419. Different techniques for EMG signal processing

J. Pauk
Bialystok Technical University
Wiejska 45C, 15-351 Bialystok
Phone: +48 85 7469222
e-mail: jpauk@pb.edu.pl

(Received:03 September; accepted: 02 December)

Abstract: Electromyography signal can be used for biomedical applications. It is complicated in interpretation, so it acquires advanced methods for detection, decomposition, processing, and classification. The techniques of EMG signal analysis such as: filtering, wavelet transform, and modeling will be presented in this paper to provide efficient and effective ways of understanding the signal. A comparison study is also given to show performance of various EMG signal analysis methods. This paper provides researchers a good understanding of EMG signal and its analysis procedures. This knowledge will help to develop more flexible and efficient applications.

Keywords: locomotion, EMG signal, wavelet transform, modeling.

1. Introduction

The main purpose for the interest electromyography (EMG) signal is clinical application. It is usually used clinically for the diagnosis of neurological and neuromuscular problems. 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. It is an electrical signal acquired from different organs. EMG is usually a function of time, described in terms of amplitude, frequency and phase [1,16]. The first recording of EMG activity was made by Marey in 1890, who introduced the term electromyography. Clinical use of surface EMG for the treatment of different disorders began in the 1960s. Hardyck was the first practitioner who used EMG [1]. In 1980s, Cram and Steger introduced a clinical method for scanning a variety of muscles using an EMG sensing device [2]. During the past 15 years, research has resulted in a better understanding of the properties of surface EMG recording. Recently a surface electromyography is increasingly used for recording from superficial muscles in clinical protocols, where intramuscular electrodes are used for deep muscle only [3]. The technology of EMG is relatively new. There are still limitations in detection and characterization of EMG signal, estimation of the phase, acquiring exact information due to derivation from normality. Traditional system reconstruction algorithms have various limitations and considerable computational complexity and many show high variance. Recent advances in technologies of signal processing and mathematical models have made it to develop advanced EMG detection and analysis techniques [4,5,6,7,16,19]. So far, research and extensive efforts have been made in the area, developing better algorithms, upgrading existing methodologies, improving detection techniques to reduce noise, and to acquire accurate EMG signals. It is quite important to carry out an investigation to classify the actual problems of EMG signals analysis and justify the accepted measures. Mathematical approach usually include: wavelet transform, time-frequency approaches, Fourier transform, Wigner-Ville Distribution, statistical measures, and higher-order statistics. Wavelet transform is well suited to non-stationary signals like EMG. Higher-order statistical methods may be used for analyzing the EMG signal due to the unique properties of statistical methods applied to random time series.

This paper relates to the upgrading existing methodologies, filtering, processing, decomposition and modeling of EMG signal.

2. Methods

There were several phases to the signal approach such as: data acquisition, data pre-processing, data modeling, data analysis and interpretation. The research have been done by using the system EMG. A surface electrode picked up on the main groups of muscles of lower limbs: the Rectus Femoris, the Vastus Lateralis, the Medial Hamstrings, the Lateral Gastrocnemius, and the Anterior Tibialis with only minimal crosstalk from adjacent muscles. Functional evaluation was carried out on 20 patients with spastic diplegia (the average age 12 yr.) after clinical evaluation. The demographic data of subjects are presented in Tab.1.

Table 1. Demographic data of subjects (±SD)

Subjects	Height (cm)	Weight (kg)
Typical	168 ± 10	65 ± 8
Spastic diplegia	162 ± 6	61 ± 5

The standard deviation values of the demographic data of each group are also given in the same table. The difficulties that the patients most commonly complained about were: climbing stairs and bending down. Gait abnormalities of these persons were usually treated with a combination of rehabilitation, orthosis, and surgery. The subjects were analyzed while walking barefoot along a straight pathway 10 m long. Patients were recruited into Glenrose Rehabilitation Hospital in Edmonton (laboratory Syncrude Centre for Motion and Balance). The motion lab uses Instrumented Gait Analysis to provide quantitative data on a subject's joint motion, net joint rotatary forces and muscle activation. Raw EMG offers valuable information in a particularly useless form. This information is useful only if it can be quantified [17]. Various signal-processing methods are applied on raw EMG to achieve the accurate and actual EMG signal. This section gives a review on EMG signal processing using the various methods.

