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GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

REHABILITATION SYSTEM DESIGN TO STRENGTH MUSCLE ACTIVITY ON LOWER ARM EXTREMITY USING REAL TIME EMG DATA

M.Sc. THESIS

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Department of Biomedical Technologies

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FEN BİLİMLERİ ENSTİTÜSÜ

GERÇEK ZAMANLI EMG VERİLERİNİ KULLANARAK ALT KOL KAS AKTİVİTESİNİ GÜÇLENDİREN REHABİLİTASYON SİSTEM TASARIMI

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To my family,

FOREWORD

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ABBREVIATIONS

ALS	: Amyotrophic Lateral Sclerosis
BLDC	: Brushless Direct Current Motor
CMAP	: Compound Muscle Action Potential
dB	: Decibel
EMF	: Electromotive Force
EMG	: Electromyography
GSMU	: Global Scale Modified Universal
GUI	: Graphical User Interface
IDE	: Integrated Development Environment
LMU	: Length Modified Universal
LSMU	: Log Scale Modified Universal
LVMU	: Log Variable Modified Universal
MAV	: Mean Absolute Error
MSE	: Mean Square Error
NMSE	: Normalized Mean Square Error
NRMSE	: Normalized Root Mean Square Error
PC	: Personal Computer
PSD	: Power Spectral Density
PWM	: Pulse Width Modulation
RMSE	: Root Mean Square Error
RPM	: Revolutions per Minute
SD	: Standard Deviation
sEMG	: Surface Electromyography
SFEMG	: Single Fiber Electromyography
SLMU	: Scale Length Modified Universal
SMU	: Scale Length Modified Universal
SNAP	: Sensory Nerve Action Potential
SNR	: Signal to Noise Ratio
ZC	: Zero Crossing

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REHABILITATION SYSTEM DESIGN TO STRENGTH MUSCLE ACTIVITY ON LOWER ARM EXTREMITY USING REAL TIME EMG DATA

ABSTRACT

Medical rehabilitation methods aim to restore limb functions lost as result of illness, accident or injury. Nowadays, rehabilitation processes have been supported by electromyography (EMG) data in harmony with the developing technology. EMG is a method of measuring electrical signals taken from nerve and muscles by using surface, intramuscular and/or needle electrodes. In this thesis, the lower arm muscle rehabilitation system was designed to strengthen the lower arm muscle activity via obtaining real time EMG data from its muscle surface. It is aimed to increased hand functions by repeating the opening and closing movement of the hand with a modified available rehabilitation system. Therefore, the EMG signal required for control of rehabilitation system was obtained from lower arm muscle by using surface electrode. In order to design for a personal rehabilitation system, individual threshold was determined from EMG signal in the experimental set where a hand was opened and closed. The threshold value of one was determined from thirty different experiments with EMG records and the rehabilitation system performance was tested with another six different experiments. Several methods were used for the determination of the threshold values. Histogram, multiplication factor based standard deviation, wavelet threshold estimation methods were used in this thesis. Wavelet threshold estimation can be calculated with several methods such as universal, length modified universal, scale modified universal, global scale modified universal (GSMU), scale length modified universal, log scale modified universal and log variable modified universal. Performance analyses of threshold determination methods were performed in the time and frequency domain. Time domain based performance analyses were determined via mean square error, normalized mean square error, root mean square error, normalized root mean square, mean absolute value, zero crossing methods, signal to noise ratio (SNR) and execution time. Frequency domain based performance analysis was tested by using power spectral density methods. Performance tests of the rehabilitation system were tested with the real time EMG data. According to the results, it was observed that the threshold determination method obtained by GSMU method was better in terms of providing execution time, SNR and SD values compared to other methods. However, the histogram method gave better result providing desired velocity pattern.

GERÇEK ZAMANLI EMG VERİLERİNİ KULLARAK ALT KOL KAS AKTİVİTESİNİ GÜÇLENDİREN REHABİLİTASYON SİSTEM TASARIMI

ÖZET

Tıbbi rehabilitasyon metotları, hastalık, kaza veya yaralanma sonucunda kaybedilen uzuv fonksiyonlarının yeniden kazandırılmasını hedeflemektedir. Günümüzde gelişen teknolojiye uyumlu olarak rehabilitasyon süreçleri elektromiyografi (EMG) verileri ile de desteklenmeye başlamıştır. EMG sinir ve kaslardan yüzey, kas içi ve/veya iğneli elektrotlarla alınan elektriksel işaretleri ölçme yöntemidir. Bu tezde alt kol kas yüzeyinden elde edilen gerçek zamanlı EMG verileri ile alt kol kası rehabilitasyon sistemi tasarımlanmıştır. Mevcut değiştirilmiş bir rehabilitasyon sistemi ile elin açma ve kapama hareketleri tekrarlanarak el fonksiyonlarının arttırılması amaçlanmaktadır. Bu nedenle, rehabilitasyon sisteminin kontrolü için gerekli olan EMG sinyali alt kol kası üzerinden yüzey elektrotu ile alınmıştır. Kişisel bir rehabilitasyon sistemi tasarlamak için, bir elin açılıp kapatıldığı deney setinde EMG sinyalinden bireysel eşik seviyesi belirlenmiştir. EMG kayıtları 30 farklı deneyle yapılarak eşik değerleri hesaplanmış ve 6 farklı deney de sistemin testi için yapılmıştır. Eşik değeri hesaplanırken farklı eşik belirleme yöntemleri kullanılmıştır. Bu tezde; histogram, çarpım faktörü tabanlı standart sapma ve dalgacık eşik değeri tahmini yöntemleri kullanılmıştır. Dalgacık eşik belirleme tahmini; evrensel, uzunluğu değiştirilmiş evrensel, ölçeği değiştirilmiş evrensel, küresel ölçekte değiştirilmiş evrensel (GSMU), ölçek uzunluğu değiştirilmiş evrensel, logaritma ölçeği değiştirilmiş evrensel ve logaritma değişken değiştirilmiş evrensel yöntemlerle hesaplanabilmektedir. Eşik belirleme yöntemlerinin performans analizleri zaman ve frekans düzleminde yapılmıştır. Zaman düzlemi tabanlı performans analizleri ortalama kare hatası, normalize ortalama kare hatası, kök ortalama kare hatası, normalize kök ortalama kare hatası, ortalama mutlak değeri, sıfır nokta tespiti yöntemleri, işaret gürültü oranı (SNR) ve uygulama süresi ile belirlenmiştir. Frekans düzlemi tabanlı performans analizleri, spektral güç yoğunluğu yöntemi kullanılarak test edilmiştir. Elde edilen sonuçlara göre, GSMU yöntemiyle elde edilen eşik belirleme yönteminin hesaplama zamanı, SNR ve SD değerleri açısından diğer yöntemlere göre daha iyi olduğunu görülmüştür. Bununla birlikte, histogram yöntemi istenilen hız örüntüsünü sağlayarak daha iyi sonuç vermiştir.

1. INTRODUCTION

Medical rehabilitation is a good recuperation way of treatment for people who encounter stroke and/or disability. Rehabilitation treatment procedures mostly aim to restore desired skills of muscle movements and help the recovery of the neural system. In either cases rehabilitation methods differ from each other with respect to the target patient; for example, an old person, who suffer from a stroke, cannot eat, dress or take a bath without help, whereas, a young person in a post-surgery period can return to work and daily normal activities by the help of ongoing rehabilitation [1;2]. In the related literature, internet-based monitoring systems are widely used for rehabilitation as it helps physical therapists to remotely monitor and observe patient activities during the period of regaining muscle strength. Zheng et al. [3] proposed that system was implemented with a web-based monitoring tool providing both therapeutic and support information for rehabilitation system. A web based-monitoring system allowed the physical therapist the ability to view the rehabilitation history of patient and provide feedback to the patient. Bae et al. [4] designed a network-based monitoring system which consists of wireless sensor modules, computers at local and remote sites connected via the internet. Kinematic information conductive towards rehabilitation was measured on human body by using wireless sensor module and the measured data was analyzed at local and host computers that were connected via internet.

There are several reported studies about portable and home-based rehabilitation systems which help patients with undergoing disabilities to adapt their daily activities. Daponte et al. [5] designed and implemented home based rehabilitation system that revolves around the body as a sensor network for measuring the range of motion of patient during rehabilitation exercises. Dowling et al. [6], a rehabilitation system was implemented for adaptive home usage. Proposed system creates custom rehabilitation exercises for the patient utilizing real time data obtained by portable sensors.

Nowadays, rehabilitation systems and processes have been supported by the electromyography (EMG) data obtained from the patient in harmony with the developing technology [7;8].

EMG, which is a diagnostic procedure of collecting and assessing situations of both skeletal muscles and related neural cells, is widely used as a biomedical signal for physical therapy and rehabilitation [9; 10]. EMG signal might be obtained by placing electrodes at intramuscular and/or surface of the muscle. Surface EMG (sEMG) is a widely used method that is carried out by placing electrodes at the surface of the muscle while intramuscular EMG utilizes needle electrodes or intramuscular electrodes [11;12;13]. EMG signals have been used in clinical trials, robotic applications, and rehabilitation systems. [14;15;16]. Processing EMG signals provide significant information about muscle function and help to diagnose various muscle and neural system diseases such as myopathy and amyotrophic lateral sclerosis (ALS) [17;18]. It is also possible to support any rehabilitation system by using valuable information obtained from EMG signals which allow the ability to control rehabilitation systems with various analysis methods. Polygerinos et al. [19] proposed an open loop sEMG logic method. The proposed method controls soft robotic glove by continuously monitoring and comparing the state of two muscle signals for three predefined conditions as flex, extend, and hold. Leonardis et al. [20] reported that the design of a bilateral training system for rehabilitation of hand grasping that utilizes robotic hand exoskeleton and online muscle contraction measurement by EMG. Herein, an artificial neural networks method was applied to EMG signal for the estimation of free hand grasping pressure. Lui at el. [21] designed and implemented an EMG-Accelerometer based upper limb rehabilitation system prototype. A feature extraction method was used in every frame of EMG data for quantifying muscle activities. In the studies of both Wang et al. [22] and Khushaba et al. [23], mechanical systems of the myoelectric prosthetic hand is controlled with feature extraction and classification methods.

In the light of the above studies about EMG based hand rehabilitation systems, the thresholding detection is presented as a challenging issue determined from various analysis methods. In order to determine threshold value of hand movements, each hand should be tested in their open or closed conditions [24;25]. As a result, hand movements can be classified with respect to the obtained threshold results. During the threshold determination process, EMG signals should be denoised and classified with time domain methods such as histogram, multiplication factor based standard deviation and wavelet threshold estimation. These classified thresholds values can be utilized for the activation of hand prosthesis and rehabilitation systems [26;27]. In the applications of rehabilitation systems, noise effects issue originated from real electrode measurements is a significant problem for EMG signal analysis. Herein, the wavelet denoising based estimation technique helps to eliminate this related noise [28;29].

Recently, the accuracy of the selection of optimal threshold determination and classification methods in biomedical applications has been widely studied. The effect of accuracy of threshold determination and classification methods is observed by performing performance analysis. Awal et al. [30] reported that performance analyses were performed to observe the accuracy of the threshold determination methods for electrocardiography denoising. Performance analyses were carried out in the time, frequency, and time-frequency domain by using statistical tools. Waris et al. [31] investigated the effect of each feature on classification error when the threshold is optimized for both surface and intramuscular EMG by computing mean absolute error, waveform length, zero crossing, slope sign changes, William amplitude and myopulse percentage rate.

In this thesis, a pre-designed rehabilitation system was enhanced in order to improve muscle activity for lower arm extremity using real-time sEMG data. Throughout the thesis, once the real-time EMG data is obtained from the healthy hand during grasping movements (opening and closing movements), it is aimed to improve functions of the other hand with weak muscle activity. Herein, sEMG called as EMG is obtained from healthy lower arm muscles by using surface electrodes. In order to adapt the system as a custom rehabilitation device of each specific patient, EMG signal was acquired in the experimental set during the repetitive grasping motion of the hand and the individual threshold value was determined. During the determination phase of these threshold values 30 different experiments were carried out and another 6 different experiments were performed for testing the rehabilitation system. In the threshold determination stage, time domain analysis including histogram, multiplication factor based standard deviation and wavelet threshold estimation methods. These methods might be evaluated via the hard or soft threshold algorithms borrowed from the related literature [30]. Time domain based performances of threshold determination methods were tested in terms of mean square error (MSE), normalized mean square error (NMSE), root mean square error (RMSE), normalized root mean square error (NRMSE), mean absolute value (MAV), zero crossings (ZC), signal to noise ratio (SNR), standard deviation (SD) and execution time. Likewise, power spectral density (PSD) was used for frequency domain based performances of threshold determination methods.

2. BACKGROUND

In this chapter, skeletal muscle anatomy and physiology, muscle contraction, EMG, and hand rehabilitation systems are briefly explained in the following sub-chapters.

2.1 Skeletal Muscle Anatomy & Physiology

Skeletal muscle might be defined as voluntary muscle. Skeletal muscle; is a muscle fiber with o long cylindrical cell structure containing many nuclei, mitochondria, and sarcomeres (Figure 2.1). Each muscle fiber is surrounded by endomysium that is a thin layer of connective tissue. Most of these muscle fibers are covered with a bunch of muscle. These muscles are grouped in a parallel arrangement that is called muscle fascicle. It is thicker than the epinimum that surrounds each of the bundle muscles. The type of tendon that encapsulates a large number of muscle fascicles within the external sheath is called epimysium [32].

