Journal of Population Therapeutics & Clinical Pharmacology

Analysis of EMG and ECG Signals on the Muscles of Water Polo Athletes using MLPNN, A cognitive, Practical and Rehabilitation Approach

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Abstract
Today, a large number of athletes perform many tests to increase the performance of their abilities related to muscle strength. One of these tests is to examine their electromyogram signal or EMG for short. In this research, advanced processes for evaluating the feature space for water polo athletes have been studied. To support the aforementioned issue, we have recorded the EMG and ECG signals from 20 athletes. For this purpose, after recording the the EMG from the muscles of Trapezius, Pectoralis, Deltoid, Triceps as well as signal processing and feature extraction, the feature space is evaluated, and finally, using MLP neural network, we have classified these four muscles for practical applications applied for Rehabilitation Purposes. After that, we first distinguished the two motion classes, Flexion & Extension, from each other, and then differentiated the extension, supination, and pronation movements from each other and then examined the third channel called the goniometer. Then, after filtering the processed data and using the KNN classifier, the percentage of accuracy of the MLP neural network used in this study demonstrated 89.93%, which indicates that using the EMG signal for athletes, the performance of the damaged muscle as well as enhancement regarding rehabilitation in cases of injuries has improved and can be expected.

Keywords: Electromyogram (EMG), Electrocardiogram (ECG), ANN, Filtering, Water Polo Athletes, Sports

2. Introduction

The purpose of using the tools in EMG and ECG is to keep the data acquired from the bioelectric activities depending on the regulation of muscle contraction and to have a general information about heart activities during exercise. Questions about the set of observations that use EMG signals revolve around what data can be discussed by measuring data from EMG signals. EMG data can be divided and categorized into the three following general groups:

Relationship between immediate aspects of EMG, ECG and related anatomical changes
The relationship between EMG, ECG and Force Generation
The relationship between EMG, ECG and Muscle Fatigue

Each category processes the EMG, ECG signals for data recording and meeting the measurement target. Researchers have developed mathematical models that relate selective factors and compare their behavior for experimental observations. Although no scientific community emphasizes existing models, the procedure on this significantly important area is clarified. Even though the impact of parameters such as speed, acceleration, and type of muscle contraction is fully understood, the interpretation of the EMG, ECG data is inconclusive, chronologically.

3. Methods and Materials

3.1. EMG and ECG Signal Recording

We have used the BIOPAC device to record the signal, able to record heart signals (ECG), brain waves (EEG), muscle activity (EMG), and eye movement (EOG), which we use only two of the aforesaid signal for the recording. In the first phase of the experiment, two channels were used, and finally, we have extended the recording up to 9 channels.

Using data signals from upper body limb muscles as well as the ECG while performing neural network algorithms, detecting four classes of movements including Flexion, Extension, and Supination, with online signal recording pronation, and for four different modes of signal, the recording has been performed and compared with each other. In general, this research includes two main parts, one is signal recording and detection of four-movement classes as well as neural network training, and the other part includes online signal recording with an identified delay plus offline input of these signals as input to the trained networks concerning the output of the aforesaid networks.

To distinguish these four-movement classes, we use the following method: First, we try to differentiate the two classes of movement from Flexion & Extension, in which movement itself includes a subset of Extension Flexion, Supination & Pronation movements. To discriminate the first two movement classes from each other due to the significant difference created by the signals recorded from the muscles and Biceps for flexion and extension movements, it is not necessary to examine the third channel, nevertheless, for distinguishing Triceps, Supination and Pronation movements from each other, we need to examine the third channel, which is, of course, the goniometer.

3.2. Electrical Characteristics

The electrical source is the membrane voltage of the muscle, which has a value of about 70 mV. The measured potentials resulting from the aforementioned method are in the range of less than 50uV and 20mV to 30mV. The repetition rate is a type of muscle stimulation of 7-20 Hz, the exact amount of which depends on the size of the muscle, previous injuries, and so on. In the case of damage to actuator units, a range between 450mV to 780mV can be expected.

3.3. Detailed Procedure

A needle electrode is implanted through the skin into muscle tissue to perform intramuscular EMG as an invasive way of recording EMG. A trained therapist, usually a natural therapist, neurologist, or physiotherapist, closely monitors electrical activity as the electrode enters the body tissue. Electrode placement activity contains valuable information about how the muscle and nerve are connected and have interaction. Under normal conditions, muscles at rest produce distinct and normal electrical sounds under normal conditions if a needle electrode is inserted. The electrical activity is then, of course, studied when the muscle is at rest.

Abnormal spontaneous activities may indicate nerve or muscle damage. If this happens, the patient is asked to contract the muscle gently. The electrode is then dipped a few millimeters into the muscle. The activity is re-evaluated; this continues until the responses of at least 10 to 20 units are collected while the patient is being appeased to relax, tolerating the pain. The effect of each electrode gives only a deeply localized picture of the activity of the whole muscle. Since skeletal muscles differ in internal structure, the electrodes must be placed in different places so that the information obtained is as accurate as possible. Against the activity of a small number of fibrils observed by the needle electrode, a surface electrode can be used to display an overview of muscle activity.

