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CLASSIFICATION OF EMG SIGNALS USING CONVOLUTIONAL NEURAL NETWORK

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ELECTRICAL AND ELECTRONICS ENGINEERING

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We certify that, as the jury, we have read this thesis and that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

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ABSTRACT

CLASSIFICATION OF EMG SIGNALS USING CONVOLUTIONAL NEURAL NETWORK

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An electrical signal is produced by the contraction of the muscles, this electrical signal contain information about the muscles, the recording of these signals called electromyography (EMG). This information is often used in studies such as prosthetic arm, muscle damage detection and motion detection. Classifiers such as artificial neural networks, support vector machines are generally used for classification of EMG signals. Despite successful results with such methods the extraction of the features to be given to the classifiers and the selection of the features affect the classification success.

In this thesis, it is aimed to increase the classification success of the daily used hand movements using the Convolutional Neural Networks (CNN), which is one of the machine learning methods. The advantage of the deep learning methods like CNN is that the relationships in big data are learned by the network. Firstly, the received EMG signals for forearm are windowed to increase the number of data and focus on the contraction points. Then, to compare the success rate, raw signals, Fourier transform of the signal, the root mean square and the Empirical Mode Decompositions (EMD) of the signals are given to four different CNN. Afterwards, to find the most efficient parameters, the results were obtained by dividing data set into three as 70% training set, 15% validation set and 15% test set. In order to test the performance of the system, 5-fold cross validation was applied. The best results are obtained from the CNN, which receive the EMD applied signal as input. Final results obtained with the cross validation is 95.90%, where 93.70% accuracy is reached without cross-validation.

When the results were examined, it was seen that the designed CNN were successful in the classification of the EMG signals.

Key words: Electromyography, machine learning, Convolutional neural network, cross validation, Fourier transform, root mean square, empirical mode decomposition.

ÖZ

EVRİŞİMSEL SİNİR AĞI KULLANILARAK EMG SİNYALİ SINIFLANDIRMA

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Haziran 2020

Kasların kasılmasıyla ortaya bir elektrik sinyali çıkar ve bu elektrik sinyali kaslar hakkında bilgiler içerir ve bu sinyallerin kaydedilmesine elektromiyografi (EMG) denir. Bu bilgiler, protez kol, kas hasarı tespiti ve hareket tespiti gibi çalışmalarında sıklıkla kullanılır. EMG sinyallerinin sınıflandırılmasında genellikle yapay sinir ağları, destek vektör makineleri gibi sınıflandırıcılar kullanılır. Bu tip yöntemlerle çok başarılı sonuçlar alınmasına karşın sınıflandırıcılara verilecek özniteliklerin çıkarılması ve en yararlı özniteliklerin seçimi, sınıflandırma başarısını çok etkilemektedir.

Bu tezde, makine öğrenmesi yöntemlerinden birisi olan evrişimsel sinir ağları (ESA) ile ön koldan alınan EMG sinyalleri kullanılarak günlük kullanılan el hareketlerinin sınıflandırma başarısının arttırılması hedeflenmiştir. ESA gibi derin öğrenme yöntemlerinin avantajı büyük veri içindeki ilişkilerin ağ tarafından öğrenilmesidir. Öncelikle alınan EMG sinyali pencerelenerek hem veri sayısı arttırılmış hem de hareketin olduğu noktalara odaklanılması sağlanmıştır. Bunun ardından başarı oranını karşılaştırmak için ham sinyaller, sinyallerin Fourier dönüşümü, kare ortalamasının kökü ve sinyallerin Ampirik Modları 4 farklı evrişimsel sinir ağına verilmiştir. Sonrasında en verimli parametreleri bulmak için ilk olarak %70 eğitim seti %15 doğrulama seti ve %15 test seti olacak şekilde üçe bölünüp sonuçlar alınmıştır. Sitem performansını test etmek içinse beşli çapraz doğrulama uygulanmıştır. En iyi sonuçlar giriş sinyaline EMD uygulanmış sinyal olan evrişimsel sinir ağılarından alınmıştır. Çapraz doğrulama yöntemi ile alınan sonuç %95.90 ve diğer ayırma yöntemiyle alınan sonuç %93.70dir.

Sonuçlar incelendiği zaman tasarlanan evrişimsel sinir ağlarının kullanılan EMG sinyallerinde başarılı olduğu görülmüştür.

Anahtar Kelimeler: Elektromiyografi, makine öğrenmesi, evrişimsel sinir ağı, Çapraz doğrulama,Fourier dönüşümü, kare ortalamasının kökü,ampirik Mod ayırma

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Finally, I must express my very profound gratitude and love to my parents for providing me unfailing support and continuous encouragement throughout my years of study and through the process of researching and writing this thesis.

Kaan Bakırcıoğlu
İzmir, 2020

TEXT OF OATH

I declare and honestly confirm that my study, titled “Classification of Emg Signals Using Convolutional Neural Network” and presented as a Master’s Thesis, has been written without applying to any assistance inconsistent with scientific ethics and traditions. I declare, to the best of my knowledge and belief, that all content and ideas drawn directly or indirectly from external sources are indicated in the text and listed in the list of references.

Full Name: Kaan Bakırcıoğlu

Signature:

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July 16, 2020

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CHAPTER 1
INTRODUCTION

Since the early ages, humanity has always tried to understand its own movement system. The most important element in the movement system is the muscular system. Electrical signals occurring in the muscles are generally used in order to understand the working principle of the muscle (Cram, 2003).

The development of electromyography (EMG) begins in 1660 with an experiment by Francesco Redi on electric fish. By 1773, Walsh showed that the muscle structure of Eel fish can create an electrical activation. Galvani, showed that electricity has the effect to initiate muscle contractions in his study in 1792. Dubios- Raymond found that the recording of the electrical activity occurring during voluntary muscles contraction in 1849. The first recording of electrical activity was taken by Marey in 1890 and the term electromyography entered the literature. Nowadays, EMG has many usage areas. Some of these areas are; muscle and nerve diseases detection, physiology studies in physical therapy centers and prosthetic hand and arm studies in hospitals (Cram, 2003).

For advanced disease detection and prosthetic application, EMG signals must be processed and characterized in detail. For this purpose the characteristics of the regional electrical signals received over the muscles are examined. Another important part is how to interpret electrical activities. Signal processing, artificial intelligence and artificial neural networks are used to solve interpretation and classification problems in biomedical applications.

After the literature research in the studies dealing with this problem, it was understood that most researches did feature extraction from the data, and they use these features in different classification techniques.

1.1 Aim of Thesis

This thesis aimed to increase the classification success of the EMG signals of basic hand movements used in daily life by using Convolutional Neural Network (CNN). CNN is a multi layered artificial neural network that is frequently used in large data sets in the field of deep learning. Basically, CNN uses the standard neural network to solve the classification problem, but uses a variety of different layers to identify parser information and detect some properties so it extract features itself. In this thesis, it is attempted to reduce the bond of classification with the signal by making the majority of feature extraction by using Convolutional Neural Network.

EMG signals received from the forearm muscles are used as a data and some different pre-processing methods have been applied to the data and compared which one is suitable for CNN classification.

1.2 Organization of Thesis

The organization of the thesis is arranged as follows; in the first chapter of the thesis, the history and development of EMG is mentioned to give an overview of the thesis and the aim of the thesis is given by mentioning a CNN. In the second chapter, the nervous system and muscle structures are mentioned first. Then the definition and properties of the EMG signal are mentioned. In the third chapter, machine learning is explained in general and then CNN is examined in detail. In the fourth chapter, the pre-processing studies and the structure of the CNN used for the classification are explained, and finally the results and comparisons of these studies are given.

CHAPTER 2
THE PHYSIOLOGICAL BACKROUND OF EMG

2.1 Muscular system

Human body has a very complex structure. The muscular system has an important role in formation of movement, as well as the skeletal system and joints. Muscular system constitutes 40-50% of human body weight. There are more than 600 skeletal muscles, and these are helping us to move our body. Like bones, also muscles protect the body's vital organs (DiGiovanna, 2000).