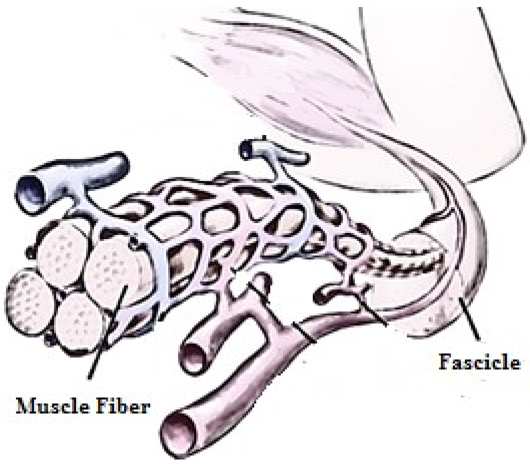


Figure 2.1: Anatomical structure of skeletal muscle [32]

Muscle fibers are classified by their histological appearance, shrinkage rates, and fatigue resistance. The slow twitch, or type I fibers, are thinner and deposited by a denser capillary web. It also appears red because it contains a large amount of oxygen-binding protein myoglobin. Fast-twitch, also known as type II fibers, differ in fatigability.

Physiological skeletal muscle contraction, the potential for membrane movement first occurs and spreads. In the meantime, the electrical energy generated is converted into an intracellular chemical signal, followed by the triggering of myofilament interaction, resulting in skeletal muscle contraction. The electrical energy generated during this process is converted into an intracellular chemical signal, followed by a skeletal muscle contraction by triggering myofilament interaction. The physiological structure of skeletal muscle is shown in Figure 2.2. Physiological skeletal muscle activity is occurred by a nerve impulse. The nerve input of the skeletal muscle fiber is taken from the center of the fibers known as motor end plates. The electrical neuronal impulse is amplified at the neuromuscular junction. The resulting generation of the endplate potential is the first step of muscle contraction [33].

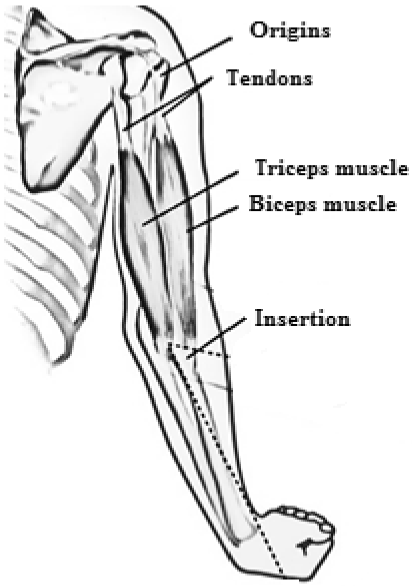


Figure 2.2: Physical structure of skeletal muscle [34]

2.1.1 Muscle contraction

Muscle contraction is generated with an impulse from the motor neuron of the muscle. When the impulse reaches the motor unit muscle fibers, the reaction begins at each sarcomere between actin and myosin filament. This reaction causes muscle and results in the sliding filament theory [35;36]. Muscle contraction consists of four distinct stages; these are given as follows;

- **Muscle activation:** At this stage, the sarcoplasmic reticulum stimulates the motor nerve to secrete calcium into the muscle.
- **Muscle contraction:** At this stage, calcium ions actin and myosin flow into the muscle cell. The actin and myosin cross bridges connected with energy.
- **Recharging:** Energy is re-synthesized to provide strong binding of actin and myosin.
- **Relaxation:** Relaxation occurs when stimulation of the nerve stops. Calcium ions are pumped back into the sarcoplasmic reticulum and link between actin and myosin is broken. Actin and myosin return to state without stimulation of nerve and causing muscle relaxation.

2.1.2 Myopathy

Myopathy defined as muscle disease might be about weakness, inflammation, contraction, and/or paralysis diseases in the muscle fibers. In the related literature, myopathy has two types such as hereditary and acquired myopathy. Hereditary myopathies are caused by a genetic defect, for example, muscular dystrophies are related to a genetic defect of the X chromosome. However, acquired myopathies are caused by our body's own system or accident and injury [36;37]. Myopathy could be diagnosed with blood tests and/or EMG data. To treat these myopathy diseases, medication, physical medicine and/or rehabilitation systems could be used by the doctors [37].

2.2 Electromyography (EMG)

EMG signals measured from electrical activities of muscles might be used for a diagnostic procedure to assess the health of muscles and the nerve cells that control motor neurons. The measurement of EMG signal procedure is typically given in Figure 2.3. The EMG signal is obtained by using measuring electrodes placed on the muscle surfaces. It is measured as an electrical activity by using each muscle electrode according to the reference electrode. The amplifier circuit stages produce raw EMG signal data and eliminate noise signals by subtracting the signal from the reference electrode. The measured EMG signal might be represented as graphical outputs, numerical values and/or sound messages [11;12] and a typical EMG signal record is shown in Figure 2.4.

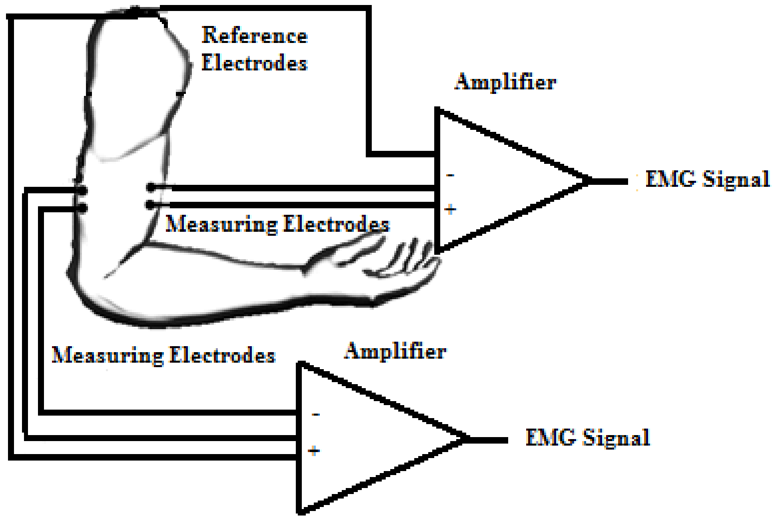


Figure 2.3: EMG recording procedure [38]

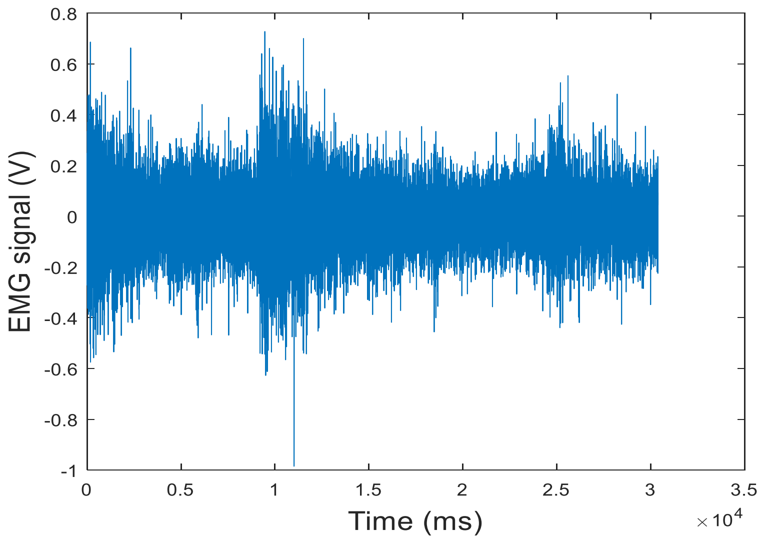


Figure 2.4: Typical EMG record

The obtained EMG signal might be used to detect abnormal electrical activities of the muscle that might bring about some diseases and illness such as muscular dystrophy, inflammation of muscles, pinched nerves, peripheral nerve damage (damage to nerves in the arms and legs), ALS, myasthenia gravis, disc herniation, etc. [11;12;17].

2.2.1 EMG circuit

EMG circuit basically consists of electrodes, amplifiers, and filters. EMG circuit diagram is shown in Figure 2.5 where pre-amplification, differential amplifiers bandpass filter, amplification, microcontroller and personal computer (PC) are constituted. A designed for EMG circuit scheme is given in Figure 2.6. Herein, the instrumentation amplifier is implemented with AD622 and differential amplifiers circuit is designed with LM324 and LM741. The AD622 based circuit amplifies the desired meaningful levels of the raw EMG signal measured from the electrodes.

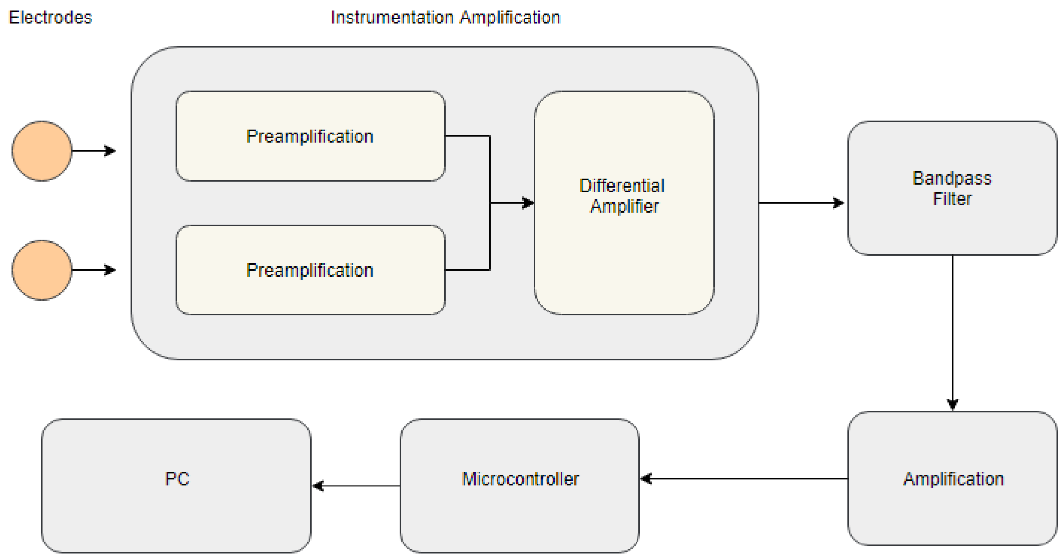


Figure 2.5: EMG circuit block diagram

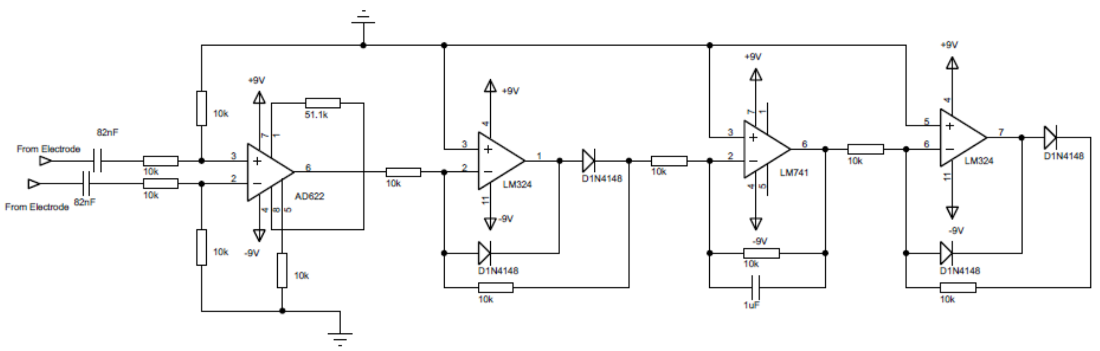


Figure 2.6: A part of the EMG circuit scheme

The EMG circuit might be used to measure several EMG measurement types such as sEMG, single fiber EMG (SFEMG), compound muscle action potential (CMAP), sensory nerve action potential (SNAP) and surface muscle recording. The SFEMG is an EMG measurement of the single muscle fiber by using needle electrodes. The CMAP measures action potentials from several muscle fibers in the same are by using surface electrodes. The SNAP is a measurement method that is obtained by electrically stimulating sensory fibers and recording nerve action potential at a point further along nerve [39].

The amplitude, filter setting, maximum frequency, and sampling frequency ranges of these EMG types are given in Table 2.1. The EMG signal has electrical potential ranges in amplitude from less than 50μV to several 300mV and frequency range from 2 Hz to more than 10 kHz [12, 39].

Table 2.1: EMG standard [39]

EMG TYPE	AMPLITUDE (μV)	FILTER SETING (Hz)	MAX. FREQUENCY (kHz)	SAMPLING FREQUENCY (kHz)
EMG (sEMG)	50-300000	2Hz-10kHz	10	20-50
SFEMG	300-10000	500Hz-5kHz	20	20-50
CMAP	100-30000	2Hz-10kHz	5	10-25
SNAP	0.1-100	5Hz-2kHz	5	10-25
Surface muscle recording	10-1000	20Hz-1kHz	<1	2-5

2.3 Hand Rehabilitation and Its Physical Therapy

The hand rehabilitation is a kind of physical therapy with hand and its upper extremities to provide the functional development of sensory and physical skills of the hand. Treatment of hand rehabilitation involves such application as computerized evaluation, education of the patient, control of pain, range of motion, soft tissue mobilization and flexibility and strengthening exercises. [20, 40, 41]. Methods of hand rehabilitation used in the treatment of many diseases such as myopathy, treatment of fraction and dislocation, nerve compression differ from patient to patient. To make an eligible treatment for personal hand rehabilitation, special hand exercises might be used (Figure 2.7).