This technique is used in some situations and conditions; for instance, in a physiotherapy clinic, muscle activity is displayed by surface EMG recording, and the patients use an auditory or visual stimulus to find out when the muscle has been activated, correspondingly. In order for EMG to be recorded, the muscle must go beyond the threshold, which must be pre-tuned, such as the noise limitations in the measurements. It is difficult to know when a muscle is at rest because it is often possible for the muscle to rest in an absolute position gradually. In this case, the threshold should be high enough to avoid position errors and miscellaneous issues, whether deliberately or inadvertently.

For the final evaluation of the patients, psychological aspects of their routines came into account by asking the patients to fill out questionnaires including questions regarding their temper, anger, stress level, anxiety, indicating a general attitude of the patient with a neuroscience and psychology vision to have a more accurate result while ignoring the false information obtained due to misconceptions and misinterpretations performed while the patients are not in normal condition during the test procedure. These factors are also significantly important because when the study-cases are facing psychological challenges, for instance, the patients are being asked if they are suffering from specific stress-related disorders or if they are under first periods of medication where their therapies are not yet stabled, to ignore their results from the final testing, in order to reduce the error of the accuracy.

3.4. Amplitude, linear phase and bandwidth

To store the main data, which is the content of the EMG and ECG signals, we need an equipment whose amplitude and phase are linear and have a suitable bandwidth, accordingly. The linear amplitude imposes that the input-to-output voltage ratio should have a linear function concerning the operating voltage range of the device. Bandwidth and frequency response are related to the amplitude being linear at all device operating frequencies.

For the original wave information to be stored, each frequency component of the signal returns similarly. The device's output signal may change in shape, and of course, any changes in the shape of the frequency expansion must be considered a result of the signal processing concerning the main wave. To add this and by its nature, the linear phase requires the phase relationship of each output frequency component of a device, which must be the same as the phase relationship at the input.

3.5. Noise Reduction and Filters

Suppose the signal detected at the electrode site contains information that is used only for the purpose of measurement, and nothing is done to correct or change this information during signal processing and amplification. In that case, the measurement accuracy is correctly performed by recording devices or output readings. This is a description of an ideal measurement system, whereas considering the optimal EMG signal, there might be no signal that is only detected at the electrode site to have some stronger signal than other common external signal sources. Noise, however, is detected in information and data depending on the location of the muscle during the recording, processing, and amplification of the signal. Noise sources generated by equipment used to detect, amplify, and record EMG are important to consider.

All conductors demonstrate some resistance to electrical current and thus produce a heating-type noise. Heat noise is caused by the accidental movement of electrodes and other free carriers and is the second law of thermodynamics (Aurell, Erik, et al. 2012). According to the following factors, thermal noise voltage depends on material resistance, temperature, and bandwidth. K as the Boltzmann coefficient, T is the temperature in degrees Kelvin, B as the bandwidth in Hz, and R as the resistance in Ohms. Heat noise is generated near to the electrodes, in the inertial leads connected to the amplifier electrodes while being as close as possible, and again generated in the internal electronic equipment of the EMG device. Therefore, in this research, to reduce the noise, filters such as notch filters have been used to eliminate power line noise using a moving average filter.

3.5.1 Notch Filter

The notch filter can be considered as a band-stop filter that is a filter attenuating frequencies in a certain range while passing all other frequencies without any tangible changes. For the notch filter, this frequency range is extremely limited while the range of the frequencies that a band attenuation filter attenuates it is having an important role. In figure 1, the notch filter used in this research is illustrated below.

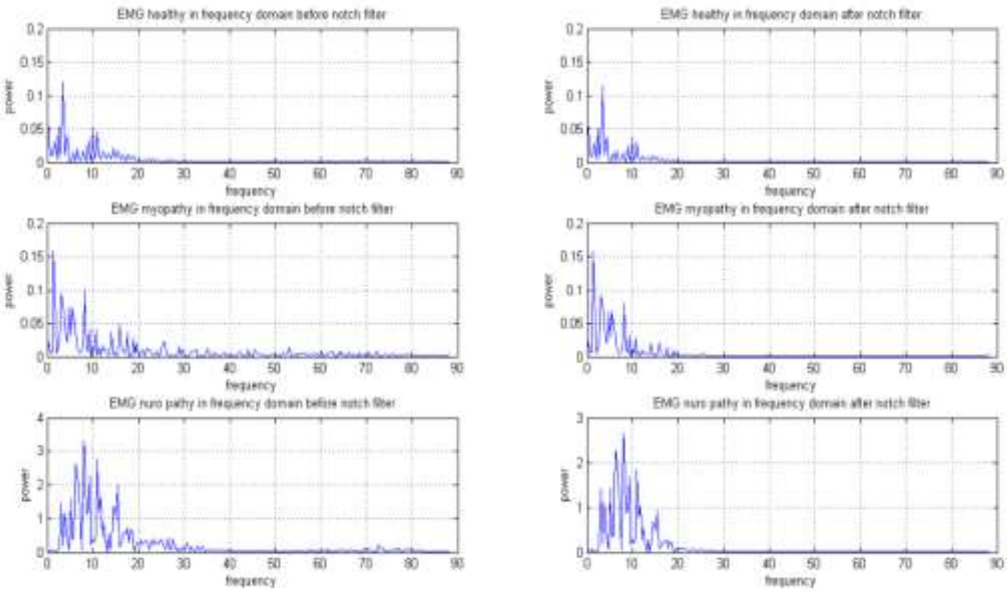

Figure 1. Notch Filter in Presence of Power Line Noise

3.5.2. Moving Average Filter

Since the speed of changes in the main signal is high, a moving average filter is used, which reduces the rate of change and helps us to maintain and have relatively more accurate processing.