3. Results

3.1. Filtering of EMG signal by using hardware filter

Filtering of the signal is important. It is used to focus on a narrow band of electrical energy that is of interest to us rather than all the electrical signals that the sensors will pick up. Electromyography (EMG) signals are usually affected by noise, which may be generated by different sources, such as the hardware employed for signal amplification and digitization, the movement of cables during data collection and the activity of motor units distant from the detection point. There are many types of filters and several methods to determine the "optimal" cut-off frequency. Types of filters include the classic Butterworth, Fourier series, Kalman, cubic and quintic spline, and finite impulse response (FIR) filters. Filter equations, such as in the Butterworth filter, are frequently recursive. Current values depend on the previous values, which introduces a phase lag into the signal. These filters are, therefore, applied in both forward and reverse directions in order to remove the phase lag. Some useful procedures aimed at minimizing the influence of noise on the detected signal are highlighted by Cram et al. [2]. In practice, the collected signal may still be corrupted by noise. If the type of noise present in a signal is known a priori then the Wiener filter, may be applied to attenuate its presence [8]. The main disadvantage of this approach is that in many practical applications the noise is unknown. Design of application specific integrated circuit for the biomedical instrument has become quite important recently. Hardware chips have also been designed to filter EMG signal to achieve the accurate signal for the prosthetic arm control and other applications like human computer interactions [9]. This paper introduces a procedure for filtering electromyography signals. There is presented the polynomial filter based on microprocessor Zilog 8 [10]. The filter consists of the following modules: AC preamplifier, oscillator, CA preamplifier, and microprocessor Zilog 8 (Z8). Communication with the filter is established via the serial port (RS232). The schematic of data filtering is presented in Fig.1.

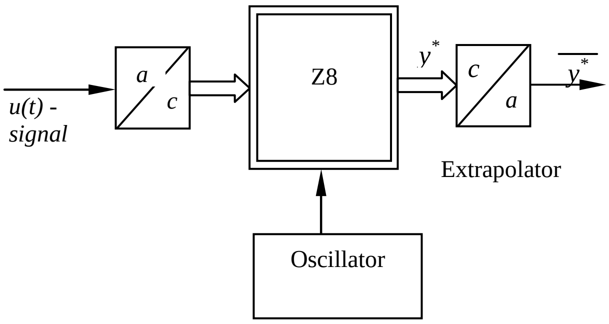

Fig. 1. Schematic of data filtering by using microprocessor Zilog 8

The velocity of data transmission is around 9600 bps. The raw information from the subject is a collection of positive and negative electrical signals, their frequency and their amplitude give us information on the contraction or rest state of the muscle. Figure 2 shows output of the filter algorithm.

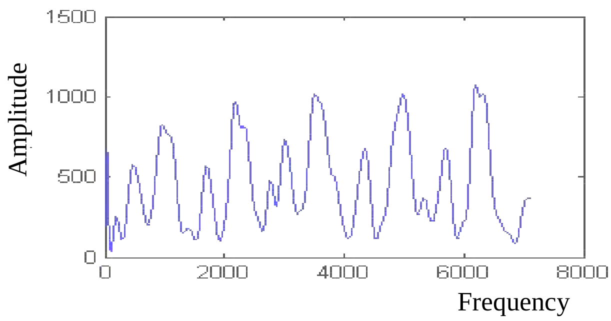

Fig. 2. EMG signal after filtering

Results obtained from the analysis of synthetic and experimental EMG signals show that the method of filtering can be successfully and easily applied in practice to attenuation of background activity in EMG signal. The main advantages of using the filter are that it is easy to implement and fast in real-time applications.