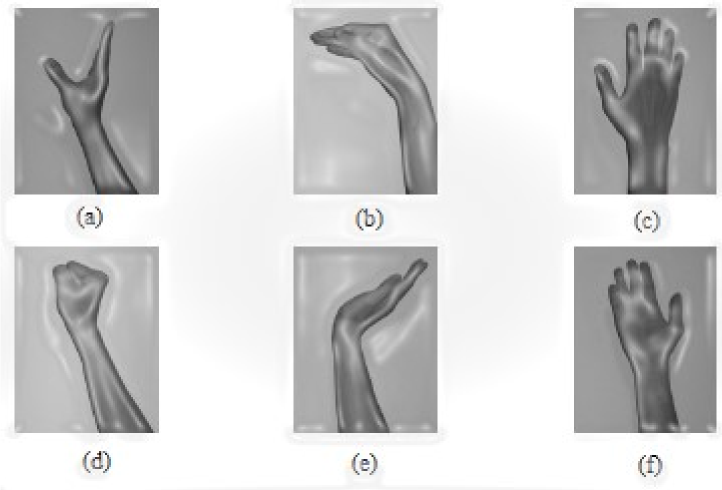


Figure 2.7: Various hand exercises for hand rehabilitation (a) Hand open (b)Wrist flexion (c) Pronation (d) Hand close (e) Wrist Extension (f) Supination [28]

3. MATERIAL & METHODS

In this chapter, the design stages of the developed hand rehabilitation system are explained and given in Figure 3.1. Herein, the subsystems of the developed hand rehabilitation system can be grouped as mechanical structure, EMG circuit with sensors and EMG analysis methods such as time and frequency domains.

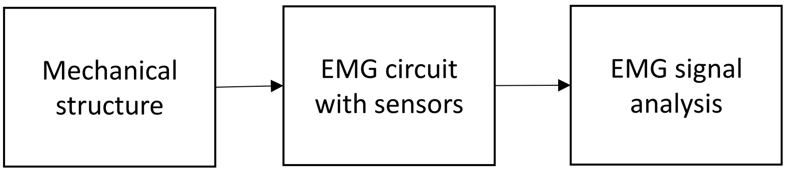


Figure 3.1: The design stages of the develop system

3.1 Mechanical Structure of the Designed System

In order to implement the proposed methodology of this thesis, a single degree of freedom hand rehabilitation system (Figure 3.2) that was designed in the study of Gezgin et al. [42] was selected.

Figure 3.2: Single degree of freedom hand rehabilitation system [42]

As seen in Figure 3.3, the most critical part of the system is composed of a dual loop Watt II six-bar linkage mechanism. Dimensional parameters of the mechanism were synthesized by considering real-life fingertip trajectory data of the index finger that was taken by utilizing motion capture cameras during successive hand grasping motion of adult subjects. As a result during rehabilitation treatment, the tip of the mechanism is able to follow the trajectory of index finger motion naturally. In order to attach the patient hand to the system, it also includes a hand attachment module that naturally adjusts the motions of the remaining fingers during the treatment.

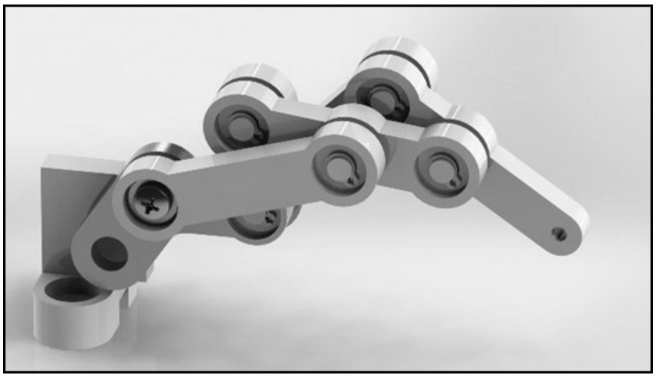


Figure 3.3: Watt II six bar linkage mechanism [42]

Actuation of the system is carried out by a BLDC actuator that includes a built in gear box, a hall-effect sensor, and encoder. Using the supplied EPOS2 controller the rehabilitation system manages to simulate the grasping motion of the human hand during continuous rotation of the actuator. In the designed hand rehabilitation system, Maxon BLDC Motor and EPOS2 motor driver were used to control for mechanical structure [43;44].

3.1.1 Brushless DC (BLDC) motor

The brushless DC motor (BLDC) is widely used as an electromechanical actuator in many engineering applications such as automotive, aerospace, robotics, medical, industrial automation, etc. [45;46;47;48]. BLDC motor is a type of synchronous motor which the magnetic field produced by the stator and rotor at the same frequency. The stator of the BLDC motor consists of windings called laminations, which are axially cut along the inner periphery and placed in slots. The stator winding is connected with different ways to give a different type of back electromotive force. These different ways give the simple control way for the users to speed and precise location of the rotor. The rotor of the BLDC motor consists of permanent magnet that can vary from two to eight pole pairs with alternate north and south poles. Topology and equivalent circuit of the BLDC motor are shown in Figure

3.4. When it compared with the other DC motors, BLDC motors have many advantages such as better speed-torque characteristics, high efficiency, high-speed ranges, long operation life, and silent operation.

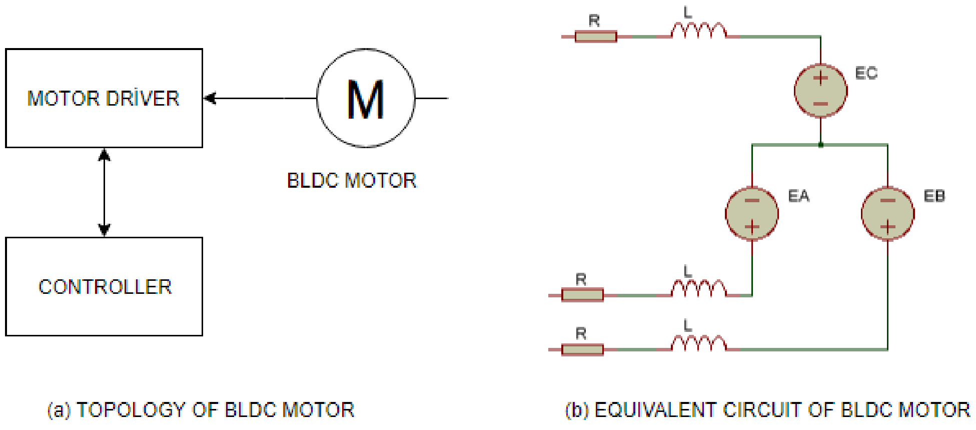


Figure 3.4: Topology and equivalent circuit of BLDC motor

Once the BLDC motor triggers out to rotate its shaft, which commutates cycle electrically, each winding of the motor generates an electromotive force (EMF) voltage. It opposes the voltage supplied to the windings and its polarity of back EMF is in the opposite direction of energized voltage polarity. Furthermore, back EMF is depending on the angular velocity of the rotor, the magnetic field generated by rotor magnets and the number of turns in the stator windings. Hence, the rotational speed and location can be measured by Hall-Effect sensors and/or sensorless method which is the use of fictitious current vectors via state estimators [49;50;51;52]**.** The simplified electronics circuit with power transistors driver of the BLDC motor is shown in Figure 3.5. Dynamic mechanical and electrical equations of the BLDC motor nonlinear model is described in from Equation 3.1 to Equation 3.3 borrowed from [49].

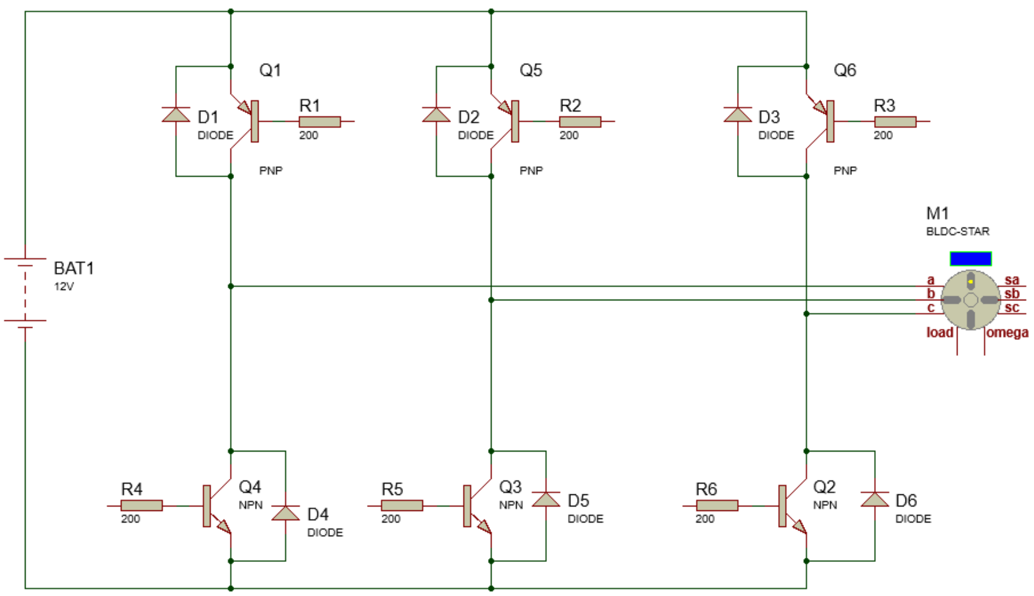


Figure 3.5: A typically driver circuit of the BLDC motor

$$\frac{d}{dt} i_q = \frac{1}{L_q}\left[-Ri_q - n\omega(L_d i_d - k_l) + v_q\right] \tag{3.1}$$

$$\frac{d}{dt} i_d = \frac{1}{L_d}\left[-Ri_d + nL_q\omega i_q + v_d\right] \tag{3.2}$$

$$\frac{d}{dt}\omega = \frac{1}{J}\left[T(I,\theta) - T_l(t)\right] \tag{3.3}$$

where L_d, L_q are the fictitious inductances on the direct-axis and quadrature-axis, v_d, v_q are the direct-axis and quadrature-axis voltages, i_d, i_q are the direct-axis and quadrature-axis currents, n is the number of permanent pole pairs, ω is the rotor angular speed, R is the winding resistance, J is the inertia momentum, $k_l = \sqrt{\frac{3}{2}}k_e$; k_e is the permanent magnet flux constant, θ is the displacement variable and $I = \left[i_q i_d\right]^T$. $T_l(t)$ is the external torque caused by the friction imposed on the shaft of the motor. $T_l(t) = b\omega + T_L$, b is the viscous damping coefficient, T_L is the external load.

In this thesis, Maxon Brushless 357242 BLDC motor is used a motor with Hall-Effect sensor to sense the rotor position. The snapshot of the BLDC motor integrated the hand rehabilitation designed system and its features are given in Figure 3.6 and Table 3.1, respectively.

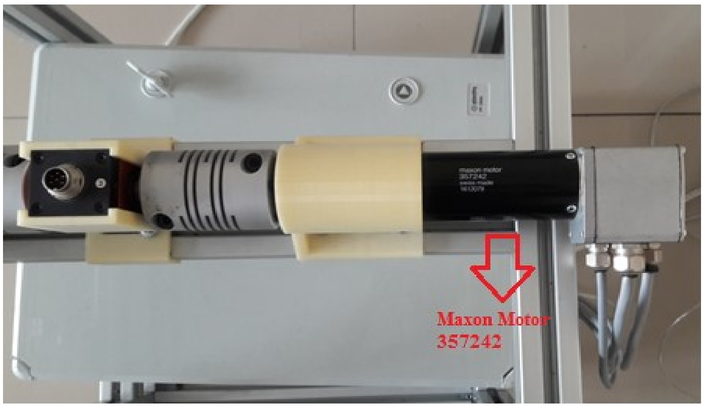


Figure 3.6: Maxon Motor (357242)

Table 3.1: Maxon Motor (357242) features [43]

Gear Box Actuator	Planetary Gearhead GP 42 C, Ø42 mm, 3-15Nm, Ceramic version
Motor	EC 45 Ø45 mm, Brushless, 250 Watt, with Hall Sensor
Sensor	Encoder HEDL 9140, 500CPT, 3 Channel, with Line Driver RS 422

3.1.2 Motor driver

The motor driver of the BLDC motor designed hand rehabilitation is EPOS2 driver in this system. EPOS2 driver has some advantages such as small size, full digital encoder, smart positioning controller with Hall-effect sensor and it can be integrated with Maxon Motor. EPOS2 motor driver can be operated via USB or RS232 communication ports and CANopen network USB port of the motor driver is used for communication with the PC controlled with EMG signal analysis.