The equation below is used as the Moving Average Equation:

$$S_i = \frac{1}{n}\sum_{j=i}^{i+\pi-1} a_j$$

The S comes from the Summation in the formula, and the values are added together and then divided by a factor of n, as illustrated in the aforementioned formula of Moving Average.

Figure 2 also expresses the Moving Average Filter performed in this research for water polo athletes regarding EMG recording**.**

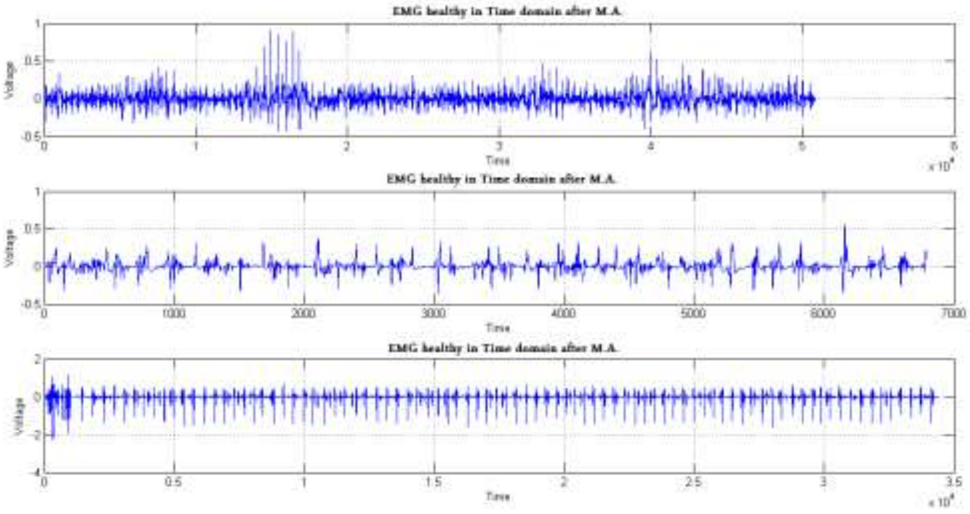

Figure 2. Moving Average Filter for Water Polo Athletes with respect to EMG

3.6. EMG Amplifiers

Amplifiers are the standard processing component in EMG equipment. Of course, the amplifier itself usually consists of multi-stage amplifiers, the most important of which, first and foremost, is the preamplifier as the first-stage amplifier.

Some of the most important functions of amplification stages are as follows:

1. Differentiating source signal and signal recording equipment
2. Converting electric current to voltage
3. Voltage Gain
4. Noise reduction

Two important characteristics of an EMG amplifier are high input impedance and differential inputs. These features have two important advantages: signal strength conversion and noise reduction weighing.

3.6.1. Signal Strength Conversion

The need to separate the reference signal from the recording equipment can be better reckoned and understood by observing the source signal. Signal power is defined as the squared value of the signal voltage divided by the source impedance. The aim is to amplify the signal strength to a level necessary for having an acceptable result from the recording equipment. This requires the most efficient power conversion between the source signal and the preamplifier. Any increase in reference impedance reduces the power available for conversion in terms of reception. Obviously, reducing reference impedance is considered a benefit, and it can be done in two different ways.

First, steps must be taken to reduce the perturbation and disturbance factors with respect to the reference impedance, such as scratching the electrode site with a grinding material as if to reduce skin resistance. The next method is to reduce the effective reference impedance by separating the source from the load. For this method, separation is done by sharing the source with an amplifier that shows a small output impedance. For differentiation, the transmission loop can be viewed as a source signal connected by two interconnected impedances and an electrolytic impedance of the skin which is formed. Another impedance is the amplifier's input impedance, which together can form a voltage divider configuration. The magnitude of the voltage drop across each connected impedance is proportional to the coefficient of each impedance with respect to the sum of the impedances; as a result, the largest the source impedance is, the higher the voltage drop across will be. In the differentiation procedure, any voltage drop across the impedance implies losing signal strength. As the value of the input impedance decreases, the power dissipation percentage decreases, and correspondingly, the transfer efficiency enhances and improves.

The high input impedance of the amplifier is coupled to the low output impedance, which is considered as the desirable characteristic of the effective reduction of source impedance during capturing signal power. The practical amplitude for the optimal input impedance concerning amplifying high homogeneity depends on the source impedance value. A good rule of thumb for this is that the input impedance should be 100 times greater than the output impedance. For a specific value of surface electrode impedance (impedance measured between electrode detection), for instance, considering 50KΩ, the optimum input impedance should be 5MΩ.

One of the most common mistakes made by people unfamiliar with electronics is assuming that the input impedance characteristic mentioned in the datasheets extends over the entire bandwidth. And this is not true to generalize this issue because any small amount of capacitor that parallels the input resistor reduces the input impedance at the desired frequency. This problem is exacerbated and deteriorated by capacitors on lead wires, which are often several times more than the capacity of the input capacitor, applying an unpleasant frequency resonance. For avoiding such error, the input impedance must also be compatible with a series including resistor and capacitor component or a bandwidth frequency that could be displayed. An acceptable frequency for surface recording is simply 100 Hz.