The maximization of the quality of EMG signal can be done by the following ways: the noisy signal should contain the highest amount of information from EMG signal as possible and minimum amount of noise contamination.

3.2. Wavelet transform

Various signal-processing methods are applied on raw EMG to achieve the accurate and actual EMG signal. Attempts to gain quantitative information from EMG recordings have been extensively investigated when signal is represented as function of time. Both the time and frequency domain approaches have been attempted in the past. I will propose the wavelet transform (WT) as an efficient mathematical tool for local analysis of non-stationary and fast transient signal. 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 [12,27]. 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]:

$$C(scale,\ position) = \int_{-\infty}^{+\infty} f(t)\cdot\psi(scale,\ position, t)dt \quad (1)$$

where:

C (scale, position) – wavelet coefficient,

f(t) – signal,

ψ(scale, position) – wavelet function.

WT will be also used to analyze signals at different resolution levels. It will be analyzed the relationship between wavelet coefficients and the time-frequency plane. The DWT is a transformation of the original temporal signal into a wavelet basis space. The time-frequency wavelet representation is performed by repeatedly filtering the signal with a pair of filters that cut the frequency domain in the middle. Specifically, the DWT decomposes a signal into an approximation signal and a detail signal. The approximation signal is subsequently divided into new approximation and detail signals. This process is carried out iteratively producing a set of approximation signals at different detail levels (scales) and a final gross approximation of the signal. This can be expressed as follows (Fig.3-4):

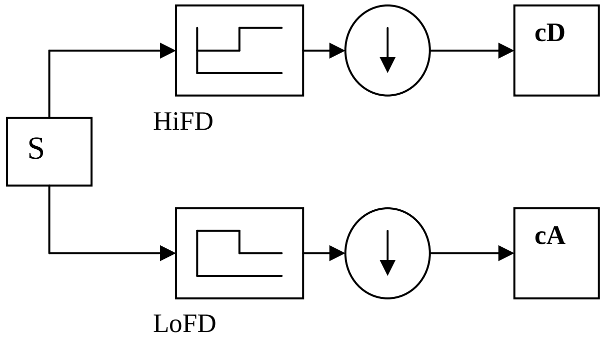

Fig. 3. Discrete wavelet transform: S – signal; HiFD – high pass filter; LoFD – low pass filter; cA – wavelet coefficients for high scale; cD – wavelet coefficients for low scale

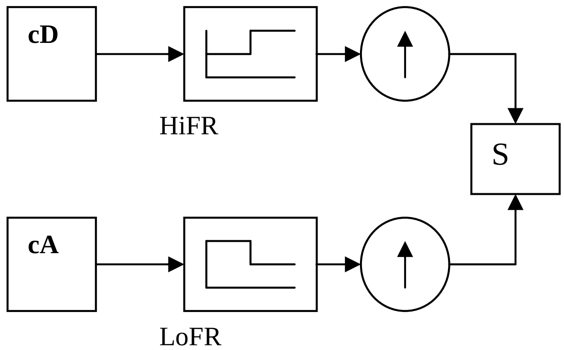

Fig. 4. Inverse discrete wavelet transform: S – signal; HiFR – high pass filter; LoFR – low pass filter; cD – wavelet coefficients for low scale; cA – wavelet coefficients for high scale

The *A* and *D* sequences obtained as the result of IDWT 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.5-6).