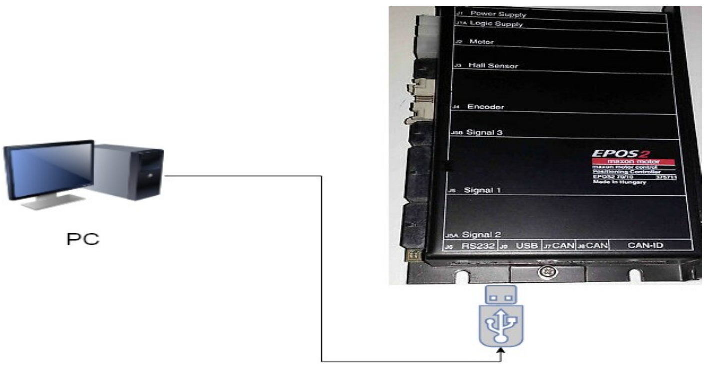


Figure 3.7: PC connection with USB port of EPOS2

3.2 Embedded System Kit for EMG Signal

The EMG measurement kit possesses sensors for gathering electrical signals of EMG generated by muscles and nerves. The measurement kit might be implemented with Arduino and/or similar microcontroller-based embedded systems [54;55]. The Arduino-based EMG sensor used in this thesis serves as a bridge connecting the human body and electronic components. The sensor measures small muscle electrical signals than amplified two times and filtered. The sensor output is recognized by Arduino. In standby mode, the output of the sensor is 1.5V. Once muscle contraction occurs, the output signal increases up to 3.3V. In this thesis, the real time EMG data is used for controlling hand rehabilitation system with Arduino based EMG measurement kit and surface electrode (Figure 3.8).

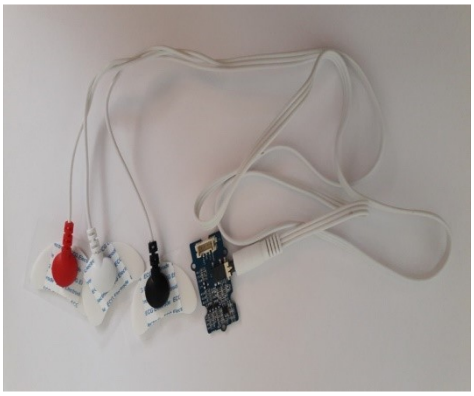


Figure 3.8: EMG measurement kit with surface electrodes

3.3 EMG Signal Analysis

EMG signal analysis is usually used for physical therapy and rehabilitation systems [56;57]. It is necessary issue that threshold detection is determined from EMG signal analysis. In the related to the literature, EMG signal analysis-based thresholding detection can be performed with several analysis methods [28;31;58]. In Ref. [58], the histogram method was used for time domain threshold determination technique. Another threshold determination method was wavelet threshold estimation methods including both time-frequency components [28]. These threshold algorithms that are used for denoising, classification and control applications consists of soft and hard thresholding algorithm [28;30]. The hard and soft threshold algorithms are given in

Equation 3.4 and Equation 3.5, respectively, where x stands for the obtained EMG data and Th stands for the threshold value. [30].

$$hd(x) = \begin{cases} 0 & |x| \leq Th \\ x & |x| > Th \end{cases} \tag{3.4}$$

$$sd(x) = \begin{cases} 0 & |x| \leq Th \\ sign(x)(|x| - Th) & |x| > Th \end{cases} \tag{3.5}$$

In this thesis, the hard thresholding procedure is used for the control of the hand rehabilitation system. Histogram method, multiplication factor based standard deviation method, and wavelet thresholding estimation methods are applied to receive real-time EMG data from the hand rehabilitation system. Herein, to determine the threshold level, EMG signals were denoised and classified with several methods such as histogram, standard deviation, and wavelet. After that, the classification of EMG signal might be used for controlling of rehabilitation systems and prosthesis application.

3.3.1 Histogram method

The histogram method, which is a kind of time domain analysis, is defined as a graphical representation of the frequency of the given data sequence determined with equal intervals [59]. To achieve the histogram method analysis, the amplitude is divided into equal intervals where the number of values is calculated. The results of this method are sketched on a graph showing the amplitude values in an axis-divided interval and the other axis shows the number of amplitude values in the intervals [58].

3.3.2 Multiplication factor based standard deviation method

The SD method is a statistically way defined as a measurement of dispersion from the mean of the given data set. The SD is calculated via a square root value of variance. As for threshold detection for EMG signal with the SD method, in the literature, there are multiple ways of SD for obtained EMG data where a multiplication factor chosen as three or five folds. In Ref. [60], extracellular of neural activity was obtained at a multiplication factor based SD method by using the needle electrodes. In this thesis, the multiplication factor based SD method was applied in real time EMG data by using the surface electrodes and the multiplication factor was selected as three and five folds.

$$SD(\times 3) = \left(\sqrt{\frac{\sum |x_m - \mu|^2}{N}}\right) \times 3 \qquad (3.6)$$

$$SD(\times 5) = \left(\sqrt{\frac{\sum |x_m - \mu|^2}{N}}\right) \times 5 \qquad (3.7)$$

where x_m stands for actual response of the test EMG data, μ is the mean of real time EMG signal and N is the length of the data.

3.3.3 Wavelet threshold estimation method

Wavelet transform can be defined in time - frequency components, however, in this thesis; it is used to find time components of a signal analyzed [61]. The wavelet transform produces a translation and a dilation of an instant window with the mother function $\Phi(x)$ [62], it is defined as follows

$$\Phi_{(s,l)}(x) = 2^{-\frac{s}{2}}\Phi\left(2^{-s}(x - l)\right) \qquad (3.8)$$

where s is the width of the wavelet width and l is the position of the wavelet, both s and l are integer that scale and dilate of this mother function. The wavelet function can be defined in the following form

$$W(x) = \sum_{k=-1}^{N-2}(-1)^k c_{k+1}\Phi(2x + k) \qquad (3.9)$$

where $\Phi(\cdot)$ and c_k stands for the mother function and the wavelet coefficients, respectively [63].

In this thesis, wavelet coefficients based on the threshold determination methods used with real EMG data are given as follows. i) Universal method is given in Equation 3.10 [28;64.], ii) Length modified universal (LMU) method is expressed in Equation 3.11 [28;65], iii) Scale modified universal (SMU) method is expressed in

Equation 3.12 [28;66], iv) Global scale modified universal (GSMU) method is given in Equation 3.13 [28;67], v) Scale length modified universal (SLMU) method is combined both LMU and SMU methods expressed in Equation 3.14 [28;66], vi) Log scale modified universal (LSMU) method is given in Equation 3.15 [28;68] and vii) Log variable modified universal (LVMU) method is given in Equation 3.16 where the constant j constant d value is associated to wavelet function and SNR, in this thesis, it is chosen as 3 [28;69].

$$Threshold_{Universal} = \sigma\sqrt{2\log(N)} \tag{3.10}$$

$$Threshold_{LMU} = \sigma\frac{\sqrt{2\log(N)}}{\sqrt{N}} \tag{3.11}$$

$$Threshold_{SMU} = \sigma\, 2^{\frac{j-J}{2}}\sqrt{2\log(N)} \tag{3.12}$$

$$Threshold_{GSMU} = \sigma\, 2^{\frac{-J}{2}}\sqrt{2\log(N)} \tag{3.13}$$

$$Threshold_{SLMU} = 2\sigma\,\frac{\sqrt{2\log(N)}}{\sqrt{N}\,2^{\frac{j-J}{2}}} \tag{3.14}$$

$$Threshold_{LSMU} = \sigma\frac{\sqrt{2\log(N)}}{\log(j+1)} \tag{3.15}$$

$$Threshold_{LVMU} = \sigma\frac{\sqrt{2\log(N)}}{\log[e+(j-1)^{d}]} \tag{3.16}$$

where N stands for sample size of a signal, σ stands for $\frac{median(|cD_j|)}{0.6745}$ with cD_j which is the detail wavelet coefficient at scale level with j from 1 to 4, J stands for 4 which is the maximum level of scale, e stands for 2.71828 and d stands for 3 as a constant.

3.3.4 Performance evaluation

After implemented the threshold determination methods, performances comparison of between the real-time test EMG data and the desired velocity response are evaluated. Performance evaluation methods consisting MSE, NMSE, RMSE, NRMSE, MAV, ZC, SNR, SD and the execution time of each method are computed for threshold determination methods are computed in the time domain [30, 31, 70].

Similarly, the power spectral density (PSD) method is evaluated in the frequency domain [30, 70].

3.3.4.1 Time domain based performance analysis

In this subchapter, the time domain based performance analyses methods are given in detail while evaluating threshold determination methods. MSE is about the average squared difference errors given in a system. In this thesis, MSE is computed the average squared difference between the desired signal and actual signal. The desired signal is defined as the velocity response of test EMG data and the test data is defined as the actual or real response of test EMG data for MSE given in Equation 3.17. The NMSE is also given in Equation 3.18. [30;71]. The RMSE is the square root of the difference between the desired signal and actual signal i.e. RMSE is the square root of MSE. It provides for computing the magnitudes of the error signal in Equation 3.19 [30;71]. The NRMSE is also given in Equation 3.20. As for another performance criteria in time domain, MAV is the average of the absolute value of signal which is given in Equation 3.21. In this thesis, MAV is computed by the average of absolute value of actual response of the test EMG data. MAV might also indicate muscle contraction levels [31;72].

$$MSE = \frac{1}{N}\sum_{n=0}^{N-1}[x(n) - x_m(n)]^2 \tag{3.17}$$

$$NMSE = 1 - \frac{\sum_{n=0}^{N-1}[x(n) - x_m(n)]^2}{\sum_{n=0}^{N-1}[x(n)]^2} \tag{3.18}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=0}^{N-1}[x(n) - x_m(n)]^2} \tag{3.19}$$

$$NRMSE = 1 - \sqrt{\frac{\sum_{n=0}^{N-1}[x(n) - x_m(n)]^2}{\sum_{n=0}^{N-1}[x(n)]^2}} \tag{3.20}$$

$$MAV = \frac{1}{N}\sum_{n=1}^{N}|x_m(n)| \tag{3.21}$$

where $x(n)$ stands for the desired velocity response of test EMG data, $x_m(n)$ stands for actual response of the test EMG data and N is the length of the data.

The ZC is providing an approximate estimation property measures the number of zero crossings of the signal given in Equation 3.22 [31;70].

$$ZC = \sum_{n=1}^{N-1}[(x_m(n).x_m(n+1) < 0) \cap (|x_m(n) - x_m(n+1)| > \varepsilon)] \quad (3.22)$$

where $x_m(n)$ is actual velocity response of test EMG data, N is the length of the data.

The SNR measured in decibel (dB) is a rate the level of the signal to the level of noise. The higher SNR value gives that signal includes useful information while the negative value of SNR means that the noise is stronger than the signal. It is given in Equation 3.23 and Equation 3.24 as follows

$$SNR = 10\log\left(\frac{P_{signal}}{P_{noise}}\right)\ (dB) \quad (3.23)$$

$$SNR_{improvement} = SNR_{output} - SNR_{input} \quad (3.24)$$

where P_{signal} is the power of signal, P_{noise} is the power of noise, SNR improvement is defined by [30]. In this thesis, SNR_{output} is the SNR of the desired velocity response of test EMG data and SNR_{input} is the SNR of the actual response of test EMG.

The SD method that might be used both domains is a way to measure the dispersion from the mean of the given any data set. The SD is given in Equation 3.25 [73].

$$SD = \sqrt{\frac{\sum|x_m - \mu|^2}{N}} \quad (3.25)$$

where x_m stands for the actual response signal in the data set, μ is the mean of the data set and N is length of data set.

3.3.4.2 Frequency domain based performance analysis

In this subchapter, the frequency domain based performance analysis method is explained in detail while evaluating threshold determination methods. The PSD is a measuring way about power contents of the signal versus frequency. It can be found two ways given in Equation 3.26 and Equation 3.27 [73].

$$PSD = S_x(f) = \lim_{T\to\infty} E\left\{\frac{1}{2T}\left|\int_{-T}^{T} x_m(t)e^{-j2\pi ft}\,dt\right|^2\right\} \tag{3.26}$$

where $S_x(f)$ is the average of Fourier transform magnitude square over T standing for time interval and $x_m(t)$ standing for the actual response signal.

$$PSD = S_x(f) = \int_{-T}^{T} R_x(\tau)e^{-j2\pi ft}dt \tag{3.27}$$

$$R_x(\tau) = E\{x_m(t)x_m{}^*(t+\tau)\} \tag{3.28}$$

where $S_x(f)$ is Fourier transform of the auto-correlation function, $R_x(\tau)$ is auto-correlation of $x_m(t)$ standing for the actual response signal, and $x_m{}^*(t)$ is complex conjugate of $x_m(t)$.

3.4 Software Implementation

In this subchapter, software implementation of the designed hand rehabilitation and control systems are explained with Arduino and Matlab package programs and numerical analysis platform, respectively [74]. Arduino software is used for gathering the real-time EMG data from the hand rehabilitation system setup via Arduino hardware based EMG sensor. Matlab numerical analysis platform provides gathering, analyzing, processing and generating the meaningful outcomes as a control signal for the rehabilitation system.