3.6.2. Noise Reduction Weighing

Maintaining high power from the EMG signal source to the preamplifier is one way to improve the signal-to-noise ratio. Another way, nonetheless, is to reduce the power of noise. For having the advantage of noise relative to the external amplifier, the most important way to reduce noise is to reject the common Mode Rejection Ration (CMRR) of the differential amplifiers. Differential amplifiers only amplify the voltage difference between the two input terminals. Each signal is a common voltage in both terminals measured relative to its common terminal.

The order in which this idealization (zero ideal) is determined in practice is known as the common-mode rejection ratio (CMRR), as introduced above. In practice, the functional measurement of EMG, CMRR, and the preamplifier is never properly known. The reason is that the impedance of the unequal source is seen by each input's terminal and the fact that it depends entirely on the unequal impedance of the electrode. The effect of this is the unbalanced impedance of the source, which causes a different voltage drop across the input terminals.

Different voltage produces a synthetic difference signal indistinguishable from any other differential signal. As a result, it is amplified by a differential signal gain. Noise generated inside the amplifier, however, is an important characteristic because it represents a significant component of the overall noise of the amplifier. This noise can be reduced to very low levels by using batteries that work with low-power preamplifiers being located after low-power amplifiers. Finally, the input current of the amplifier must be recognized well. This characteristic is of high importance because it represents the minimum signal that can be amplified. Lower input bias current is needed to minimize the effect of changes in the impedance of the electrode source, which is usually the result of electrode motion, and this is, of course, performed for better power consumption and consideration of power efficiency. For desirable results, Ohm's law is applied.

The amplitude of the motion perturbation can be equal to the change in the source impedance multiplied by the input bias current, which gives the desired condition when there is less input bias current for directly coupled differential amplifiers.

3.7. Neuromuscular Facilitation

Electrical stimulation is now widely used therapeutically to initiate and facilitate deliberate muscle contractions, although it is impossible to distinguish it from the strengthening effect mentioned previously. This type of flow utilization can be used in the following situations:

- When pain or injury inhibits deliberate contraction, for instance, quadriceps stimulation, especially of the internal medial part after knee surgery or knee injuries (Erikson and Haggmark, 1979). Another example is the stimulation of the cuff muscles and the Achilles tendon in chronic cases and after surgery, as well as in Achilles tendon injuries.

- In cases where muscle activity is not effectively controlled voluntarily. Examples include stimulation of the pelvic floor muscles in situations of administrative incontinence to regain urinary control in this group of patients (without nerve damage) (Cawely and Hendriks, 1992); Stimulation of the abductor Hallucis muscle, for the treatment of the early stages of toe deviation outward, and in flat feet and metatarsal pain, where voluntary control of the lumbar muscles is necessary and desirable.

- When we want to show the patient-specific muscle activity with normal movement. For example, in cases of hysterical paralysis.

- For children with cerebral palsy, strengthen muscle contraction and provide the feeling that the child can add and strengthen a weak reaction by adding the effect of electrical stimulation to the contraction. (Carmick, 1991).

- In the final stages of repairing peripheral nerve lesions to encourage voluntary contractions during the re-denervation process.

- In case of need to train new muscle activity, in muscle graft or motor nerve cases.

3.8. Functional electrical stimulation

Functional electrical stimulation is the electrical stimulation of the lower motor neuron to initiate contraction in paralyzed muscles in order to produce functional movements, correspondingly. Regular and frequent muscle stimulation increases strength, and it may also be where increased muscle strength occurs during regular and frequent muscle stimulation.

There may also be a positive effect on muscle spasms. Similarly, deltoid muscle stimulation has been used to prevent Glenohumeral joint dislocation in hemiplegic patients (Baker, 1987).

Implementing more complex systems for paraplegic patients who are unable to control voluntary movements in the lower extremities allows them to gain control of standing and walking and some daily movements having a non-poor posture (Mizrahi, 1993).

Electrical stimulation to control spasticity has the effects of electrical stimulation of muscle on spasticity which has not been clearly established and the reported results are also contradictory.
Part of this discrepancy in the reported results is due to problems measuring and defining spasticity. Generally, there are three methods related to this issue:

1. Stimulation of antagonisms that cause inhibition of agonists.
2. Stimulation of spastic muscles
3. Alternative stimulation of agonist and antagonist muscles

For the latest low-frequency method (3 to 35 Hz) with pulses of 0.2ms, used a few minutes daily and for several weeks. Unevenly pulsed pulses (trophic electrotherapy) are used to stimulate the sensory nerve, which is consistent with the principle of further enhancing the presynaptic inhibition of motor neurons by afferent stimulation and thus reducing spasticity.

Another method is to use a mesh glove to stimulate the whole hand with pulses of 0.3ms and a frequency of 50 Hz, which completes the circuit with electrodes placed on the patient's forearm (Dimitryevic et al., 1996). Both low-intensity and high-intensity stimulation of the sensory threshold of hemiplegic patients for 30 minutes per day showed that this treatment reduces sit-ups and enhances residual voluntary activity, while the patient does not neglect the daily routine activities, it makes better use of the organs.

In Hemiparesis (semi-paralyzed) patients, Lagasse and Roy (1989) investigated the effects of a functional electrical stimulation training program on the rate of simultaneous contraction of spastic muscles during forearm opening (maximum velocity). The pattern of electrical stimulation was adjusted specifically for each patient according to the electromyography parameters obtained from the non-affected limb. This treatment reduced the rate of simultaneous contractions of antagonists.

