20ms smoothing window.	pRMS, mRMS and iEMG. .	The magnitude of EMG activation was determined using 3 methods
Carlo J.DeLuca [39]	12:Norma subjects Age: 19–63 years, with mean age 30.3 years	Filter: band pass of 0.15 Hz - 450 Hz	sEMG spectrum is obtained for analysis..	The SNR ratio will increase with higher corner frequencies, the rate of sEMG signal loss will also increase.
GurmanikKaur [40]	3: Normal subjects 5: Myopathic subjects 4: Motor neuron diseased subjects.	Filter:3Hz-10KHz, band pass filter.	EMG is segmented using threshold and mean absolute value.	The success rate for technique using peaks to extract MUAPs is 95.90%, for technique using BEPS and EEPs, is 75.39% and for technique using DWT, is 66.64%.
Rodriguez-Carreno [10]	10: Normal subjects	Filter: 3 Hz frequency high-pass filter. Hamming window used to eliminate baseline fluctuations	DWT is applied to detect and isolate MUAP segments from BLS.	Spectral content of the BLF is estimated, and this estimation is used to design a high-pass FIR filter that cancel the BLF present in the signal.
Sadhana Pal [42]	Normal subjects	Filter: 3Hz-10KHz band pass filter. Power spectrum density is estimated using FFT	Segmented with absolute values.	Digital filter approach is efficient and reliable on the basis of the quantity of the removal of BLF.
Naiquan (Nigel) Zheng [43]	10: Normal subjects	Filter: Sampled at 1KHz and passed through a high-pass 4th order butter filter and rectified.	Integration and ANOVA used to identify significant differences in mean EMG and COV.	Mean values were greatest with the INT method and least with the ARV method. COV was the least with INT and no differences among others.
Angkoon Phinyomark [45]	Normal subjects	Filter: band-pass of 10-450 Hz and amplifier with 60 dB gain.	RMS, Willson amplitude. SNR, calculation.	As the SNR decreases, the percentage error of each feature increases.

ICA-Independent Component Analysis, MAV-mean absolute value , Peak RMS- pRMS, mean RMS- mRMS, integrated EMG- iEMG, sEMG-segmented EMG , BLS-base line segment, BLF-base line filtering, Coefficient of variability -COV.

Table 4. Comparison of some research works on EMG Classification

First Author	Case Studies	Processing techniques used	Methodology	Conclusion
C.D. Katsis [2]	10 : normal subjects 20 : myopathy 20 : motor neuron disease.	Filter: Bandpass filter (3 Hz—8 kHz). Templates are used for decomposition of EMG.	SVM is used to classify, normal, myopathic, and neuropathic conditions.	The approach addresses automatic MUAP classification to neuropathic, myopathic or normal classes directly from raw EMG.
M.I. Ibrahimy [3]	3: normal subjects Age : 27-32 years	Filters: 20-500 Hz 6th order band pass Butterworth filter. DWT used for EMG decomposition.	Time domain, frequency domain, and statistical features are used for EMG classification using ANN.	The designed ANN has successfully classified the EMG signals from hand movements.
M. Zecca [35]		Filter used: 250 to 2000 Hz band pass filter.	Time domain features, Time frequency features are used.	EMG-controlled prostheses for restoration of some hand functions.
He Huang [6]	Movements:wrist hand, and fingers.	Filters: 5-500 Hz, 6th order band pass Butterworth filter.	Combining TMR and EMG.	Clinical implementation of a multifunctional prosthetic control.
Christos D. Katsis [4]		Filter: 3Hz-8KHz Bandpass filter.	Use of 2 stage classifier for MUAP classification	MUAPs are decomposed and classified according to the pathology using an ANN.
AhmetAlkan [41]	Biceps and triceps muscles for 4 different movements from same subject	Filtering, Rectification and Smoothing of raw EMG signals.	The feature vectors are generated by using MAV.	Discriminant analysis and SVM classifier are used to classify 4 different arm movement signals.
MukeshPatidar [44]	20:Normal subjects 20: myopathicsubjects	The size of EMG is 1000 sample. EMG is arranged in matrix of 10 x 100.	Singular value decomposition is used to produce low rank approximationof 10 singular vectors. Back propagation NN is used for pattern classification.	Neural network provided 96.75% accuracy in classification of Myopathy and normal EMG signals.
Muhammad IbnIbrahimy [46]	3: Normal subjects Age: 25-32 years	Filter: 6-th order Butterworth band-pass withcut-off frequency of 20-500Hz. Notch filter with 3db gain and cut-off 49-51 Hz.	DWT, applied for decompositions of EMG with mother wavelet functions. ANN is used to classify EMG.	Optimal design of Levenberg-Marquardt based ANN classifier performed well with average classification success rate of 88.4%
R. Aishwarya [47]	27:Normal subjects	Filter: Second order Butterworth band pass with cut off frequencies 20 Hz and 500 Hz. Sampling at 2 KHZ.	AR model is used. Features extracted: Histogram, Mean frequency	Feature vectors obtained from EMG histogram and mean frequency are combined and given as input to neural network for classification.
J. Senthil Kumar [48]	Upper limb amputed subject	Band pass filter with frequency range 10Hz - 1KHz is used.	Feature vectors are extracted. NN is employed.	STFT used for spectral analysis. ANN with back propagation algorithm is used to classify EMG
J. Rafiee [49].	6:Normal subjects	Filter: 10Hz–3000 Hz Band pass filter	CWC-SSis calculated.	Optimal classification of hand movements.
Samuel K. Au [50]	Ankle foot amputed subject	Filter: 7th order Butterworth filter. TheEMG data normalized with respect to the maximum voluntary contraction	Two control schemes to predict the amputee's intended ankle position: a neural network approach and a muscle model approach.	Both controllers demonstrate the ability to predict desired ankle movement patterns qualitatively.

SVM- support vector machine, CWC-SS-Continuous wavelet coeffecients of segmented signals

waveform length, slope sign changes, feature reduction, Willison amplitude, spike duration, area, phases, mean, median, histogram, signal to noise ratio, percentage error has been extracted using STFT, WT and DFT. To remove the motion artifacts and artifacts from power lines, Butterworth filters, Chebyshev filters and Notch filters with suitable bandwidth and orders are used in many articles. It has also been discussed that the acquired EMG signals are rectified and smoothed using moving average window, root mean square and linear envelope techniques. The removal of noise using DWT is also discussed by M. I. Ibrahimy *et. al.* The preprocessing methods such as data windowing, adjacent and overlapping windowing are explained by Farzaneh Akhavan Mahdavi *et. al.* The methods of determination of magnitude of EMG activation like pRMS, mRMS and iEMG is explained by Doug Renshaw *et al.* In the review it has also been explained that the MUAP overlapping problem is solved using Independent Component analysis methodology. The Cross-correlation technique is also employed between the superimposed waveform and the template MUAP for EMG decomposition. It has been discussed that Artificial Neural Network, Support Vector Machine are used as the classifier to classify the EMG signal after its decomposition. It is also discussed in the review that Analysis of Variance is used to access statistical differences.

Conclusion

It can be known from the above discussions that the raw EMG signal is filtered using suitable bandpass filters. Different types of filters with different bandwidths are used by various authors. The filtered signal can be full wave rectified and smoothed using linear envelope, root mean square and moving average window methods.

The different features of EMG can be extracted using DFT, WT, STFT, DWT methods. Different types of classifiers are mentioned in the literature survey for EMG classification. The suitable classifiers can be used to classify the normal and paralysed EMG signals.

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