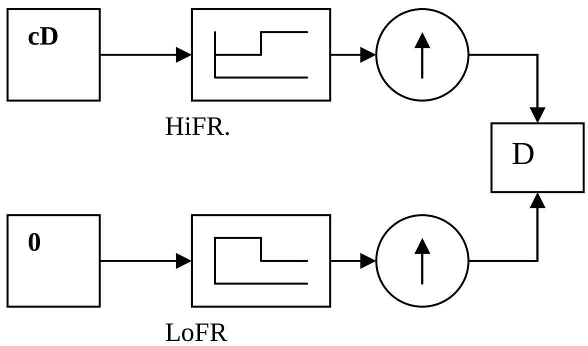

Fig. 5. The reconstruction of detailed sequence; 0 – the signal is equal 0; HiFR – high pass filter; LoFR – low pass filter; cD – wavelet coefficients for low scale; D- detailed sequence

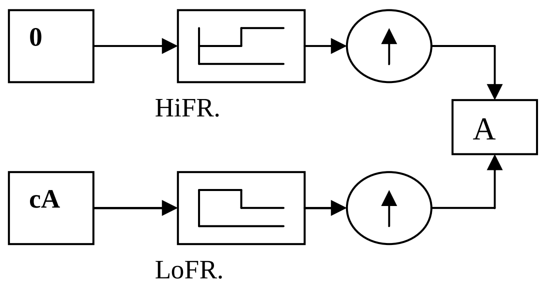

Fig. 6. The reconstruction of approximation sequence; 0 – the signal is equal 0; HiFR – high pass filter; LoFR – low pass filter; cA – wavelet coefficients for high scale; A- approximation sequence

The scales *c* were chosen in conjunction with the sampling 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 7. 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 scale and low frequency. The detailed sequences $(d_1$- $d_5)$ have the lower scale than a_5. The biggest scale has signal d_5, and the lowest scale has signal d_1. Those are the signals with the highest frequency.