3.4.1 Arduino based software design

Arduino is an open-source electronics hardware and software platform [75]. Arduino contains either an 8-bit or a 32-bit microcontroller and integrated development environment (IDE) that used to write and upload computer code using the C or C++ programming languages. The most popular Arduino boards can be used for many electronics based projects [76]. In this thesis, ATmega328p based Arduino is used. The board has 14 digital input/output pins, of which six can be used as pulse width modulation (PWM) outputs. It has six analog inputs. Memory is 32KB of flash memory, 2KB of static random access memory and 1KB of electrically erasable programmable read memory [76].

3.4.2 Matlab based software design

Matlab providing a numerical analysis platform is a matrix-based language allowing natural expression of computational mathematics [77-78]. Engineers and/or scientists use Matlab programs because it includes mathematical tools, computation, algorithm development, modeling and simulation, data analysis, signal processing, the control systems, application development, graphical user interface (GUI) toolboxes and useful solutions with functions [77]. In this thesis, the Matlab R2017b version was used because previous versions of Matlab were not supported to EPOS2 motor controller. The MinGW-W64 compiler was used for building C and C++ applications [79].

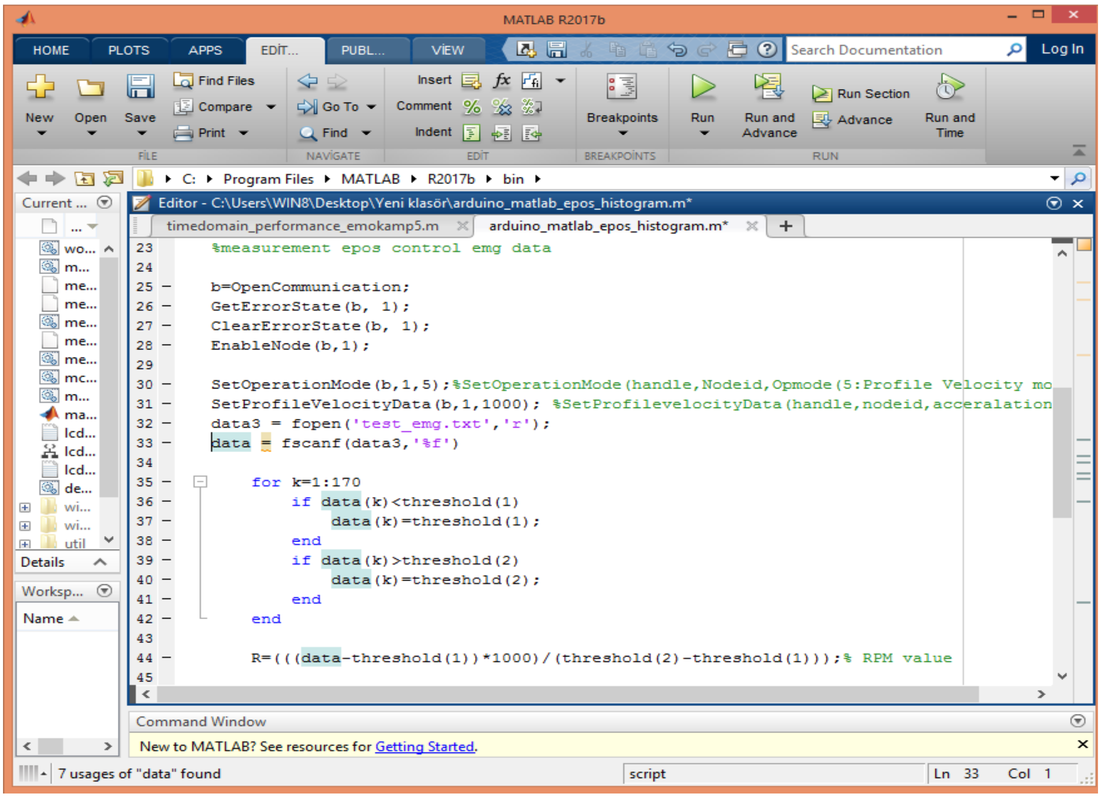


Figure 3.9: A part of Matlab code for the designed system

4. ENHANCEMENT OF A HAND REHABILITATION SYSTEM TO STRENGTHEN MUSCLE ACTIVITY ON LOWER ARM EXTREMITY USING REAL TIME EMG DATA

In this chapter, enhancement of the existing hand rehabilitation system will be explained in detail by considering hardware and software stages (Figure 4.1). Hardware stage includes the mechanical structure and the electronic system hardware including microcontroller based Arduino electronics card with EMG measurement kit and BLDC motor driver called EPOS2 controller. Software stage includes the code written in Matlab and C programs.

Figure 4.1: The design stages of the developed hand rehabilitation system

4.1 Design of the Mechanical System

As it was mentioned in previous chapters rehabilitation system that was utilized in this thesis is mainly composed a single degree of freedom Watt II six-bar linkage that was designed by using kinematic synthesis procedures [42]. In order to implement proposed methodologies, rehabilitation robot was enhanced as an EMG based system. Figure 4.2 shows the overall rehabilitation system with its main components. The mechanical system is controlled via Maxon BLDC with EPOS2 motor driver.

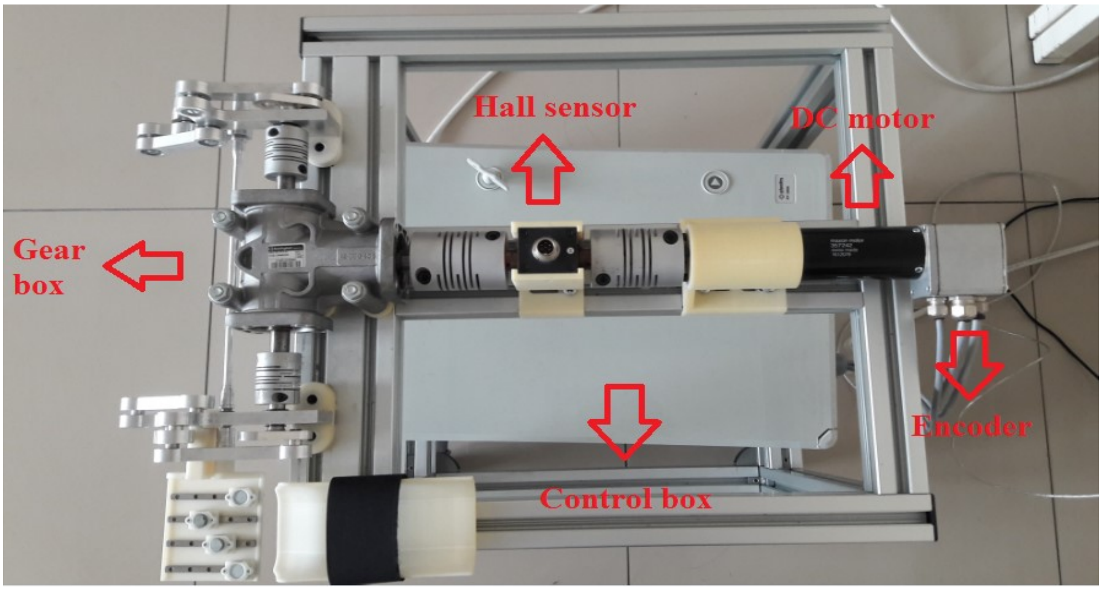


Figure 4.2: The snapshot of the mechanical system

4.2 Software Design

Software implementation to the target rehabilitation system was carried out by using Arduino IDE, Matlab, C program and MinGW-W64 compiler for the motor driver (Figure 4.3). Real-time EMG data was gathered via Arduino based EMG measurement kit. Obtained data was recorded and processed for signal processing in order to have meaningful outcomes in Matlab. EPOS2 motor driver of BLDC motor was controlled by Matlab and serial communication driver files and libraries were installed with Matlab-center. In this thesis, threshold determination methods were performed in Matlab environment with histogram, multiplication factor based standard deviation and wavelet threshold estimation methods.

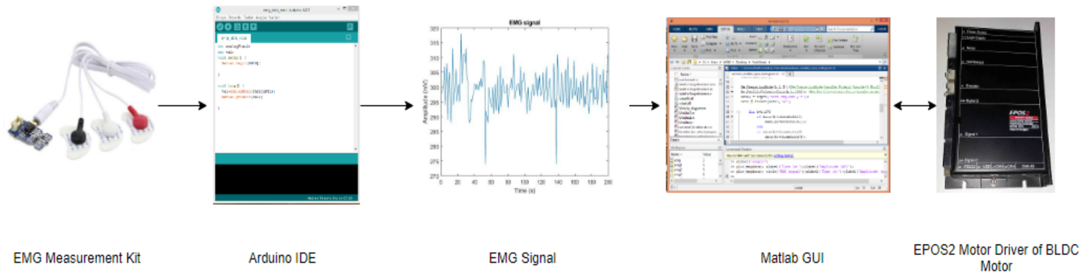
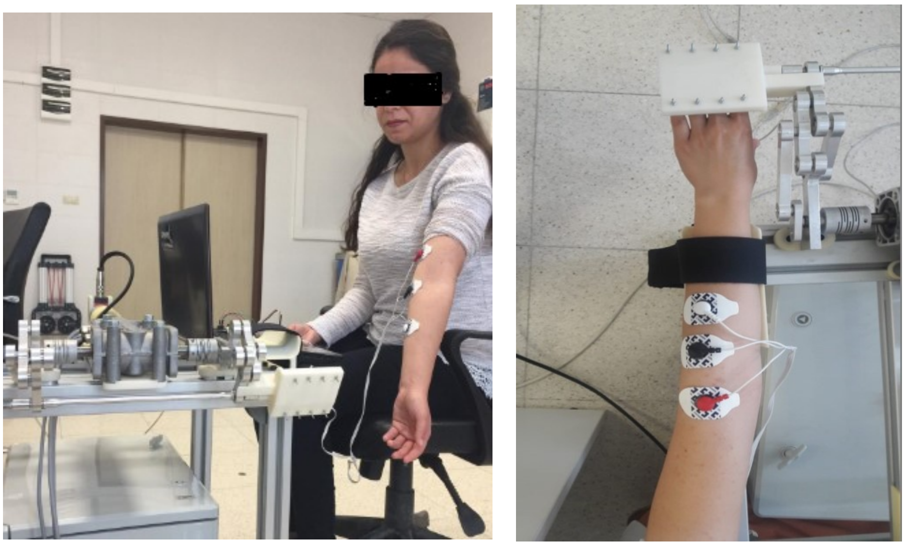


Figure 4.3: The software design of the developed hand rehabilitation system

5. EXPERIMENTAL RESULTS

In order to obtain experimental results of the developed EMG based hand rehabilitation system, real-time EMG data was gathered from the healthy arm of the volunteer by using Arduino based EMG sensor. Implemented experimental setup of the hand rehabilitation system can be seen in Figure 5.1 where the data was obtained from the surface of the lower arm muscles by using surface electrodes. Test procedure of experimental setup is also shown in Figure 5.2. In light of given procedural approach rehabilitation of the hand with decreased physical functions was aimed to be rehabilitated with EMG data obtained from healthy arm.



(a) (b)

Figure 5.1: The experimental setup of (a) the hand rehabilitation system (b) EMG sensors connected to the lower arm

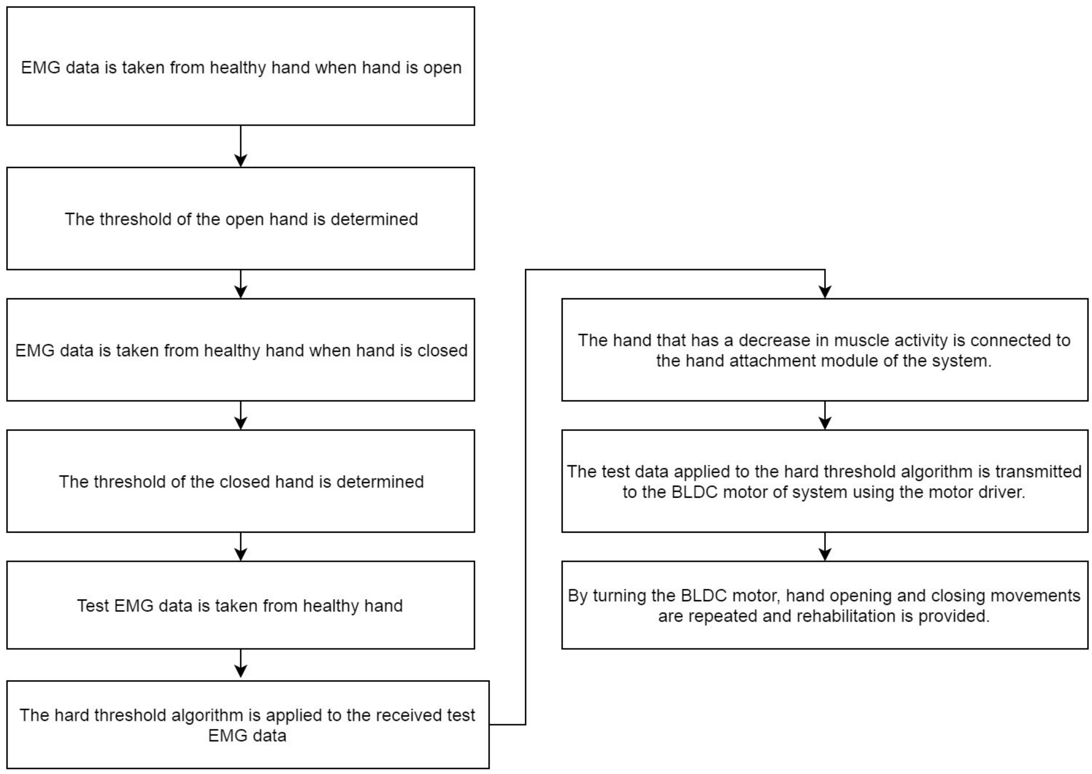


Figure 5.2: Test procedure of experimental set

Obtained real-time EMG data from the experimental setup of the hand rehabilitation system was processed via Matlab to determine the threshold values. To find out the suitable threshold determination values, 30 different experiments were performed under several muscle contractions such as relax, strength or exhausted in terms of hand open and close positions. During these experiments in order to determine the individual threshold value of a person who makes repetitive grasping motion, EMG signals were evaluated. One of the obtained real-time EMG data from these experiments can be seen in Figure 5.3.