2.1.1 Structure of the muscles

There are different types of muscles in the body like skeletal muscle, smooth muscle and cardiac muscle. Smooth muscles are located in the walls of hollow organs except heart. Heart walls covered with cardiac muscle, these two types of muscles contract involuntary. Skeletal muscles connected to nerve system to move bones by contracting and relaxing in response to voluntary messages (Başpınar, 2014). This part will give information about skeletal muscles. Important features of skeletal muscles are listed as follows:

- Transmit the excitation signal through the entire muscle.
- During contraction and relocation movement occurs chemical energy is converted into mechanical energy.
- It serves as a partial support to the skeletal system and spinal cord.
- Provides movement, steepness and shaping (Bağcı, 2016).

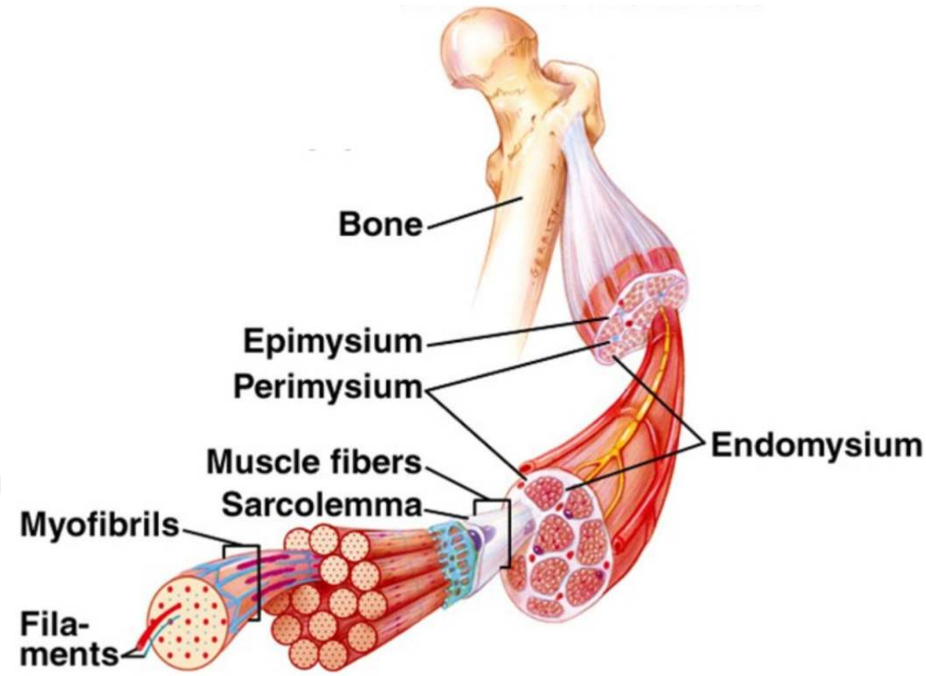


Figure 2. 1: Structure of the muscle (Jason LaPres, 2009)

The structure of the muscles can be seen in Figure 2.1. Muscular body has a bundle structure. Filaments are the smallest part of muscles and they are covered by myofibrils. Myofibrils are surrounding with muscle fibers and they have a protective sheath called Endomysium. Skeletal muscle cells have a nucleus; need a blood supply and need to communicate with nervous system in order to function properly. Endomysium's role in muscle is transmission of force from muscle fibers to the tendons. The difference between endomysium and the perimysium is, perimysium has lager variations and organize muscle groups. Finally, whole muscle bundle are surrounding with epimysium. All skeletal muscles are covered by an epimysium. This is a dense, fibrous connective tissue that envelops the entire muscle to protect it from injury or friction from surrounding structures. Organization of skeletal muscle can be shown in different way with Figure 2.2 (Klieger, 2009).

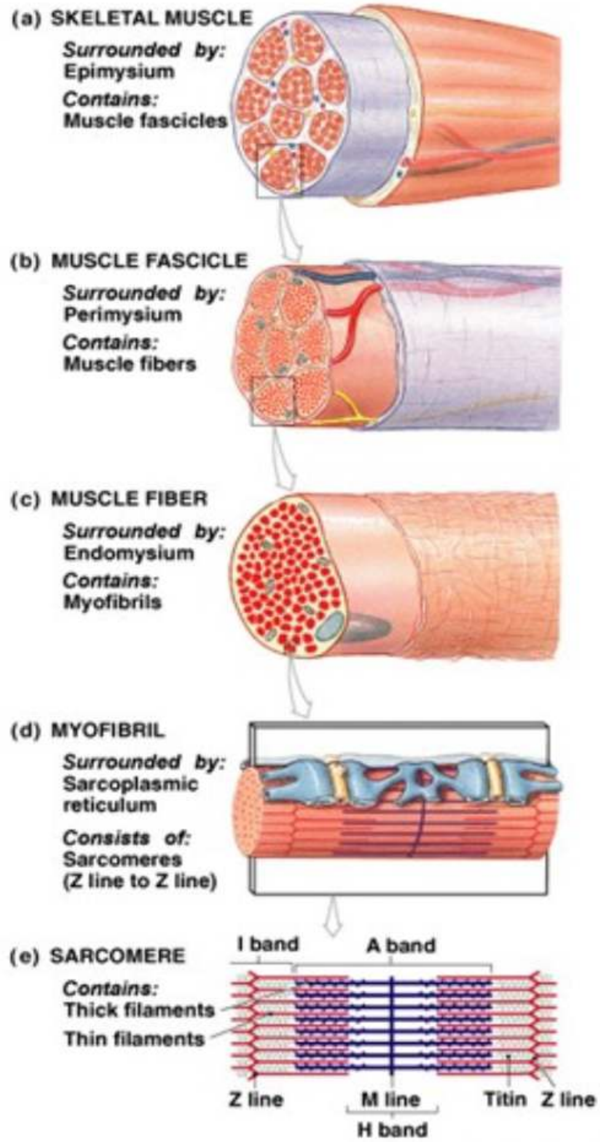


Figure 2. 2: Organization of muscle tissue(Jason LaPres, 2009)

2.1.2 Function of Muscles

Muscular system has lots of function in human body like mobility, circulation of blood, vision and organ protection. This part will give more information about three main skeletal muscle functions in the body: maintaining the body shape, providing the necessary support for strength and balancing body temperature. Muscles allow different movements depending on the joint it is attached to. Muscles that reduce joint angles are called flexors and muscles that increase joint angles are called extensor muscles.

Mobility: Main function of muscular system is to provide movement. With the contraction of muscles, gross and fine movements appear. Gross movements are large and coordinated motions such as walking, running and swimming. Fine movement includes smaller movements like writing, speaking and facial expressions. Most of the muscular movements are under conscious. But some contractions are reflexive, for example, withdrawal of the hand when the needle sticks (DiGiovanna, 2000).

Stability and Posture: The contracted muscles support the respiratory, circulatory and skeletal system to remain stable and maintain the proper position while movement is taking place or the body is in balance. Skeleton muscles help about posture of the body. Good posture required strong and flexible muscles. Long term, poor posture lead to joint and muscle pain (DiGiovanna, 2000).

Temperature regulation: Most of the people are in colder environments than normal body temperature and their bodies lose heat. Therefore, stabilize the body temperature prevent the heat loose is very important for the continuation of vital activities such as heartbeat, respiration, and the functioning of brain activities. Body heat occurs as a result of many different chemical reactions. Muscle system is providing highest heat in the human body. Some of the reasons for this, it covers a large area in body and it works even if the body is not moving, that helps to heat production. This heat production is higher during exercises (DiGiovanna, 2000).