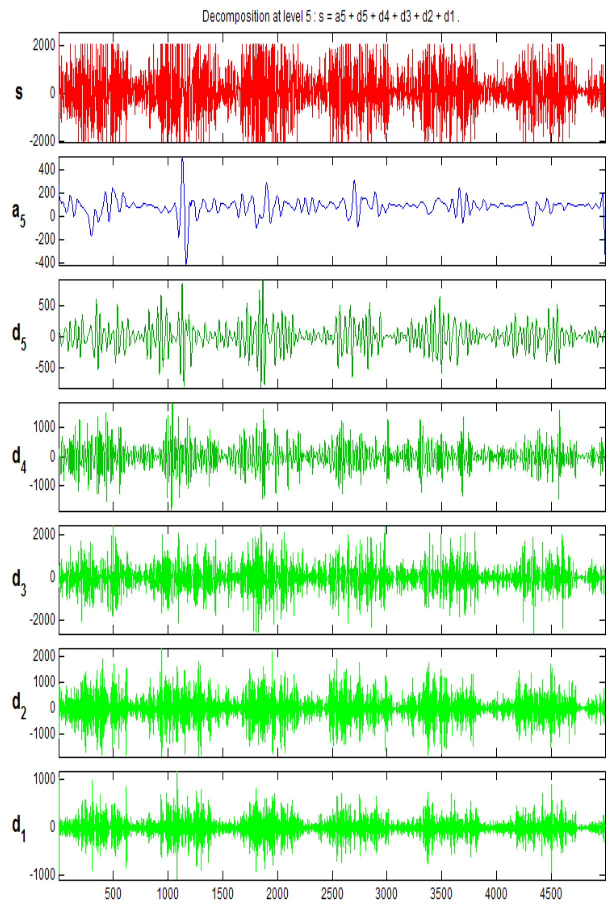

Fig. 7. Wavelet decomposition

3.3. Regression model of EMG signal

In 1975, Graupe and Cline first introduced the autoregressive moving average model (ARMA) to represent EMG signals. The empirical result of Graupe and Cline shows that the EMG could be considered stationary over sufficiently short time intervals [1]. Sherif has emphasized the non-stationary nature of the EMG and used an autoregression, integrated moving average model (ARIMA). He characterized the non-stationary nature of the EMG during different phase of muscle activity [5]. Since 1983, Doerschuk has approached a problem similar to Graupe and Cline, namely control of prosthetic devices from EMG signals, by autoregressive models of multiple EMG signals [6]. In 1986, Zhou represented the surface EMG as an autoregressive model with his delayed intramuscular EMG signal as the input [7]. The model, referred to as "tissue filter," relate the intramuscular EMG signal waveform to the surface EMG. Assuming that prototypes of intramuscular and surface EMG signals are available, the parameters of the time series model that transforms the intramuscular signals to the surface signals are identified. The identified model is then used in estimating the intramuscular signal from the surface signal. This model is illustrated using real EMG waveforms. Hefftner in 1988 evaluated the previous models and selected an autoregressive model for EMG signature discrimination because of its computational speed [13]. Graupe in 1989 proposed a non-stationary identifier of time-varying autoregressive parameters [9]. In 1992, Tohru considered that the more precise model such as ARMA or ARIMA was not necessary for dynamic muscle movements [14]. The computation cost of ARIMA model is high, and the determination of the model order is complex and sometimes difficult. AR model was chosen by Tohru mainly because of its computational cost which is a problem in the simulation. Their investigation was based on AR model parameters computed by quasi-stationary processing. The regressive (time series model) has been used to study EMG signal. A surface electrode were picked up EMG activity from all the active muscles in its vicinity, while the intramuscular EMG is highly sensitive, with only minimal crosstalk from adjacent muscles. Thus, to combine convenience and accuracy there is a great need to develop a technique for estimating intramuscular EMG and their spectral properties from surface measurement. Researchers have represented sEMG signal as an AR model with the delayed intramuscular EMG as the input. Model studies have been performed to characterize the human gait of typical subjects and patients with lower limbs deformities [11,15].

Presented by author approach of muscle activity is based on regression function (Eqn.2).

$$\hat{Y}_n = \underline{u}_n \cdot \underline{a}, \quad n=1,2,\ldots,N, \qquad (2)$$

where:

$\hat{Y}_n$ – output data of model (EMG signal in *n* instant),

$\underline{u}_n$ – input data of model (EMG signal in *n* instants before),

$\underline{\underline{a}}$ – unknown model coefficients,
N – sample size.

The matrix $\underline{\underline{a}}$ is determined by Eqn. 3-4:

$$\underline{\underline{a}} = \left(\underline{\underline{U}}^T \cdot \underline{\underline{U}}\right)^{-1} \cdot \underline{\underline{U}}^T \cdot \underline{Y}, \tag{3}$$

where:
$\underline{\underline{U}}$ - the matrix of input data,
$\underline{Y}$ - the vector of output data,

$$\underline{\underline{a}} = \left[a_1 \quad a_2 \; \ldots \; a_k\right]^T, \; k=1,2,\ldots,K, \tag{4}$$

where:
K – the coefficient size.

The regression model presents the relationship between the muscle activity in n instant and muscle activity in n instants before. Below is presented the method of model identification.

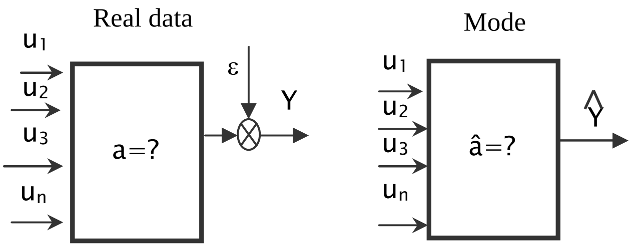

Fig. 8. Method of model identification: u_n – input data, Y– output data, a– unknown model coefficients, ε - noise