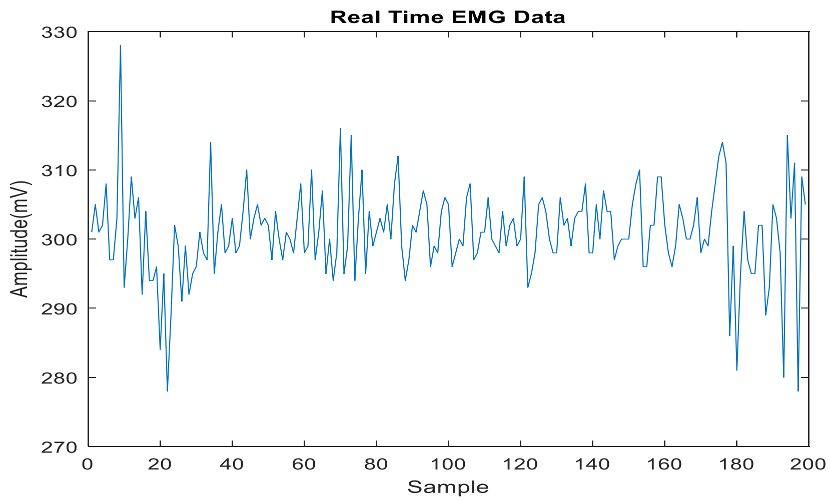


Figure 5.3: One of the obtained real-time EMG data from the volunteer

In these experiments, minimum of the individual threshold value was taken as the lower threshold when the hand was opened. Maximum value of the individual threshold value was also taken as the upper threshold value when the hand was closed. In light of this, if the received test EMG data is calculated as higher than the determined maximum threshold value, the maximum threshold value is updated as the value of the received test EMG data. However, the minimum threshold value was set to 0 value because of the hard threshold algorithm borrowed from [30].

After the determination of the minimum and maximum values of the individual thresholds, the BLDC motor whose velocity response lies between 0 and 1000 revolutions per minutes (RPM) might be controlled. That is to say, minimum of the threshold value was set to 0 RPM whereas the maximum of the threshold value was set to 1000 RPM. One of the BLDC motor velocity responses can be seen in Figure 5.4 as an example. According to the data obtained from the healthy arm, the rehabilitation of the unhealthy hand was performed.

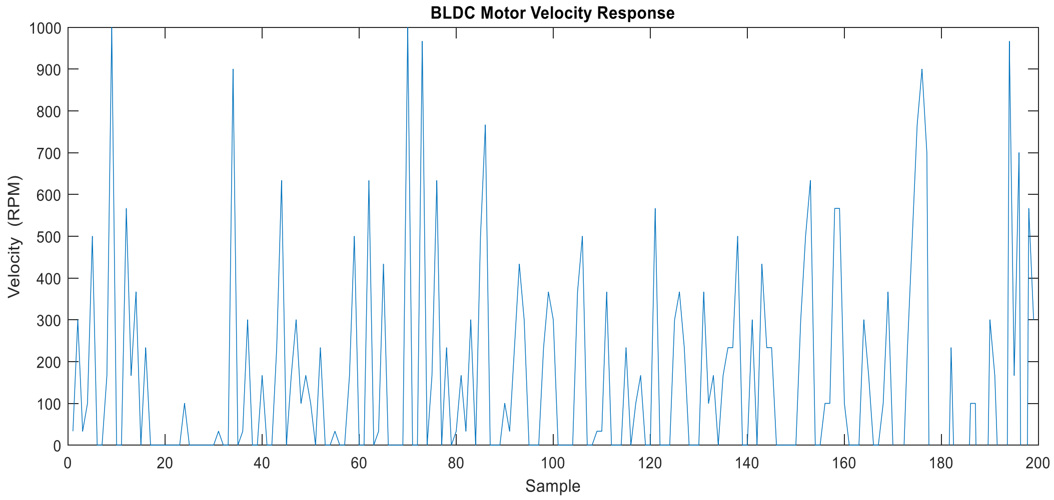


Figure 5.4: One of the BLDC motor velocity responses obtained from the real-time EMG data

5.1 Results of Threshold Determination Methods

In this subchapter, performances of threshold determination methods were evaluated with histogram, multiplication factor based standard deviation and wavelet threshold determination methods. These methods are called as universal, LMU, SMU, GSMU, SLMU, LSMU and LVMU. Each method was performed via the hard threshold algorithm borrowed from [30] for the EMG data of 30 different experimental results while the hand was in closed position as the open hand position was set to the 0 value. The values of the threshold determination methods were computed as the maximal values and the obtained results of them are shown in Table 5.1.

Table 5.1: Results of threshold determination methods when hand is closed for each 30 experiments

Threshold Determination Method	**Threshold value (mV)**
Histogram method	304.6667
Standard deviation method (x3)	9.6672
Standard deviation method (x5)	16.1120
Universal method	6.5399
LMU	0.6540
SMU (j=3)	4.6244
GSMU	1.6350
SLMU (j=3)	0.9249
LSMU (j=3)	4.7175
LVMU (j=3, d=3)	2.8317

In order to test the developed rehabilitation system performance, another 6 different experiments (named as from 31st to 36th data set) of the obtained EMG data from the experimental setup were used in order to determine the individual threshold values for each person for the personalized treatment. In the experimental setup, the results of the threshold determination methods for 31st test EMG data are given in Table 5.2 Multiplication factor based standard deviation methods (x3 and x5) are generally applied to the EMG data received by needle electrode, however, in this thesis, the multiplication factor based standard deviation was firstly applied to the EMG data received by surface electrodes.

Table 5.2: Results of threshold determination methods for 31st data set

Threshold Determination Method	**Minimum threshold value (mV)**	**Maximum threshold value (mV)**
Histogram method	295.5	327.5
Standard deviation method (x3)	3.3838	16.7628
Standard deviation method (x5)	5.6396	27.9380
Universal method	3.4110	10.2330
LMU	0.2418	0.7254
SMU (j=3)	2.4119	7.2358
GSMU	0.8527	2.5582
SLMU (j=3)	0.3420	1.0259
LSMU (j=3)	2.4604	7.3815
LVMU (j=3, d=3)	1.4381	4.3142

After the determination of the threshold values from the algorithms in Table 5.2, 31st data set from the hand rehabilitation system was used as the desired response named the real-time EMG data set, likewise, the actual response of the hand rehabilitation system is named as the velocity response for the BLDC response of the hand rehabilitation system. Both real-time test EMG data and velocity responses are depicted in Figure 5.5 in terms of the histogram and the multiplication factor based standard deviation methods. Similarly, both responses are depicted in Figure 5.6 in terms of the Wavelet threshold estimation methods. In this thesis, wavelet threshold estimation methods, “wavedec” command is used to find wavelet coefficient in Matlab. This command performs a 3-level wavelet decomposition of the signal using the order 1 Daubechies wavelet with the level 1 detail coefficient used.

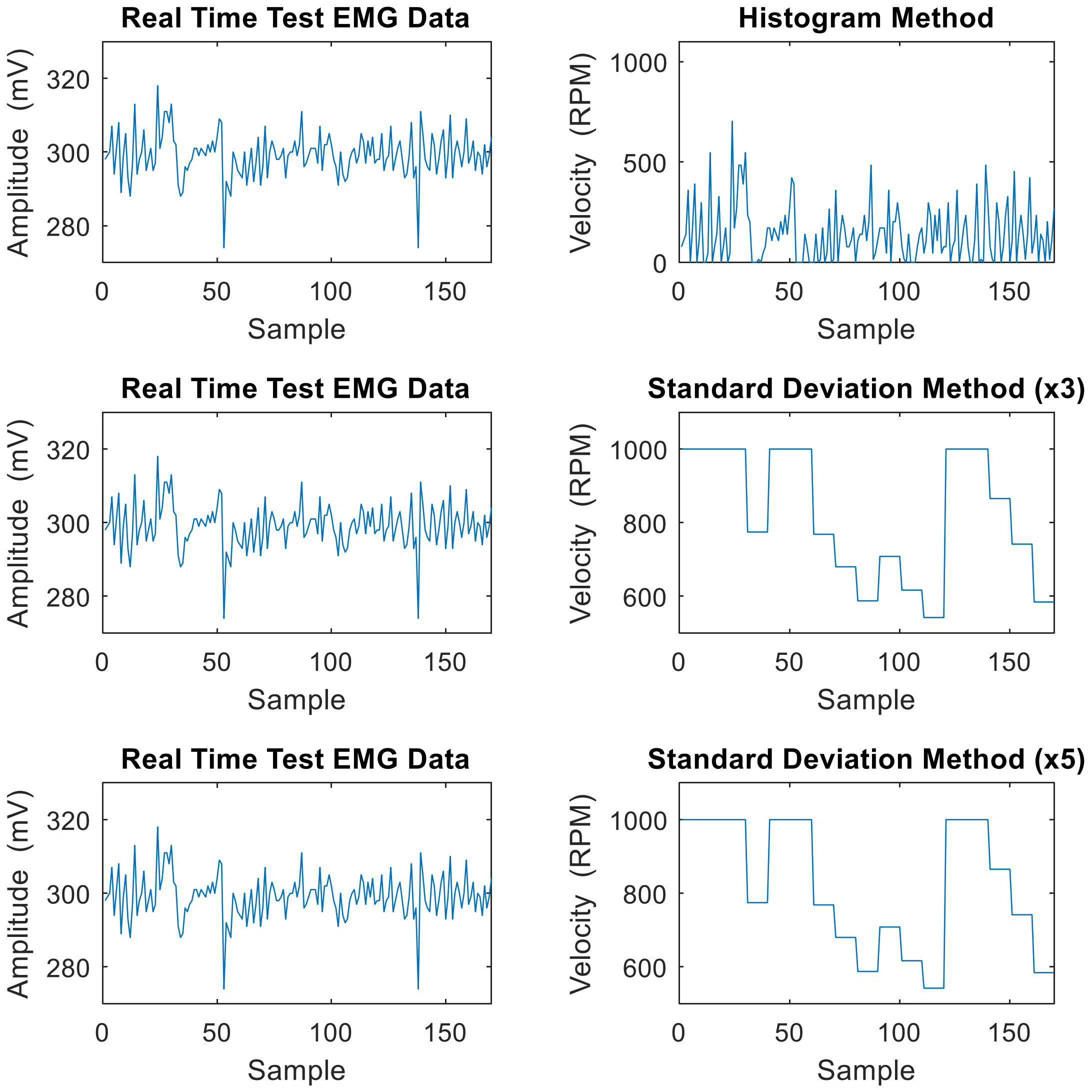


Figure 5.5: Real time test EMG data and the velocity response of histogram and multiplication factor based standard deviation methods using EMG data of no.31