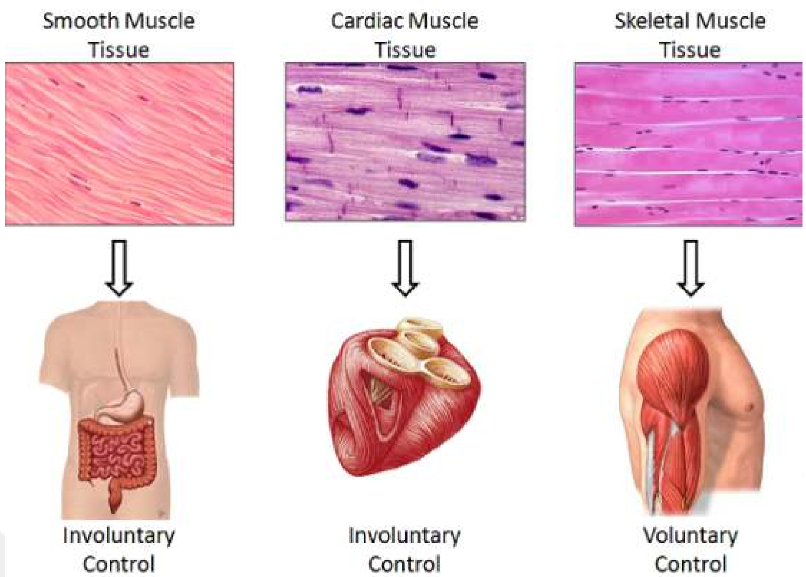


Figure 2. 3: Muscles type according to their structure. (Jason LaPres, 2009)

There are 3 types of muscle, Smooth muscles are located in organs walls, cardiac muscle cover the heart walls and these two muscle type is contract involuntary. Third type is skeletal muscles; these muscles are connected to nerve system so they are working voluntary. Figure 2.3 shows the types of muscles.

2.1.3 Action potential and Muscle contraction

Muscle contraction is started with a message from the nervous system. When this message reaches the muscle, the reaction begins. This contraction occurs according to “Sliding Filament Theory”. In this theory, during contraction actin and myosin covering each self and reducing the amount of covering during rest. Therefore, muscles get shorter in contraction and they get longer in rest as shown in Figure 2.4 (Erol, 2012).

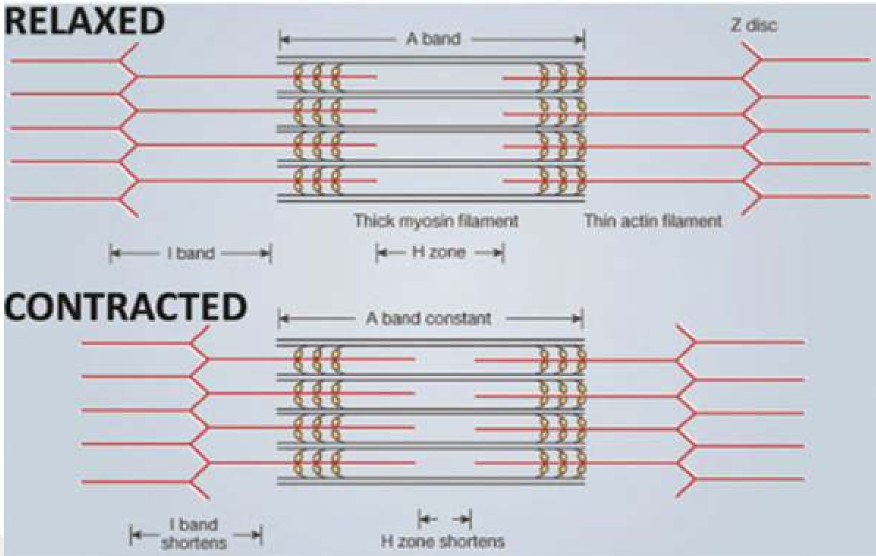


Figure 2. 4: Muscle relaxation and contraction (Digiovanna, 2000)

Physiologically, action potential refers to instantaneous increases and decreases in the electrical potential of a cell. The action potential is taken part in communication between neurons and intracellular activities in other cells. For instance, action potential in muscle cells takes the first step in muscle contraction, while it stimulates the secretion of insulin in beta cells of the pancreas (Lodish et al., 2000).The action potential is result of the polarization change created by sodium and potassium ions in the cell membrane.

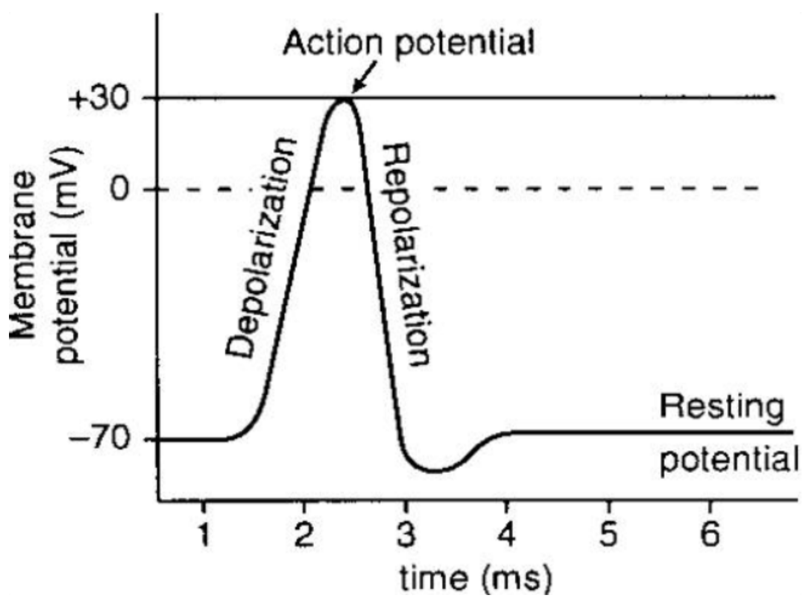


Figure 2.5: Action potential. (Lodish et al., 2000)

When the cell membrane potential is close to resting potential, ion channels are closed. The rapid opening of the channels indicates that there is a potential difference above the threshold value in the cell. As can be seen in Figure 2.5, the intracellular is 70 mV negative compared to the extracellular. Chemically or physically cell when stimulated, the electrical potential changes, the cell membrane is polarized and becomes 30 mV positive between intracellular and extracellular. When this potential difference passed the threshold value, Sodium (Na+) and Potassium (K)+ ions start to action. In first Na+ channels are opened and Na+ ions are passed from that channel. This ion movement called as depolarization. After short time from depolarization, repolarization starts with the opening K+ channels and activating K+ ions and muscle pass to the resting (Bağci, 2016; Lodish et al., 2000).

2.2 Electromyography

When the muscles in the human body contract a bioelectricity signal emerges. The level of this electrical signal is proportional to the activity. Electromyography (EMG) is a medical electro diagnostic tool that allows evaluation and recording of electrical activities performed by skeletal muscles. It is literally related to electrical activity as "electro", "myo" means muscle in old Greek and "gram" is means the amount of recording (Başpınar, 2014). EMG signals occur as a result of polarization of Na+ and K ions as mention in section 2.1.3.

Power and frequency values are recorded when measuring EMG signals. Characteristic features of the EMG signals are the amplitude range varies between 0-10 mV and 0-1.5 mV (RMS) values. Although signal energy is in the frequency range of 50 to 500 Hz, it often takes values in the range of 50-150 Hz (Bağcı, 2016). These signals can used to diagnose treatment and control the prostheses automatically. In some prostheses cases, according to EMG signals taken from cut or destroyed muscles, produces personally designed limb to provide movement. A raw EMG signal is shown in Figure 2.6. These signals have low amplitude so they can be affected easily by the noises.