The best results were obtained for approach where the EMG signal in n instant depends on EMG signal in three instants before. The relative error was around 2%. The vector $\underline{Y}$ and matrix $\underline{\underline{U}}$ are expressed as Eqn.5:

$$\underline{\mathbf{Y}} = \begin{bmatrix} \mathbf{Y_3} \\ \mathbf{Y_4} \\ \mathbf{Y_5} \\ \vdots \\ \mathbf{Y_N} \end{bmatrix} \qquad \underline{\underline{\mathbf{U}}} = \begin{bmatrix} \mathbf{Y_2} & \mathbf{Y_1} & \mathbf{Y_0} \\ \mathbf{Y_3} & \mathbf{Y_2} & \mathbf{Y_1} \\ \mathbf{Y_4} & \mathbf{Y_3} & \mathbf{Y_2} \\ \vdots & \vdots & \vdots \\ \mathbf{Y_N} & \mathbf{Y_{N-1}} & \mathbf{Y_{N-k}} \end{bmatrix} \tag{5}$$

where:
$\underline{\underline{U}}$ - the matrix of input data,
$\underline{Y}$ - the vector of output data.

To study the performance of the regression model of muscle activity, several realizations of a number process models were generated and the model coefficients were estimated. The regression model coefficients for patients with spastic diplegia are presented in Table 2. The standard deviation values of the model coefficients for muscles are also given in the same table. EMG model coefficients of patients with spastic diplegia were compared to the EMG model coefficients of typical subjects [10].

Table 2. Regression model coefficients of patients with spastic diplegia (±SD)

Muscles	a_1	a_2	a_3
Medial Hamstrings	1,43±0,2	-0,93±0,13	0,42±0,08
Rectus Femoris	1,62±0,25	-1,15±0,15	0,55±0,13
Tibialis Anterior	1,27±0,11	-0,87±0,2	0,27±0,05
Vastus Lateralis	1,41±0,21	-0,95±0,18	0,23±0,05
Lateral Gastrocnemius	1,36±0,15	-0,76±0,15	0,35±0,07

The value of model coefficient a_1 and a_3 for the Medial Hamstrings and the Tibialis Anterior is higher for subjects with spastic diplegia. For the Vastus Lateralis, the Rectus Femoris, and the Lateral Gastrocnemius the value of model coefficients a_1 and a_3 are higher for typical subjects. Analysis of model coefficients shows, that there is no significant difference of coefficient a_2 in each group. Statistical analysis was performed on the whole population of typical subjects, those with spastic diplegia. A characterization of the difference was obtained by computing the following parameters such as: the standard deviation, correlation, and variance.

Table 3. Statistical parameters of the regression model (±SD)

Groups	Correlation	Variance
Typical subjects	0.91±0.04	0,005±0,001
Spastic diplegia	0.92±0.06	0,007±0,002

, (5)

The indicators show that proposed model is correct. The major advantage of mathematical modeling is description a signal just by few coefficients. The proposed method can be applied during clinical diagnosis, but it needs to determine model coefficients for different pathologies.

4. Conclusion

Electromyography is a good tool for the documentation of muscle activity. EMG signal carries valuable information regarding the nerve system. Signal conditioning and signal processing are very critical to obtain a reliable results from surface EMG. Although, many literatures have already suggested various techniques to improve the quality of acquired signals, the noisy nature of EMG signals is still harness for enlarging the application of EMG for various clinical studies. Hence, still there is an eminent request for novel techniques that address improving the quality of measured EMG signals. Therefore, this topic is highly significant and interesting for most investigators and clinicians in field of movement analysis and kinesiology. So the aim of this paper was to give information about methodology to analyze the signal. Techniques for EMG signal such as: filtering, decomposition process, and modeling were discussed in this paper. It is very likely that applying EMG data helps to define gait pathology in a large number of patients. With the help of advanced computing software, mathematical modeling has proved to be convenient and powerful method for monitoring human gait. The advantage of proposed model is possibilities to classify human gait to different groups of pathology. The considerations introduce an incomplete analysis of spacious problems connected with classification and improvement of apparatus of human gait, which is the result of the limited number of collected data.

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The work has been approved by the appropriate ethical committees related to the Syncrude Centre for Motion & Balance in Edmonton. I thank dr A. Liggins for help in the collection, analysis and interpretation of data.

This paper is supported by Foundation for Polish Science and grant W/WM/6/08.