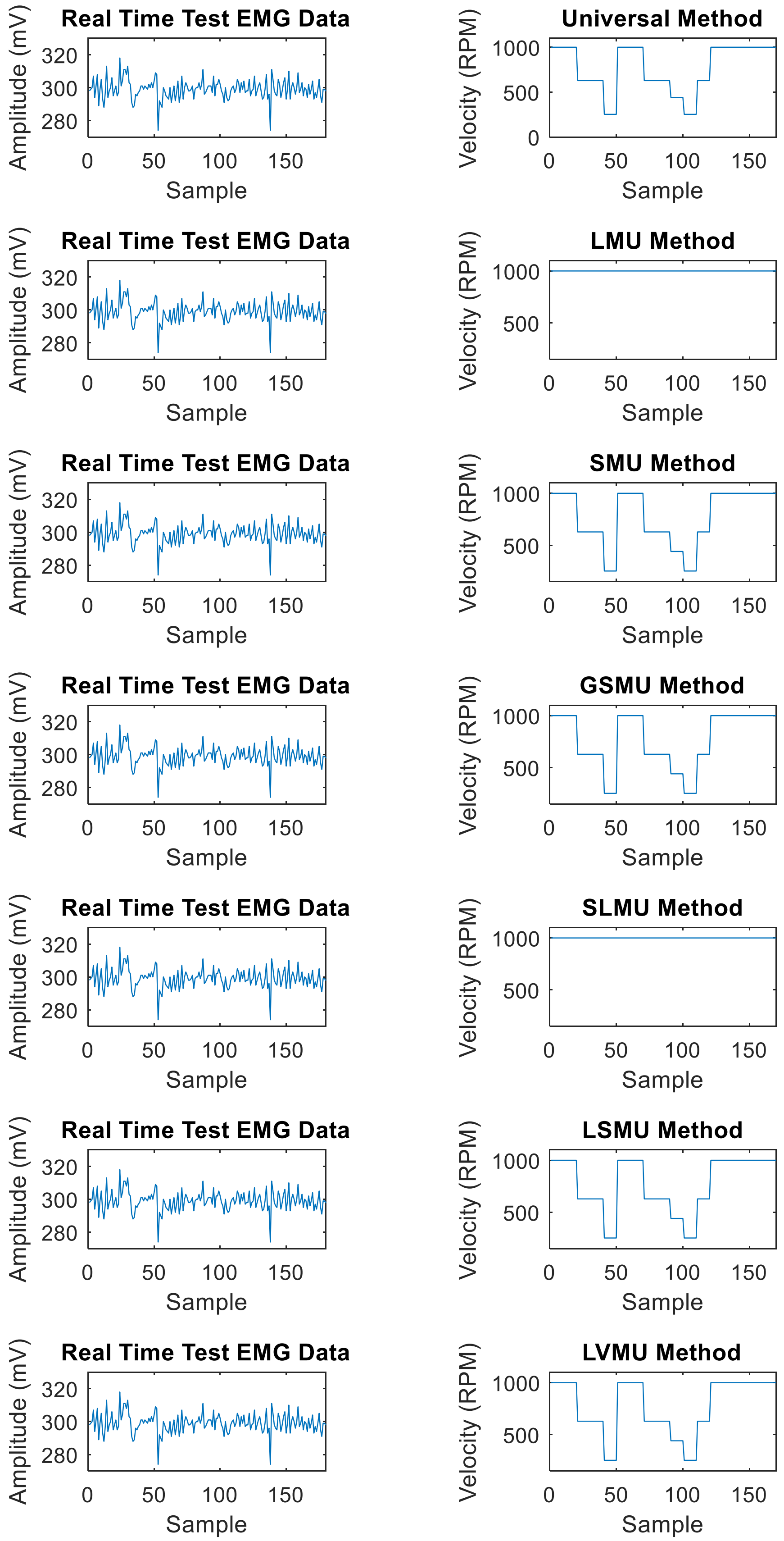


Figure 5.6: Real time test EMG data and the velocity response of wavelet threshold estimation methods using EMG data of no.31.

5.2 Performance Analysis

After the determination of the threshold values from the algorithms in Table 5.2 for 31st data set from the hand rehabilitation system, performances comparison of between the real-time test EMG data and the desired velocity response were evaluated to compare their performances results. Results of the time domain based performance analyzes are given in Table 5.3 where the results of MSE, NMSE, RMSE, NMRS, MAV, ZC, SNR, SD and execution time were computed by using test EMG data set. ZC was computed as 0 for all methods i.e. the data sets does not have the sign change.

The results of MSE shows that the histogram method has the lowest value as 112180 while SLMU has the highest value as 484850. As for the NMSE results, histogram method has the lowest value as 0.0239 whereas the other methods are identically equal each other as nearly 0.54. When RMSE results of the threshold determination methods were compared with each other, histogram method results were better than the results of the other methods. Similarly, NRMSE value has the best result as 0.0204 whereas the other methods are also identically equal each other as about 0.33. As for MAV results, the histogram method gives the better result than the other results because the result of the histogram method is nearly 223 mV and the closest value of threshold value 327 mV in Table 5.2 where, in this thesis, the MAV value is indicated the muscle contraction level. However, the SNR result of the GSMU method has the best performance value as 14.9418. When it is come to execution time evaluation of the threshold determination method in online method, a quick response of the method algorithms is important for evaluating the EMG signals so the results of the standard deviation method x3 and x5 have the minimum values as 0.062 and 0.065 respectively. However, the other performance results of both standard deviation methods are not better than the histogram and GSMU method.

Table 5.3: The results of the time domain based performance analyses for EMG data of no.31

Threshold Determination Method	**MSE**	**NMSE**	**RMSE**	**NRMSE**	**MAV**	**SNR**	**SD**	**Execution Time (s)**
Histogram Method	**112180**	**0.0239**	**324.8226**	**0.0204**	**223.3295**	0.2798	143.2684	1.672
Standard deviation method (x3)	353600	0.56	587.0326	0.3374	868.9073	-3.8975	176.6785	**0.062**
Standard deviation method (x5)	353600	0.56	587.0326	0.3374	868.9073	-3.8975	176.6785	0.065
Universal	364410	0.5393	601.9268	0.3214	850.8906	9.9520	276.547	0.215
LMU	484400	0.5133	695.9668	0.3028	996.9266	-14.5601	76.0325	0.223
SMU	302960	0.5565	550.4186	0.3340	812.8781	11.3298	273.4349	0.300
GSMU	364410	0.5393	601.9268	0.3214	850.5961	**14.9418**	314.9794	0.240
SLMU	484850	0.5134	696.2868	0.3024	996.9266	-13.8431	**750.2003**	3.816
LSMU	484400	0.5138	695.9671	0.3028	996.9266	-14.5601	76.0325	0.270
LVMU	364410	0.5393	601.9268	0.3214	850.8906	9.9520	276.247	1.756

As for the frequency domain based performance analysis, the responses of each method PSD were computed by using Welch's method. Throughout the determination of the threshold values from the algorithms in Table 5.2 for 31st data set from the hand rehabilitation system, responses comparison between the real-time test EMG data and the desired velocity response are depicted to compare their PSD performances responses each other in Figure 5.7 and Figure 5.8. PSD of the test EMG data shows that bandwidth is nearly 10Hz, however only PSD of histogram methods give the acceptable results nearly 10 Hz when the other methods responses are compared. In this thesis, PSD is computed with Welch's method given in Equation 3.27. The input signal is divided into the longest possible segments to obtain as close to but not exceed 8 segments with a 50% overlap. Each segment is windowed with a Hamming window. The modified periodograms are averaged to obtain the PSD estimate.

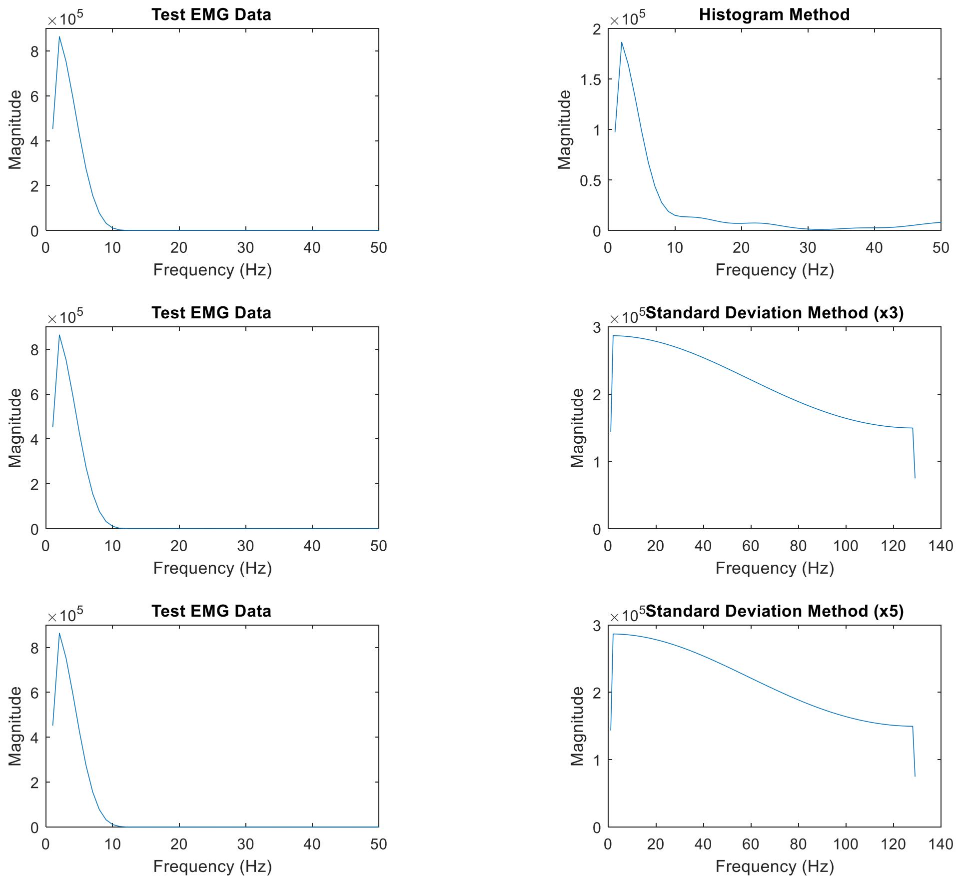


Figure 5.7: PSD of real time test EMG data and PSD of histogram and multiplication factor based standard deviation methods for using EMG data of no.31.

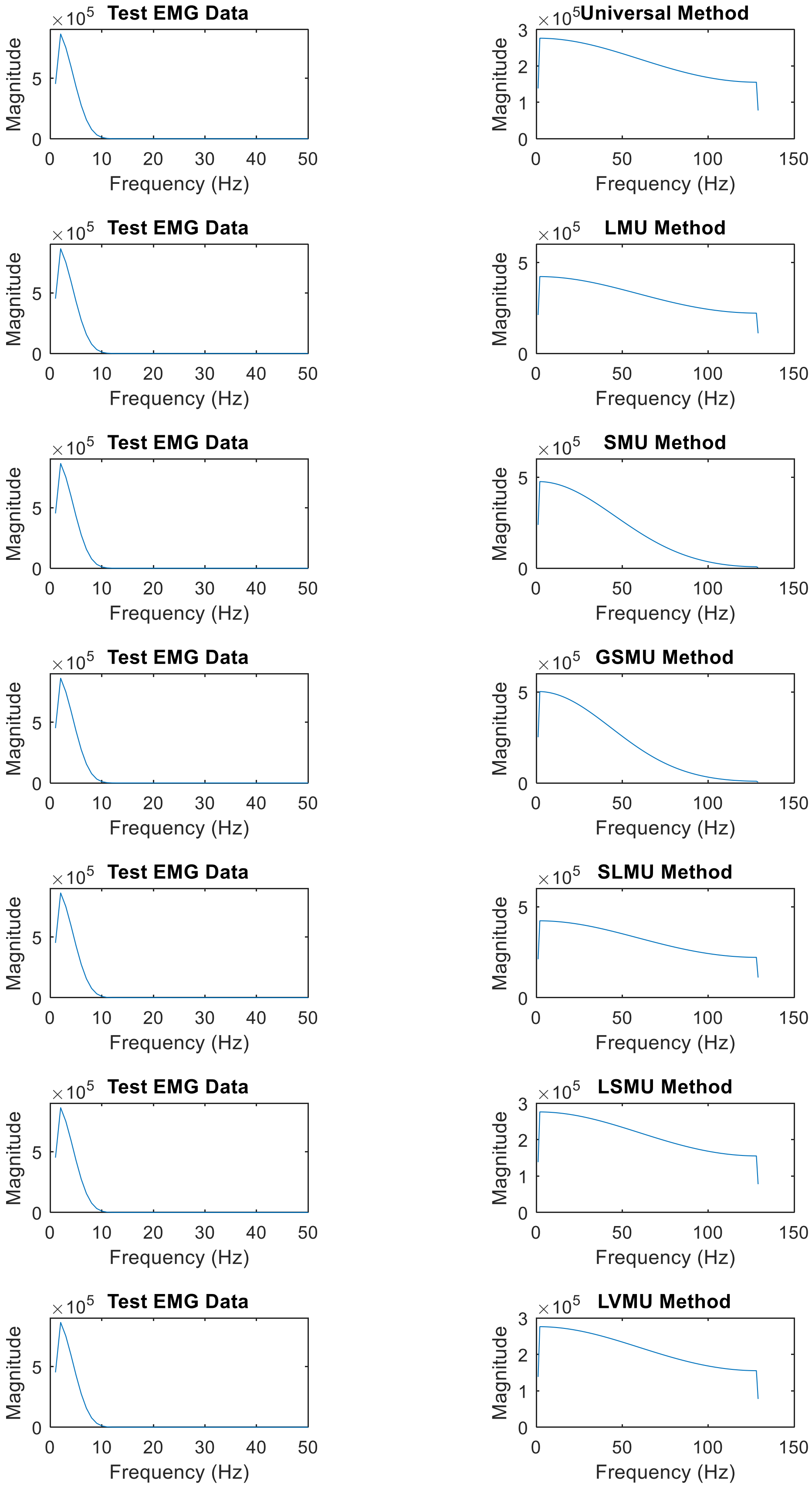


Figure 5.8: PSD of real time test EMG data and PSD of wavelet threshold estimation methods for using EMG data of no.31.