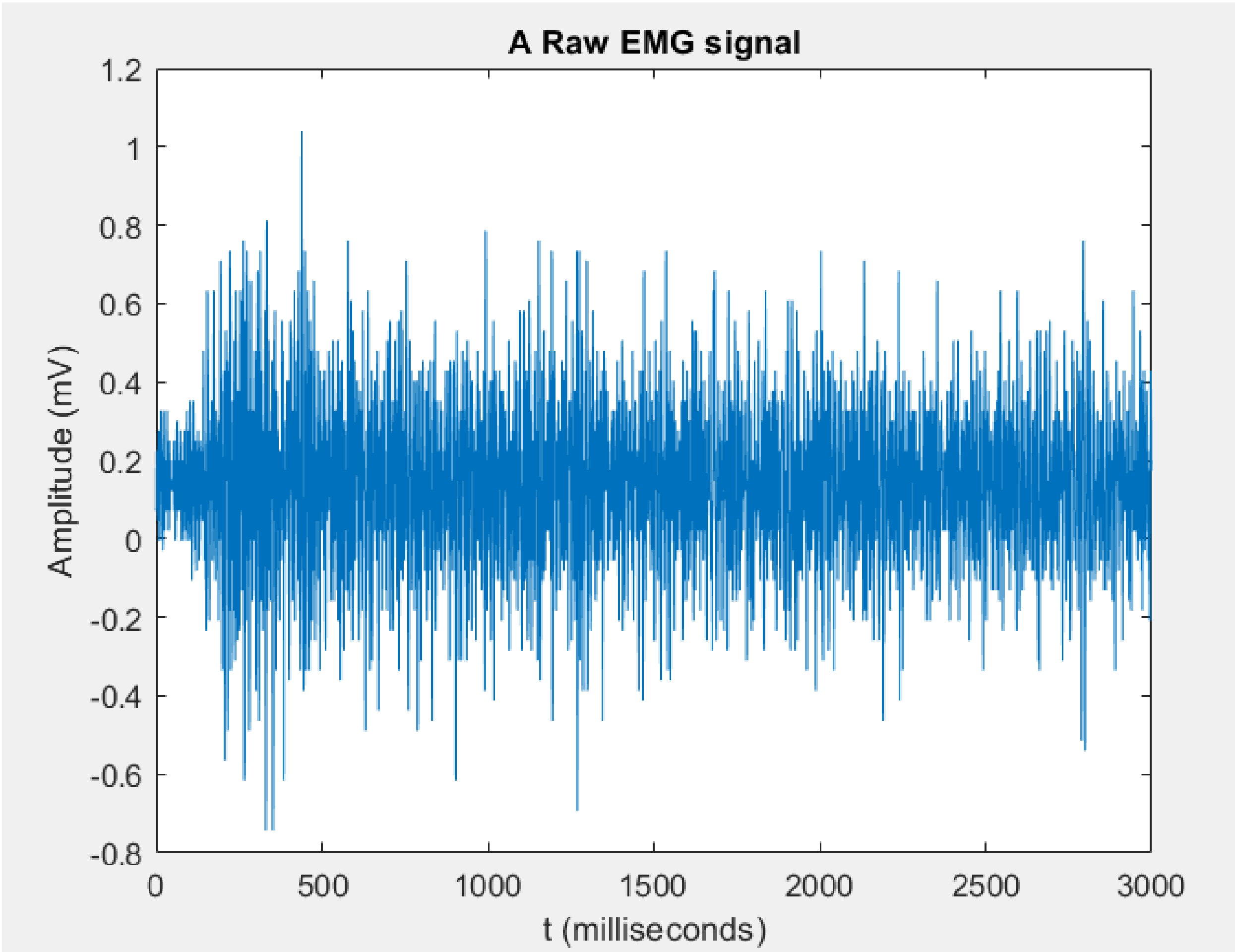


Figure 2. 6:A raw EMG signal

2.2.1 Measurement of Electromyography

To obtain meaningful EMG signal, muscle should be in action. Electrodes are used to observe and record potential changing in the muscle. There are several ways to observe EMG signals but surface electrode and intramuscular electrodes are main 2 types of to get EMG signals.

Surface EMG (sEMG) record the muscle activity for the surface on the skin that is why it has limited information of the muscle activity. At least 2 electrodes are needed to get measurement because sEMG recordings display the voltage difference between two electrodes. Figure 2.7 shows the connection of sEMG.

In intramuscular EMG (iEMG), needle electrodes are applied by immersing them in the muscles. In other words, the signs come from the muscle itself, not from the surface of the body. Although iEMG is more stable, sEMG is much more common to use because iEMG bothers the patient, they are used in cases where sEMG are insufficient (De Luca, 2006).

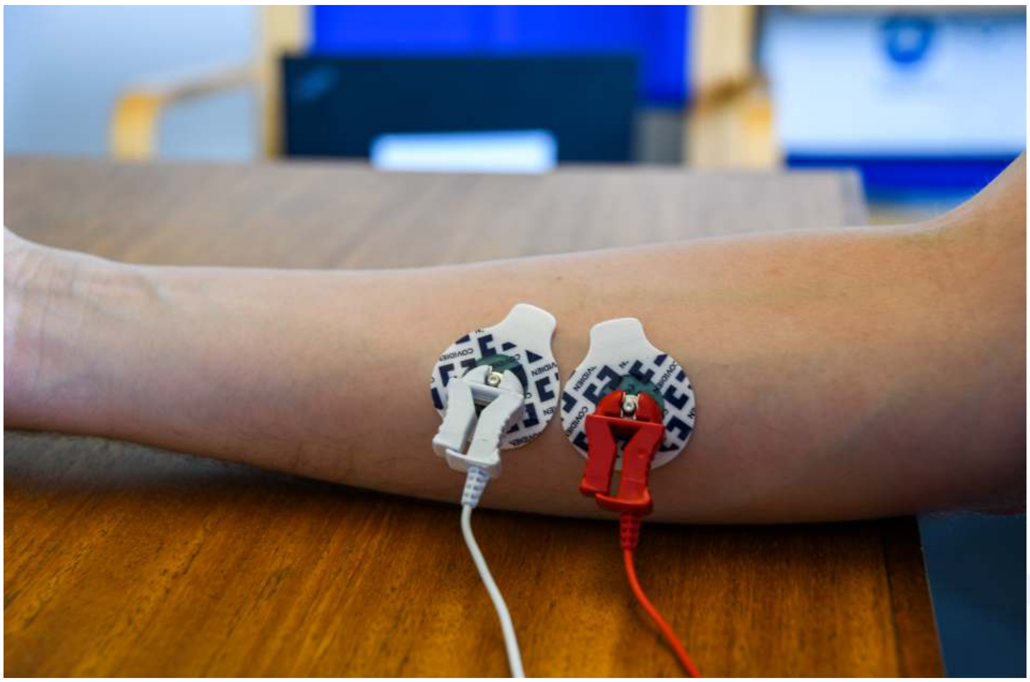


Figure 2. 7: Surface EMG electrodes.

When recording the sEMG signal, there are two main issues. The first one is the signal-to-noise ratio. It is defined as an electrical signal that does not belong to the EMG signal. The second one is to preserve frequency components of the EMG signal. While EMG signal is recorded, main signal may be affected by neighbor muscle's electrical activities therefore; electrodes should be on midpoint of the muscle to fully detect activation (Reaz et al., 2006). Figure 2.8 shows the difference between iEMG and sEMG signals for same contraction.

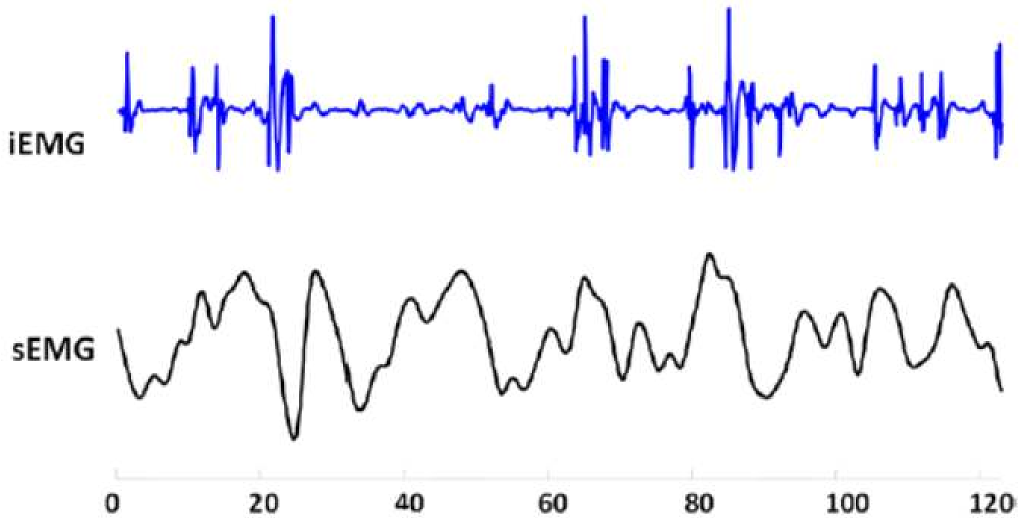


Figure 2. 8: EMG signals comes from iEMG and sEMG (Reaz et al., 2006)