While the reported electrical stimulation results on the treatment of chest spasticity are contradictory, none of which have confirmed that "electrical stimulation exacerbates chest spasticity" (Baker, 1987).

4. Domain Related Approaches

4.1. Signal Amplitude with respect to DDF

The DDF, the density distribution function, is a representation of a signal that reveals some of its hidden properties. DDF in sampled signals is determined by counting the number of samples whose amplitude value is between x and dx, while dx is a small change in the domain's value. As a result, the number of samples per dx is determined and can be represented by a histogram curve.

If the number of available samples of the signal is large enough, DDF can be considered a good approximation of the probability function. Accordingly, figure 3 demonstrates the statistical parameters, including mean and variance.

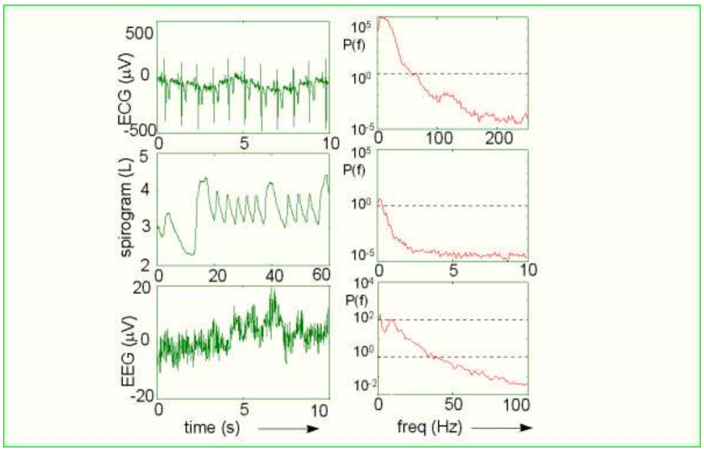

Figure 3. DDF of Signals, Signals in Left vs DDF in the Right

4.2. Frequency Spectrum and Filtering

The basic idea of the frequency spectrum concept is that each signal is made up of a combination of sine and cosine functions. The frequency spectrum, nevertheless, is obtained from Fourier analysis. Fourier analysis indicates that frequencies are present in the signal. Considering the Fourier Transform of the signal, the signal itself can be obtained with the help of Inverse Fourier Transform.

In many cases, the properties extracted from the signal's frequency spectrum are much more useful than the temporal properties. Figure 4 illustrates the frequency spectrum of several vital signals, including ECG, Spirogram, and EEG (quasi-periodic EEG components around 10 Hz).

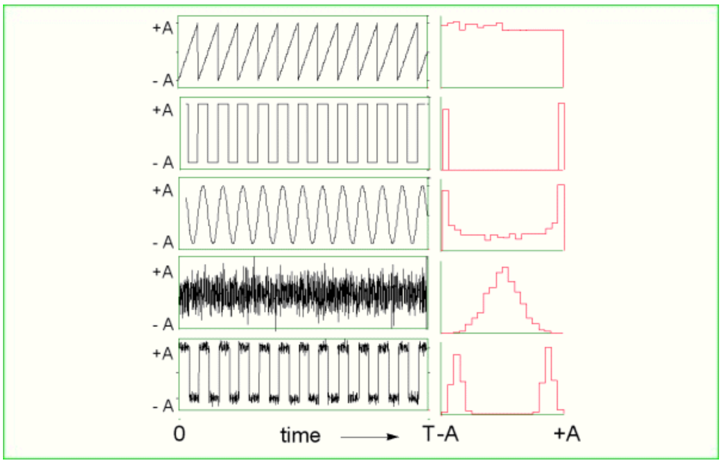

Figure 4. Frequency Spectrum of Vital Signals

Signal filtering removes unwanted frequency segments from the frequency spectrum of the signal. In filtering, the Fourier Transform of the signal is implemented to determine its spectrum. The undesirable frequency components of the signal are then removed from the spectrum, and finally, the filtered signal in the time domain is obtained by applying Inverse Fourier Transform.

Common linear filters are considered as below and followed by figure 5.

- Low Pass Filter (LPF)
- High Pass Filter (HPF)
- Band Pass Filter (BPF)
- Band Stop Filter (BSF)

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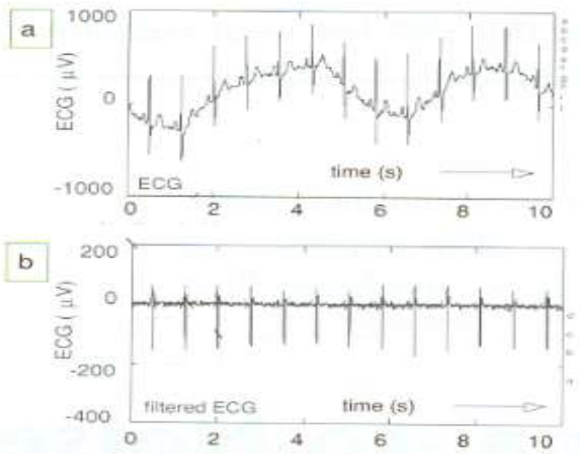


Figure 5. Demonstration of LPF, HPF, BPS and BSF

A simple example of a vital signal filter is the usage of a Band Pass Filter in ECG signal processing. The frequency band of the ECG signal is between 0.15 and 150 Hz. Nonetheless, in the recording procedure of the signal, the unwanted noise is inserted because of muscle activity and disturbance of the baseline and due to changes in the contact impedance of the electrode and the body and unwanted offset potentials. Baseline oscillations have a frequency below 1 Hz, and muscle noise has a frequency above 150 Hz. The filter passes frequencies between one and 150 Hz (Figure 6).