5.3 Proposed Hybrid Threshold Method and Performance Analysis

According to the results of the performance analysis given in Table 5.3, it is obvious that none of threshold determination methods performs the best results for all performance criteria. Therefore, a hybrid method is proposed by selecting the methods that give good results from each different criteria of these threshold determination methods. The hybrid method is aimed to improve the criteria in which two methods yield poor results. Histogram method has been one of the preferred methods in hybrid method since it gives good results in MSE, NMSE, RMSE, NRMSE and MAV performance criteria. Although the SLMU method gave good results in SD criteria, it was not preferred in hybrid method because it gave bad results in execution time. In the hybrid method, instead of the SLMU method, the SNR criterion and the computational time GSMU method which is better than the SLMU method was preferred. In this proposed hybrid method, the results of the histogram and GSMU methods were normalized using the min-max normalization method. Then normalized data were collected at different rates to obtain a single data. These rates are respectively 50% histogram- 50% GSMU, 70% histogram-30% GSMU and 30% histogram-70% GSMU. Real-time test EMG data and velocity responses are shown in Figure 5.9 in terms of the hybrid methods. Result of performance analyses of hybrid method are given Table 5.4 where the results of MSE, NMSE, RMSE, NMRSE, MAV, SNR and execution time.

The result of MSE compared with histogram, GSMU and other hybrid methods results, the 30% histogram- 70% GSMU hybrid method give the best result as 111810. As for the NMSE results, the 30% histogram- 70% GSMU has the lowest value as 0.6958 whereas the other hybrid methods are identically equal each other as nearly 0.8. Similarly, the result of RMSE compared with histogram, GSMU and other hybrid methods results, the 70% histogram- 30% GSMU hybrid method gives the best result as value 121.7804. As for NRMSE results, the 70% histogram-30% GSMU hybrid method gives the better result than other hybrid method results. When MAV results of histogram, GSMU and hybrid methods were compared each other. In MAV results, when the histogram method gave the best result as 223mV, the 70% histogram- 30% GSMU hybrid method result was the closest result as value 324.3068. However, the SNR result of the 30% histogram- 70% GSMU hybrid method gives the best result than other hybrid methods. As for the SD results, the 30% histogram- 70% GSMU hybrid method gives the best result as value 187.6036 compared to other hybrid methods. When it is come to execution time evaluation of the hybrid methods, a quick response of the method algorithms is important for evaluating the EMG signals so the results of the 70% histogram- 30% GSMU hybrid method has the minimum values as 0.4524.

As for the frequency domain based performance analysis, the responses of each method PSD were computed by using Welch's method. Throughout the comparison of the responses between the real-time test EMG data and the desired velocity response of hybrid methods are depicted to compare their PSD performances responses to each other in Figure 5.10. PSD of the test EMG data shows that bandwidth is nearly 10 Hz; similarly, PSD of all hybrid methods gave the acceptable results nearly 10 Hz.

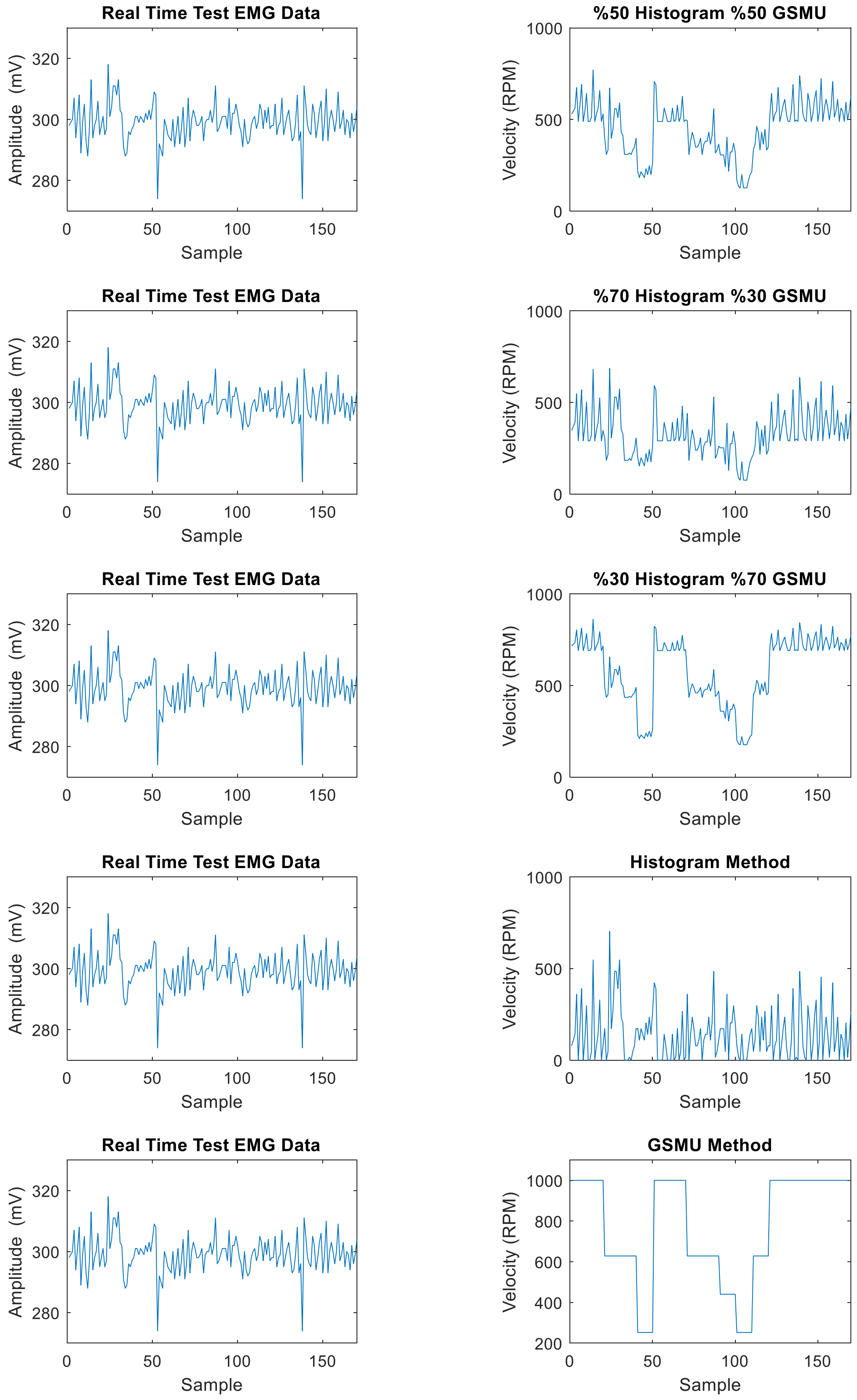


Figure 5.9: Real time test EMG data and the velocity response of hybrid methods using EMG data of no.31

Table 5.4: The results of the hybrid threshold methods for EMG data of no.31

Rates	**MSE**	**NMSE**	**RMSE**	**NRMSE**	**MAV**	**SNR**	**SD**	**Execution time(s)**
%50Histogram %50GSMU	433110	0.8064	308.1138	0.1020	450.1247	0.3566	145.6917	0.5836
%70Histogram %30GSMU	148300	0.8774	**121.7804**	**0.0633**	**325.3068**	-0.0817	123.2166	**0.4524**
%30Histogram %70GSMU	**111810**	**0.6958**	334.3775	0.1658	576.6941	**3.5244**	**187.6036**	0.5454
Histogram	112180	0.0239	324.8226	0.0204	223.3295	0.2798	143.2684	1.672
GSMU	**364410**	**0.5393**	601.9268	0.3214	850.5961	**14.9418**	**314.9794**	**0.240**

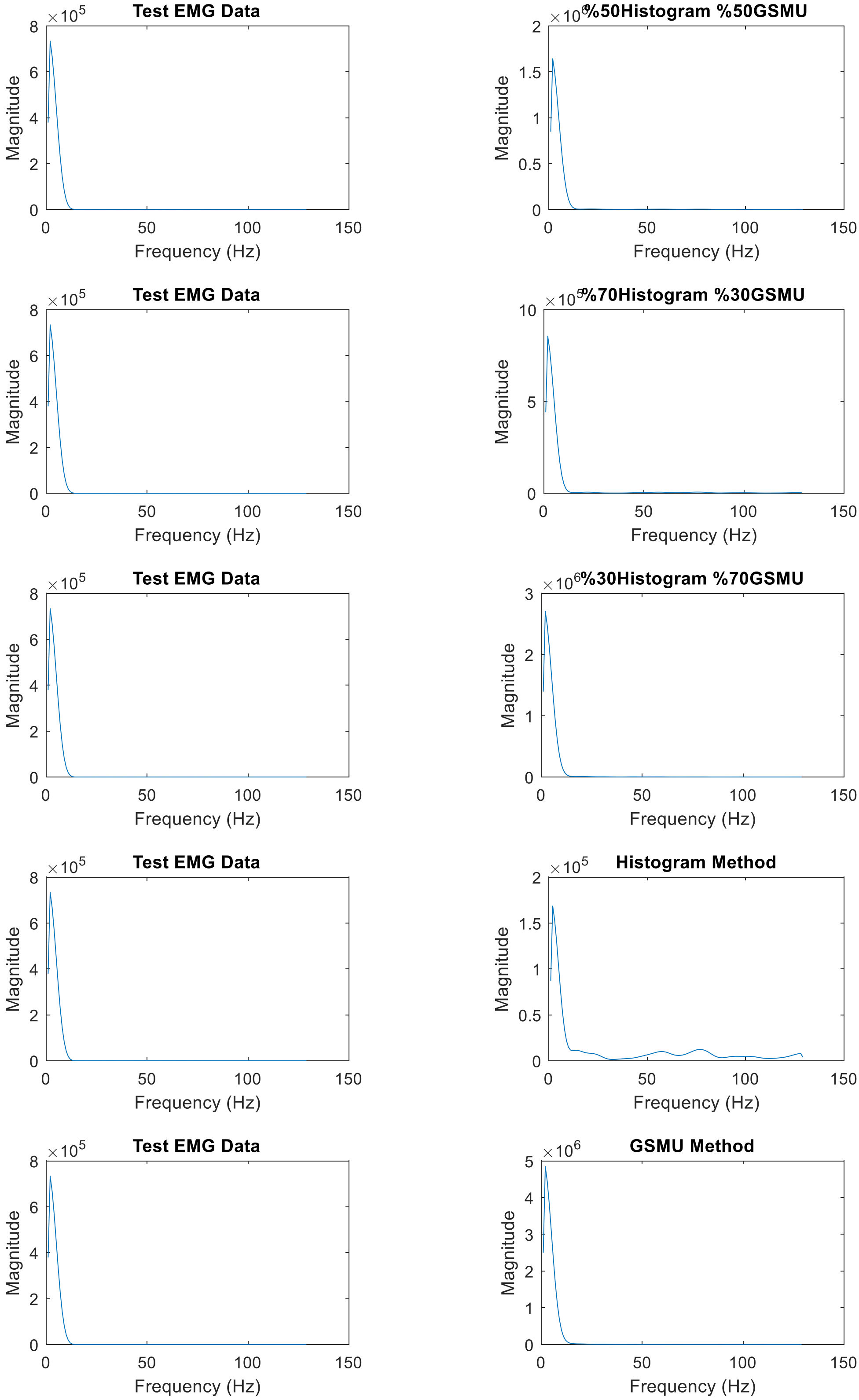


Figure 5.10: PSD of real time test EMG data and PSD of hybrid methods for using EMG data no. 31

6. CONCLUSIONS

In this thesis, the developed hand rehabilitation system design and applications are performed to strengthen the activity of lower arm muscle by using real time EMG data. In the experimental setup, the EMG signal is measured when the hand is open and closed for determining individual threshold values. 30 different experiments are performed under several muscle contractions such as relax, strength or exhausted. To test the developed rehabilitation system performance, another 6 different experiments are performed to compare performances of the threshold determination methods. In the threshold determination phase, histogram, multiplication factor based standard deviation (SDx3 and SDx5) and wavelet threshold estimation methods where the hard threshold algorithm is used to find the upper and lower values of the threshold values. As for performances of threshold determination methods, MSE, NMSE, RMSE, NRMSE, MAV, ZC, SNR, SD and execution time are computed and compared their results each other. Histogram method shows good performances such as MSE, NMSE, RMSE, NRMSE and MAV stands for 112180, 0.0239, 324.8226, 0.0204 and 223.3295, respectively. However, the SNR and execution time results of GSMU method stand for as 14.9418 and 0.240s which are better than the other methods, respectively. In the same way, histogram threshold method shows a good performance as nearly 10Hz for PSD responses. Hybrid method was developed according to performance analysis results. In this hybrid method, histogram method which gives good results in MSE, NMSE, RMSE, NRMSE and MAV criteria, and GSMU method which is good in SNR, SD and execution time criteria are used. Improvements were made in the criteria that both methods gave poor results. Hybrid method obtained with %30histogram-%70GSMU hybrid method gives better results in terms of MSE, NMSE, SNR and SD stands for 118810, 0.6958, 3.5244 and 187.6036, respectively. Similarly, results of the RMSE, NRMSE, MAV and execution time compared hybrid methods; the %70histogram-%30GSMU hybrid method gives the best result as values 121.7804, 0.0633, 325.3068 and 0.4524 respectively. In conclusion, the histogram method might be used because it gives the closest response comparing with the desired velocity pattern named as the real-time test EMG data. Therefore, the developed hand rehabilitation system might be used for individual treatment person.

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- **Şahin, S., Bayraktar, M., Evren Şahin, K.** 2016: Design and Implementation of Experimental Setup for Neural Data Stimulator by Using LabVIEW - Studies in Politics, Education, Health, Engineering and Sociology (SPEHES2016), 22-23 April 2016 İzmir, Turkey
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