Noise can be defined as all of the unwanted electrical signals in the EMG signal. Since EMG signals have low amplitude, they are affected by noise. To understand low value EMG signals, noise characteristics of EMG needs to be analyzed. There are many reasons of electrical noise, some will be mentioned below;

- ***Equipment noise:*** All electronic devices generate noise, this noise cannot be eliminated but it can be reduced by using high quality components.
- ***Electromagnetic noise:*** Our body is constantly under electromagnetic radiation from radio and television signals, electric power cables, bulbs etc. This radiation creates a source of noise on the body. This noise can have amplitude 1-3 times larger than the EMG signal and frequency with around 50 Hz.
- ***Cross talk:*** EMG signal from an unwanted muscle called crosstalk. It can be reduced by choosing smaller electrode and put them on the right muscles.
- ***Inherent instability of the signal:*** EMG signals are randomly distributed. Between 0 to 20 Hz components are unstable because they are affected by the firing rate of the motor units. They can be considered as noise and it should be removed (Reaz et al., 2006; Taşar, 2016).

Signals are collected with the help of the electrode and amplifiers. A differential amplifier is used as the first amplifier. Before the signal is recorded, it can be pretreated to eliminate low, high frequency noises and artifacts that may be caused by the system.

2.2.2 Features of EMG signal

EMG signal shows a stochastic (random) structure and defined by the Gaussian distribution function. Amplitude of EMG signal ranges from 0 to 10 mV (peak to peak). Available signal energy is in the frequency range of 50 to 500 Hz and dominant energy varies between 50 and 150Hz. Signals that can be used, they carry energy above the electrical noise level.

EMG signals are obtained from electrodes that are mounted directly on the skin; therefore signals are the combination of the action potential of muscles under the skin. Since these action potentials occur at random intervals, the EMG signal can have positive or negative voltage at any time.

Motor Unit Action Potential (MUAP), is the sum of the muscle action potentials of a single motor unit consisting of all muscles. The simple mathematical model of the EMG signal is shown in equation (De Luca, 2006).

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

In equation, $x(n)$ shows EMG model, $e(n-k)$ processed point, $h(k)$ MUAP, $w(n)$ zero average Gaussian noise and N is number of motor unit pulses.

2.3 Feature Extraction Methods of EMG Signal

The feature extraction is necessary to obtain relevant data structure from raw signal by keeping the most important information and removing unnecessary data. The obtained vector is called as feature vector and supplied to the classification algorithm. Commonly, time domain, frequency domain and time-frequency domain features are used for EMG classification (Eroğlu, 2013).

2.3.1 Time Domain

Time domain is the most common method of feature extraction in EMG classification. Because, it does not need any transformation, also it can be computed easily and quickly. This method uses signal amplitude in calculations of feature extraction so as a result gives information about amplitude, frequency and duration of signal.

- ***Integrated Absolute Value (IAV):*** IAV is found by adding absolute values of EMG to each other. It can be accepted as a signal power estimator. The equation is given below:

$$IAV = \sum_{i=1}^{N} |x_i| \tag{1}$$

where, x_i is the sampled EMG data value N, length of the sample.

- ***Mean Absolute Value (MAV):*** MAV is found by dividing IAV by the length of the sample. MAV is very useful and also common in control systems by muscles because it gives muscle contraction levels (Phinyomark et al., 2009).

$$MAV_k = \frac{1}{N}\sum_{i=1}^{N} |x_i| \tag{2}$$

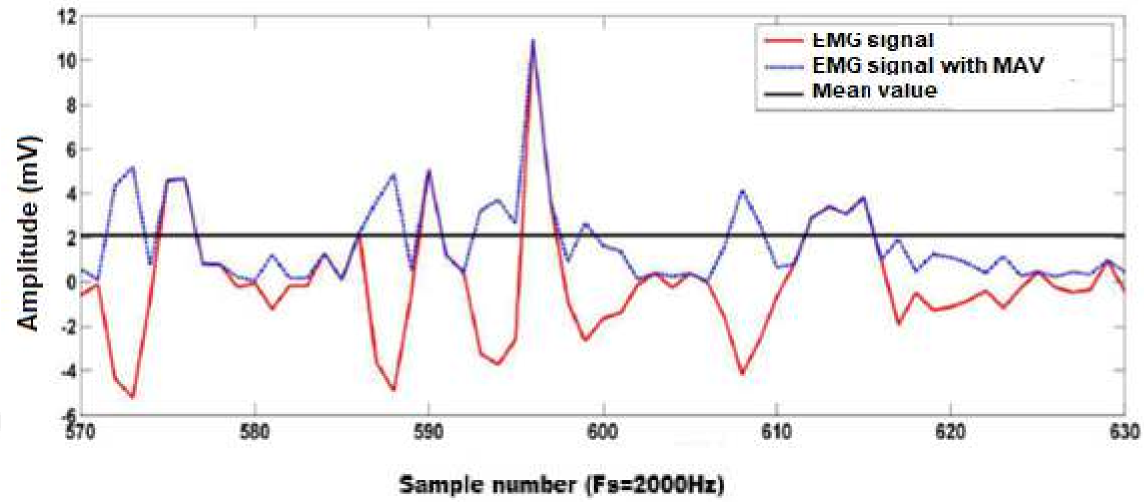


Figure 2. 9: Difference between MAV emg signal and original EMG signal (Eroğlu, 2013)

- ***Wilson Amplitude (WAMP):*** WAMP is calculated by counting the number of times a threshold has passed the previous EMG sample. If difference is over the threshold it turns 1 otherwise it turns 0. This feature is an indicator of firing MUAP and the muscle contraction level.

$$WAMP = \sum_{i=0}^{N} f(|x_i - x_{i+1}|)$$

where

(3)

$$f(x) = \begin{cases} 1 & if\ x > threshold \\ 0 & otherwise \end{cases}$$

Figure 2.10 shows the points where an EMG signal passed the threshold values which is chosen 10mV for this sample.

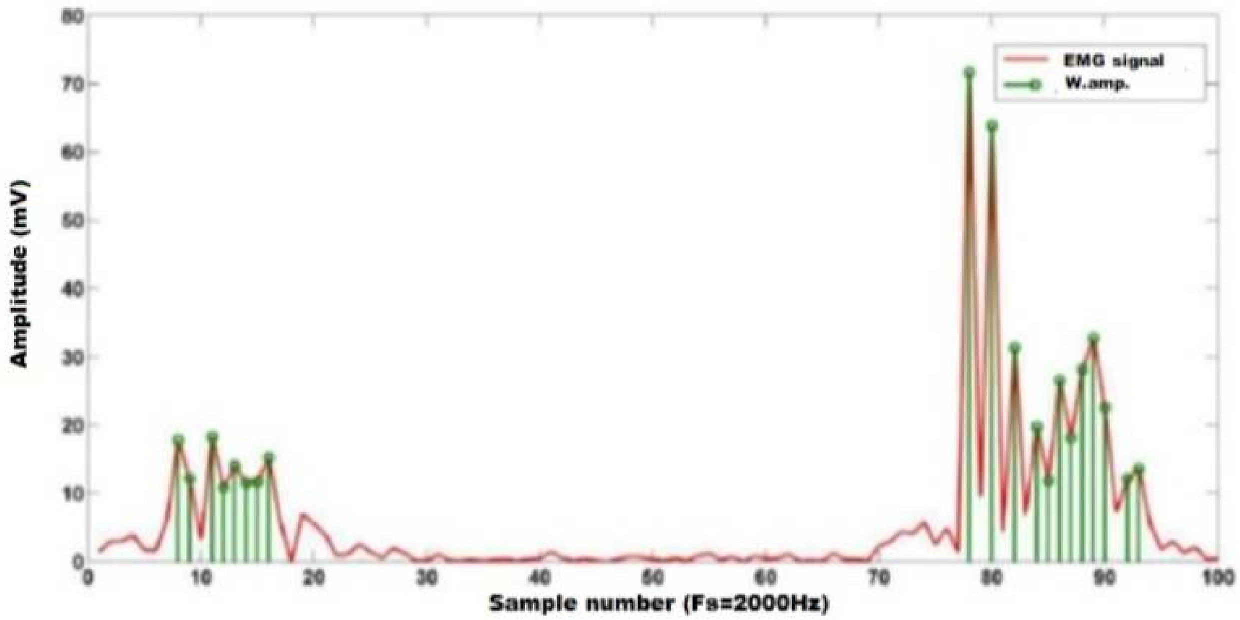


Figure 2. 10:EMG signal with WAMP value calculated (Eroğlu, 2013)

- ***Root Mean Square (RMS):***RMS is calculated by squaring all data in EMG sample and summing them, then dividing the sum by the number of sample, last taking the square root of all equation (Eroğlu, 2013).