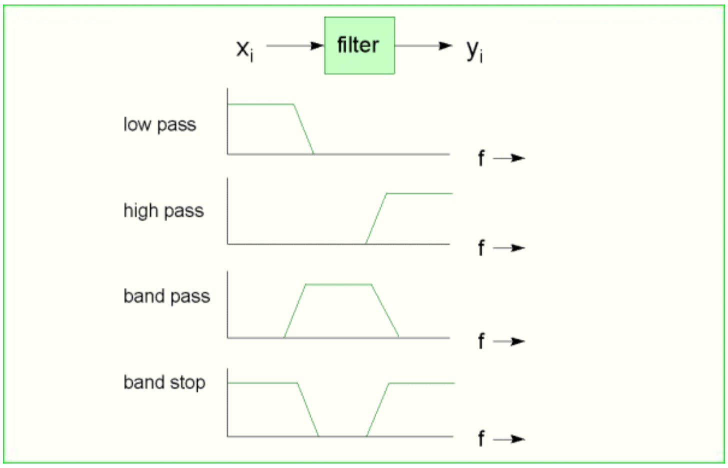


Figure 6. Application of Band Pass Filter in ECG Signal Processing

4.3. Signal to Noise Ratio

There is disturbance or noise in the recording and transmission of all vital signals. For instance, in ECG recording during physical activity, low-frequency baseline disturbances, on the one hand, high-frequency electromyogram signals due to muscle activity, on the other hand, affect the signal.

Therefore, it is necessary to use methods to increase the signal-to-noise ratio, abbreviated as SNR, which means that the recorded signal containing the original information in the presence of the noise must both be processed in such a way that the noise is minimized.

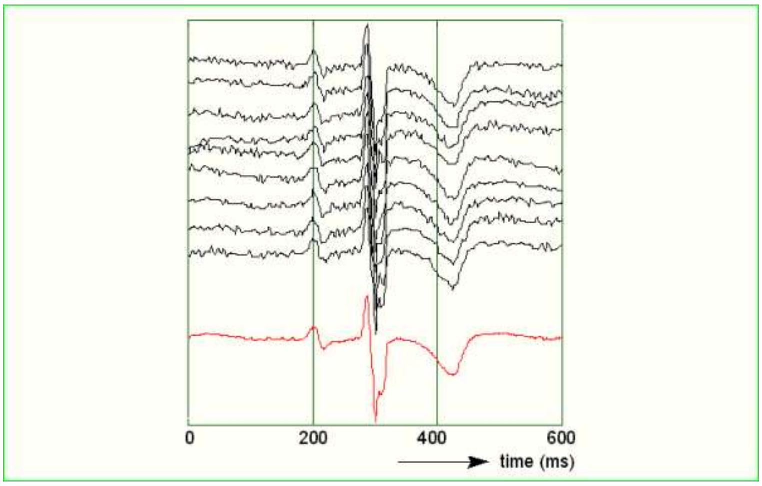


Figure 7. Simultaneous Averaging of ECG for increasing SNR

Simultaneous averaging is one of the easiest ways to reduce the signal-to-noise ratio of quasi-periodic signals such as ECGs.

This method assumes that the ECG information signal is of a certain nature while the statistical signal noise is normal. In this method, first, the starting moment of the waveform is determined, and simultaneous averaging is applied (Figure 9).

In this method, the sum of all signals (for example, k to the signal) is calculated. The result is a signal whose magnitude is k times more than the original waveform.

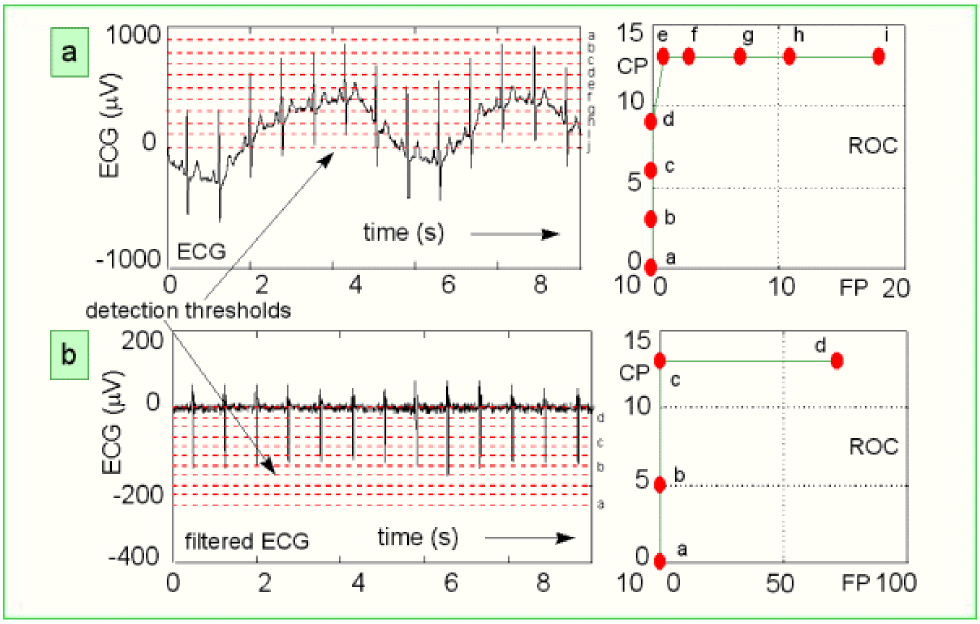
Therefore, by scaling, an improved version of the signal is obtained. It is clear that by increasing the number of signals, this method will lead to a better result, correspondingly.