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} {x_i}^2} \tag{4}$$

- ***Variance (VAR):*** Difference between samples from each other can be found with VAR.

$$IAV_k = \frac{1}{N}\sum_{i=1}^{N} (x_i - \bar{x})^2 \tag{5}$$

- ***Zero Crossing (ZC):*** ZC calculates how many times the signal passes through the zero point. This calculation is sensitive to noise like WAMP, so a certain threshold level needs to be determined.

$$ZC_k = \sum_{i=1}^{N-1} f\ (x)$$

$$f(x) = \begin{cases} 1, & if\{x_i > 0\ and\ x_{i+1} < 0\}or\{x_i < 0\ and\ x_{i+1} > 0\}and|x_i - x_{i+1}| \geq \varepsilon\} \\ 0, & otherwise \end{cases} \tag{6}$$

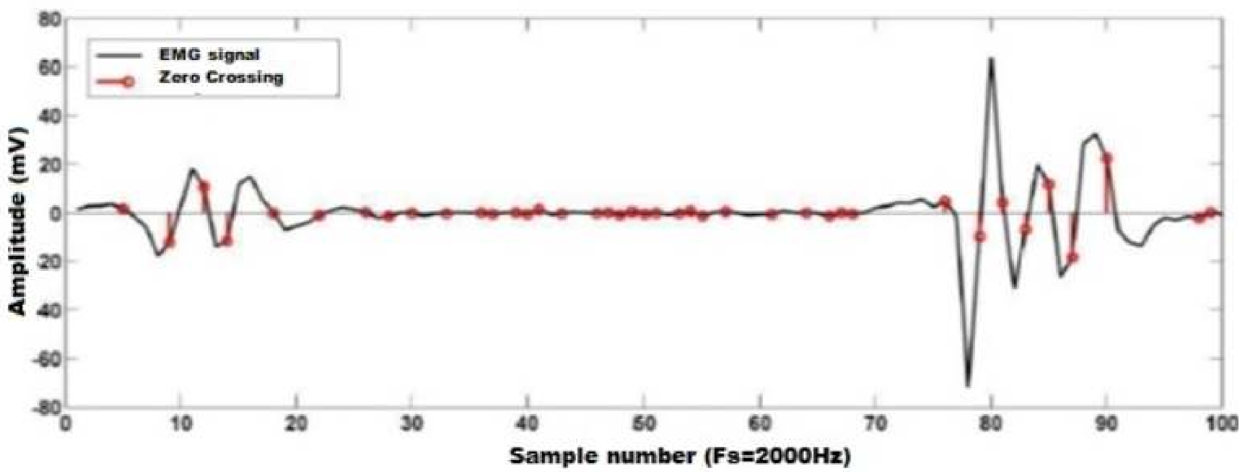


Figure 2. 11: Zero crossing graph of sampled EMG signal (Eroğlu, 2013)

- ***Slope Sign Changes (SSC):*** SSC displays and counts the transition of EMG amplitude from positive to negative or reverse. This is a method to show the frequency information of EMG signal.

$$SSC_k = \sum_{i=1}^{N} f\ (x) \tag{7}$$

$$f(x) = \begin{cases} -x, & if\{x_i > x_{i-1} and\ x_i > x_{i+1}\} or \{x_i < x_{i-1} and\ x_i < x_{i+1}\} \\ & and \\ & |x_i - x_{i+1}| \geq \varepsilon\ or |x_i - x_{i-1}| \geq \varepsilon \\ 0, & otherwise \end{cases}$$

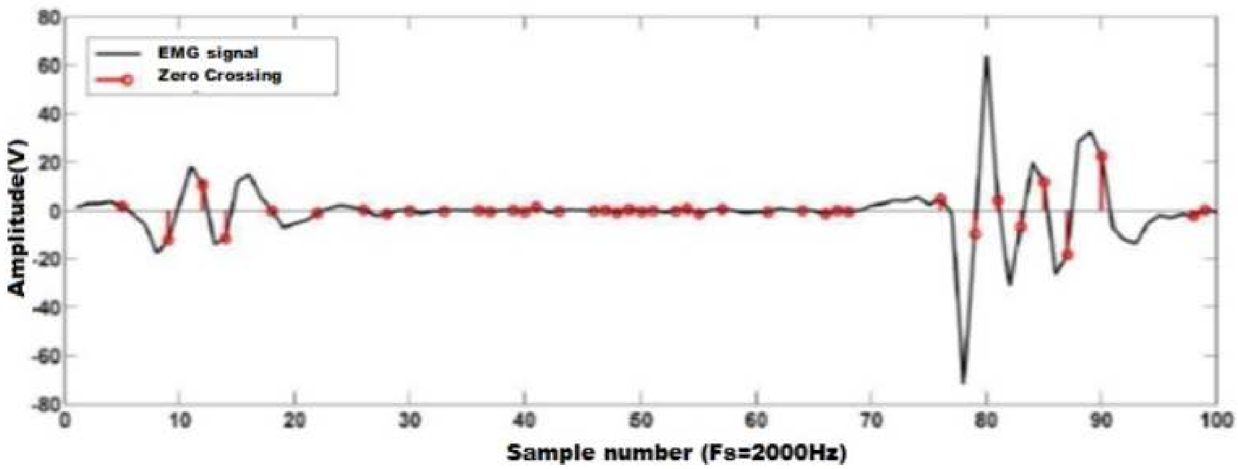


Figure 2. 12: SSC display on EMG signal (Eroğlu, 2013)

2.3.2 Frequency Domain

This method uses power spectrum density of signal to feature extraction. It is also good way to find feature but it need more time and calculation than feature extraction in the time domain. There are many different ways to do feature extraction with frequency domain. Some of them are given below (Phinyomark et al., 2009).

- ***Power Spectral Density (PSD):*** PSD gives information about strength of the variations as a function of frequency so we can see strong and weak frequency variations. Equation is given below.

$$PSD = S_x(f) = \lim_{T\to\infty} E\left\{\frac{1}{2T}\left|\int_{-T}^{T} x_m\,(t)e^{-j2\pi t}dt\right|^2\right\} \tag{8}$$

Consider $x_m\,(t)$ is a signal and $S_x(f)$ is the average of Fourier transform magnitude square over T standing for time interval.

- ***Frequency Median (FMD):*** FMD can calculate by dividing PSD into two equal parts. (Oskoei and Hu, 2006).

$$FMD = \frac{1}{2}\sum_{i=1}^{N} PSD_i \tag{9}$$

where, N is the length of the PSD.

- ***Frequency Ratio (FR):*** FR can be used for to see difference between contraction and relaxation of a muscle in frequency domain by applying fast Fourier transform to signals in time domain.

$$FR_j = \frac{|F\,(.)|_{j\;low\;freq}}{|F\,(.)|_{j\;high\;freq}} \tag{10}$$

$F(.)$is the FFT of EMG signal and Threshold for dividing a low frequency band and a high frequency band can be decided after some trails.

2.3.3 Time-Frequency Domain

With time-frequency domain we can see the energy of the signal both in time and frequency. Rather than time domain this method need a transformation so it could be hard to computationally.

- ***Fourier Transform (FT):*** With FT, a signal can expressed as the sum of cosine and sine functions in different frequency, phase and amplitude. FT gives a frequency spectrum of the real signal. The Fourier transform allows the solution of non-periodic functions and it can be reversible.

$$FT: \hat{x}(f) = F\big(x(t)\big) = \int_{-\infty}^{\infty} x(t)e^{-i2\pi ft}\,dt \tag{11}$$

$$Reverse\ FT: x(t) = F^{-1}\big(\hat{x}(f)\big) = \int_{-\infty}^{\infty} \hat{x}(f)e^{i2\pi ft}\,dt \tag{12}$$

- ***Short time Fourier Transform (STFT):*** The signal is divided into sections in STFT analysis and each section is considered partial stationary. With FT, stats of frequency can be learned but time is missing in that transform. STFT gives the both information frequency and time resolution. The disadvantage of STFT is that each divided Fourier transform have equal size limitation, since the time interval is fixed, energy distribution may be false.

$$STFT_k\,(t,\omega) = \int W^*(\tau - t)x\,(\tau)e^{-j\omega\tau}dt \tag{13}$$

$W\,(t)$ shows window function, * is the complex conjugate, T shows time and W is angular frequency.

- ***Wavelet Transform (WT):*** WT and STFT have similarity. Difference is, STFT localizes the signal in term of frequency and time but it cannot suitable for all signals. Information can be lose for some signals which has short duration period so WT gives larger time window to catch low frequency and smaller window for higher frequency.

$$W_x\,(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t)\psi^*\left(\frac{t-b}{a}\right) dt \tag{14}$$

$x(t)$ is the input signal, ψ^* is the complex conjugate of the wavelet function and $\psi^*\left(\frac{t-b}{a}\right)$ is the shifted and scaled version of the wavelet.

2.3.4 Empirical Mode Decomposition

Empirical Mode Decomposition method is such a technique which shows the nonlinear and non-stationary signal by a sum of proper turns. This makes possible to register surface area in the complex plane. The point of the EMD method is to disintegrate the nonlinear and non stationary signal $x\,(t)$ into a sum of intrinsic mode functions (IMFs). Each IMF fulfills two essential conditions:

- The quantity of extreme and the quantity of zero crossings must be the equivalent or differ at most by one,
- At any point, the mean estimation of the envelope characterized by the local maxima and the envelope characterized by the local minima is zero.

These two conditions ensure that all the maxima of an IMF are positive and all its minima are negative. Given a signal $x\,(t)$the EMD calculation can be summarized as follows:

1. Identify all local minima and local maxima of the given signal $x\,(t)$. Make an upper ($e_{max}\,(t)$) and a lower ($e_{min}\,(t)$) envelope adding between progressive local maxima and local minima separately.

2. Calculate the running mean: $m(t) = \frac{e_{min}(t)+e_{max}\,(t)}{2}$

3. Subtract the mean from the signal to remove the detail: $d(t) = x(t) - m\ (t)$

4. Repeat the entire procedure replacing $x\ (t)$ with $m\ (t)$ until the last remaining is a monotonic function (Bajaj & Pachori, 2012; Sapsanis et al., 2013).

CHAPTER 3
MACHINE LEARNING FOR CLASSIFICATION

The process of understanding of EMG signals can be reviewed in three main steps. These are preprocessing, feature extraction and classification process. When the literature is examined, it is seen that the preprocessing steps like data sampling, straightening and filtering are quite similar in studies. The difference between in these studies start in feature extraction and classification steps. These studies used feature extraction to obtain multiple features in time and frequency domain as described in the previous chapter. Different machine learning techniques have been used to increase the classification success. Artificial neural networks and newly introduced Convolutional Neural Networks will be examined in detail in this chapter.

3.1 Neural Networks

A neural network is a mathematical model which have been inspired and developed by the problem solving capacity of the human brain. Fundamental neuron of neural network is a simple mathematical function. This mathematical model has three basic function; multiplication, addition and activation. An artificial neuron consists of five parts. They are inputs, weights, addition function, transfer function and output. This main model called the sigmoid neuron (Neapolitan, 2018).

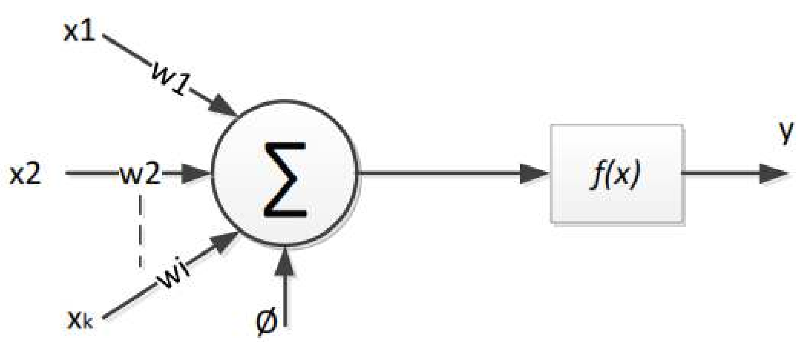


Figure 3.1: Sigmoid neuron

The representation of K entry artificial neuron is given in Figure 3.1. In this Figure$x_1, x_2,\ldots,x_k$ are inputs and y is the output. Each of the input values is multiplied by weight after summed with bias. The value from the cell passes though the transfer function known as the activation function. y is the output from one cell and it can be input for other cells.

$$y\ (k) = f\left(\sum_{i=1}^{m} w_i(k).\, x_i(k) + b\right) \tag{15}$$

This equation is a mathematical representation of a Multi neural network. $x\ (k)$ is the input values from $i = 0\ to\ i = m,\ w\ (k)$ is the weight values from $i = 0\ to\ i = m$ and b is bias , f(.) is transfer function and $y\ (k)$ is output values with variable k.

As seen in equation, the basis unknown variable is the transfer function in neural network model. Transfer function is selected according to the problems that neural network needs to solve. Usually these transfer function are selected:

Unit step (threshold): The output is depending on total input is bigger than or less than some threshold value.

Sigmoid: This function consists of logistic and tangential functions. The values of tangential function range from -1 to +1 and 0 to 1 for logistic function.

Linear: Transforms the weighted sum inputs to an output using linear function.

Piecewise linear: The output is proportional to the weighted output. It has limitation in Y axis.

Gaussian: Gaussian functions are bell-shaped curves that are continues. The output is interpreted depending on how close the net input is to a chosen value of average (Başpınar, 2014; Ian Goodfellow, Yoshua Bengio, 2018).

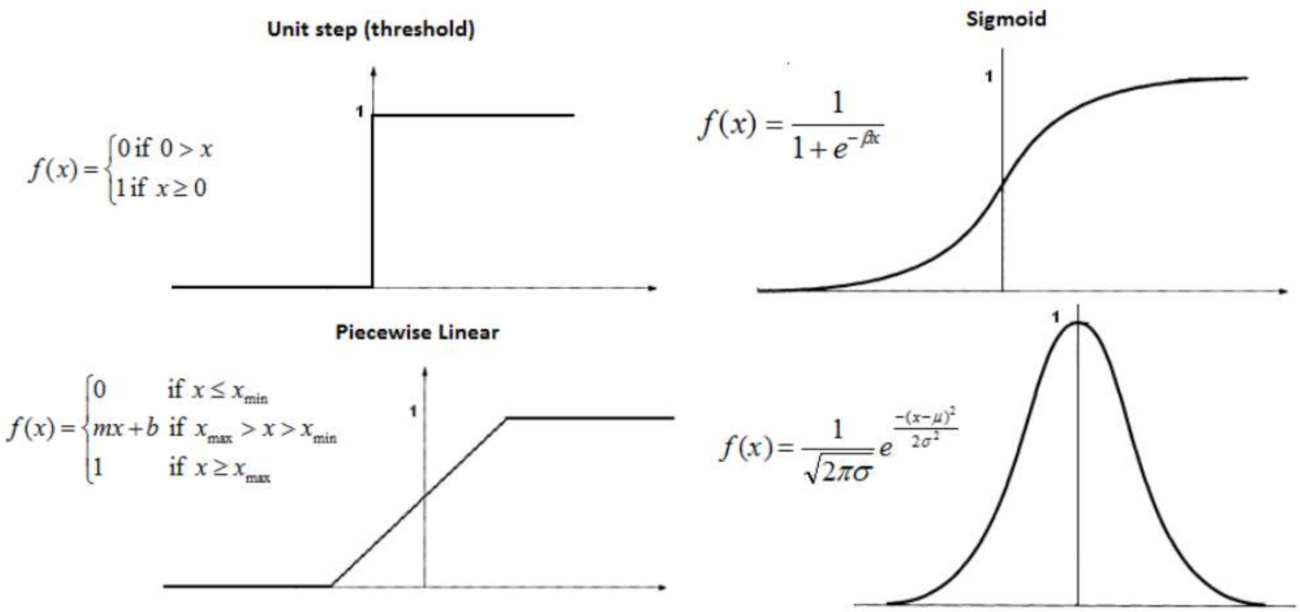


Figure 3. 2: Graphs for some transfer functions commonly used in machine learning.