4.4. Signal Recognition Methods

In recognizing the important parts of the signal, it is necessary to go through the following steps. First, the signal must be recorded close to the source of its output so that the signal-to-noise ratio, SNR, is as high as possible, meaning to have a very low value of noise with respect to the signal itself. Second, pre-processing should be done such as filtering as if by maximize the signal-to-noise ratio of the parts of the signal that need to be detected, can be bolded.

This recognition method is based on the minimum value of "false positive" (FP) and the minimum value of "false negative" (FN). Figure 8, clearly shows the application of using the aforesaid method with respect to the region of convergence in QRS Complex diagnosis in ECG.

Figure 8. Application of ROC Curve on QRS Complex, Diagnosis related to ECG



5. Conclusion and Results

In this project, we recorded EMG signals from 20 patients. First, we distinguished between the two movements classes Flexion & Extension, which Extension movement itself includes a subset of Extension and Pronation movements. To distinguish the first two movement classes from each other for flexion and extension movements, there was no need to examine the third channel due to the significant difference created by the signals recorded from the Triceps and Biceps muscles; however, for distinguishing between extension, supination and pronation movements, the third channel was needed to be examined, which is a goniometer as introduced. We processed the recorded signals using MATLAB and then tested them by neural network and then classified them based on KNN into four movements of classes, including extension, flexion, supination, and pronation. How to detect movements by the computer is that first, the signal of each person is recorded separately. After passing through the appropriate filter and preprocessing steps that were done on the signals, the signal of each person is recorded offline and with the label of the type of movement classified through two separate KNN networks, given that the first network separates the flexion movement from the other movements. The second network distinguishes the three modes of extension, supination, and pronation from each other. After training the networks and identifying the neighborhoods, we have recorded the signals online. To process the signals online, we need to determine the period for the system delay. Based on research studies and our experiment, this delay is considered about 4 seconds. It can be calculated based on the moment which is in the desired state. The conclusion that can be drawn is that by designing a virtual hand on the computer, you can benefit from advantages such as lower cost and greater accuracy and more repeatability. Electromyography (EMG) is an experimental method of expanding, recording, and analyzing electrical signals in muscles. Physiological changes in muscle fiber membranes generate muscle electrical signals. Nevertheless, due to its complex structure, the muscle is also responsible for some of the control functions and feedback pathways. It should be noted that the EMG signal is also used in the diagnosis of neuromuscular disorders such as muscular dystrophy, congenital myopathy, peripheral neuropathies, polio, etc. In this research, using advanced processes to evaluate the feature space for Waterpolo athletes has been studied.

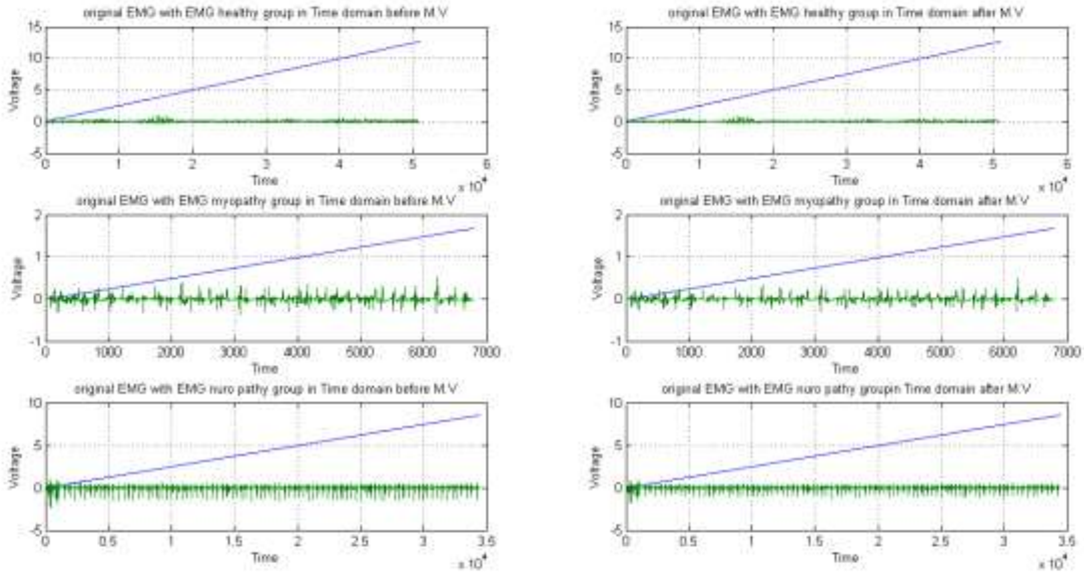
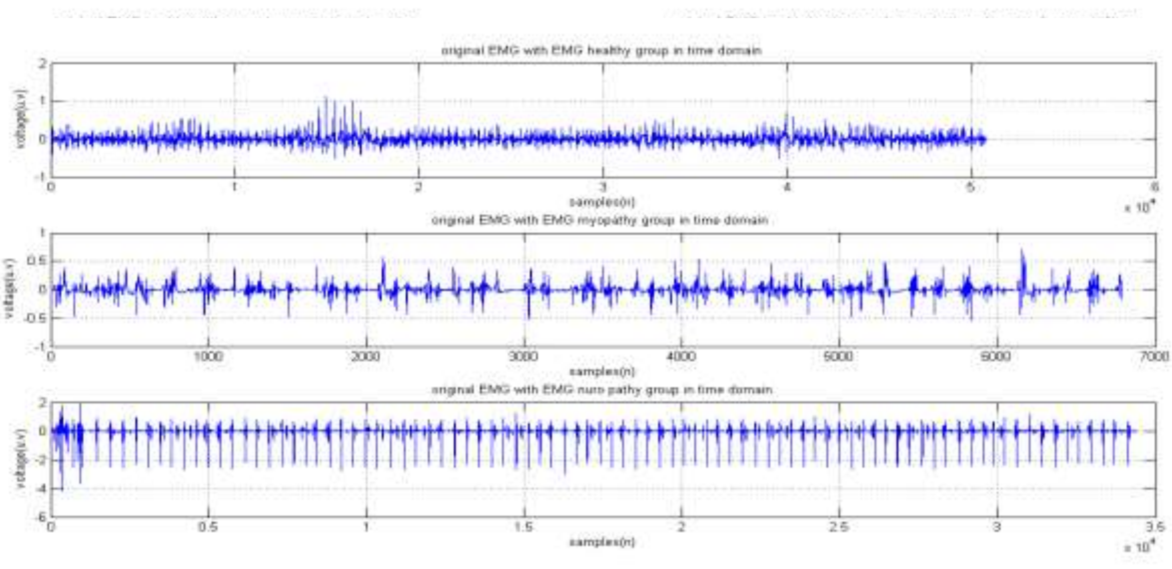


Figure 9. Results of EMG Signals through Neuropathy in Time Domain

For this purpose, after recording the EMG signal from the muscles of Trapezius, Pectoralis, Deltoid,



Triceps and signal processing and feature extraction, the feature space was evaluated and finally, using MLP neural network, these four muscles were classified to be used in practical systems used through rehabilitation and biofeedback.

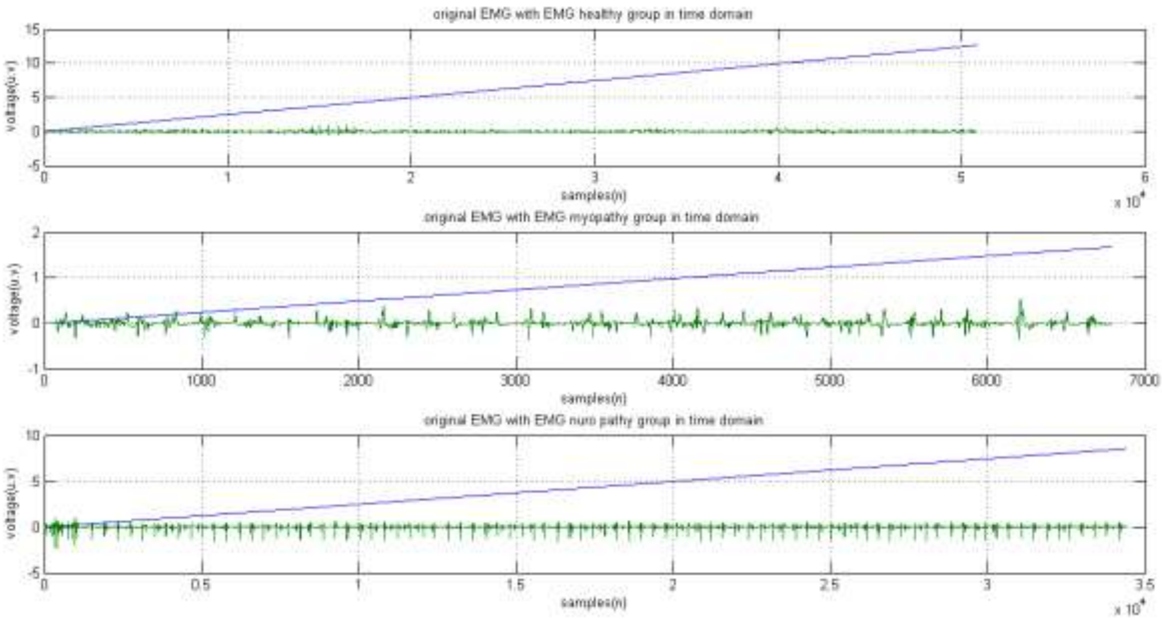


Figure 10. Continues of the Results of Figure 9

The recorded surface EMG signal was processed and extracted in time, frequency, and time-frequency domains and phase space. The classification results of these signals were performed using an artificial neural network that reports a class separation accuracy of 89.93%. Shoulder problems and discomforts are common in throwing sports. Using the EMG signal for athletes, performance improvement, injury reduction, as well as rehabilitation in case of injury can be expected.

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