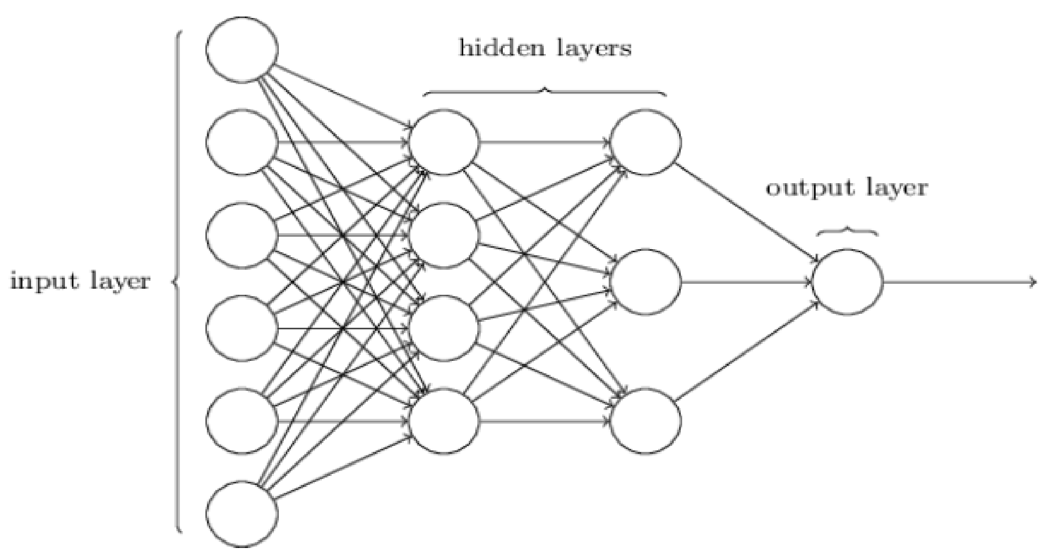


Figure 3. 3: General Structure of Multi Layer Perception (Neapolitan, 2018)

Input Layer: Input values are taken from the outside world. Input layer contains as many cells as the number of entries from the outside world .Inputs are transmitted to the next layers without any processing.

Hidden layer: The number of hidden layers between the input layer and output layer varies depending on the designer, and sometimes there will not be any hidden layer in network. The number of neurons in the hidden layer is determined regardless of the number of inputs and outputs, and in a multi layer network there can be different numbers of neurons in each interlayer. Number of neurons in layer increases process complexity and time increases too, however, if it contains a large number of neurons, it can solve more complex problems.

Output layer: Information from hidden layers is processed in the output layer and the network outputs are produced. The outputs produced in this layer are either sent to the outside world or sent to the network back to recalculation of the new weight values if it is a feedback network.

Sigmoid neuron is useful for simple problems but main reason to create neural network system is solving complex problems. For that kind of problems Multi layer perceptions (MLP) can be used. It has a structure in which many neurons with activation function are connected to each other hierarchically. There are different types of neural networks; they are generally divided into feed-back and feed-forward networks.

A feed-forward network: Hidden layers and outputs. The system works only in one direction. Each processing component makes its calculation dependent on a weighted sum of its inputs. The new determined values at that point become new input values that feed the following layer. This procedure proceeds until it has experienced all the layers and decides the output. Feed-forward network are frequently used in data mining (Başpınar, 2014).

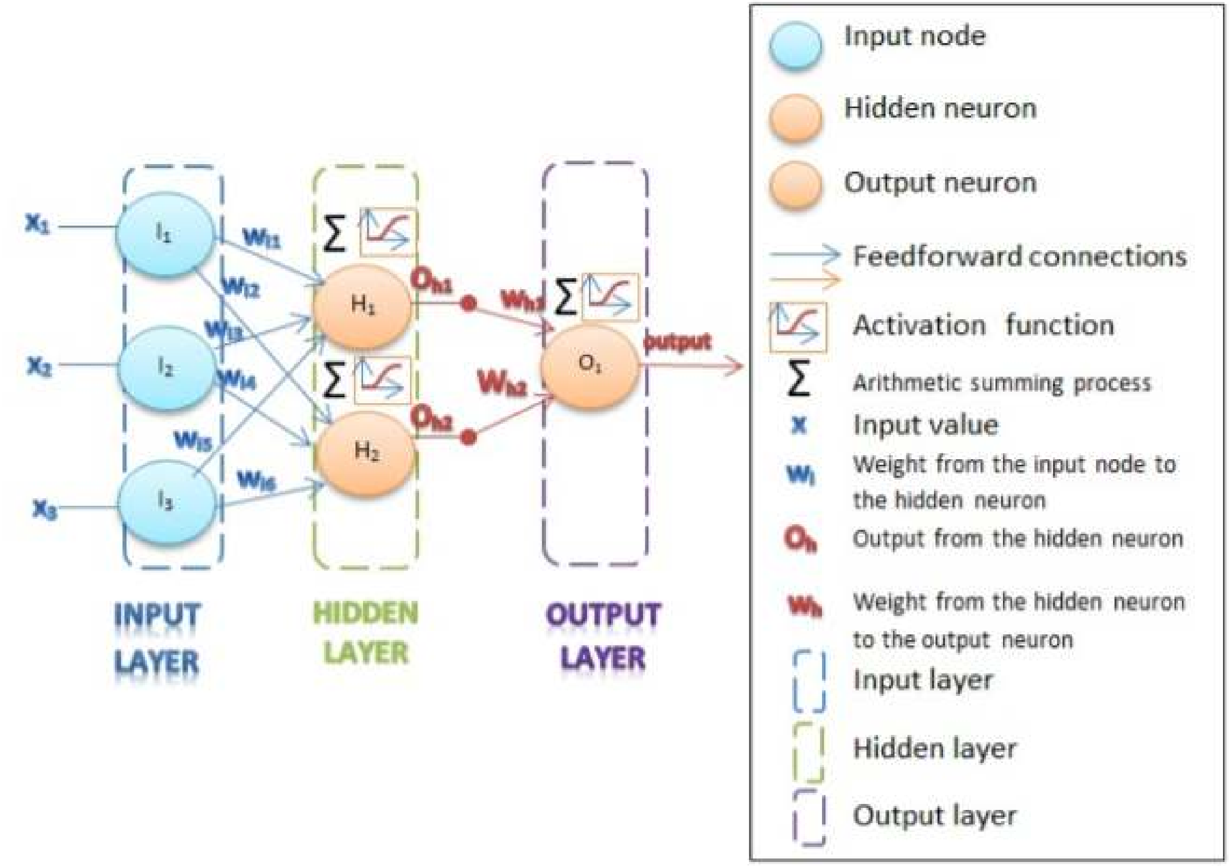


Figure 3. 4: A feed-forward network (Rechy-Ramirez & Hu, 2015)

A feed-back network: Has feed-back paths meaning signals can use the bothway forward and backward. Every conceivable connection between neurons is permitted. It turns into a non-linear dynamic network which changes continuously until it arrives at a condition of balance. Feed-back networks are frequently used in associative memories and optimization problems where the system searches for the best arrangement of interconnected components.

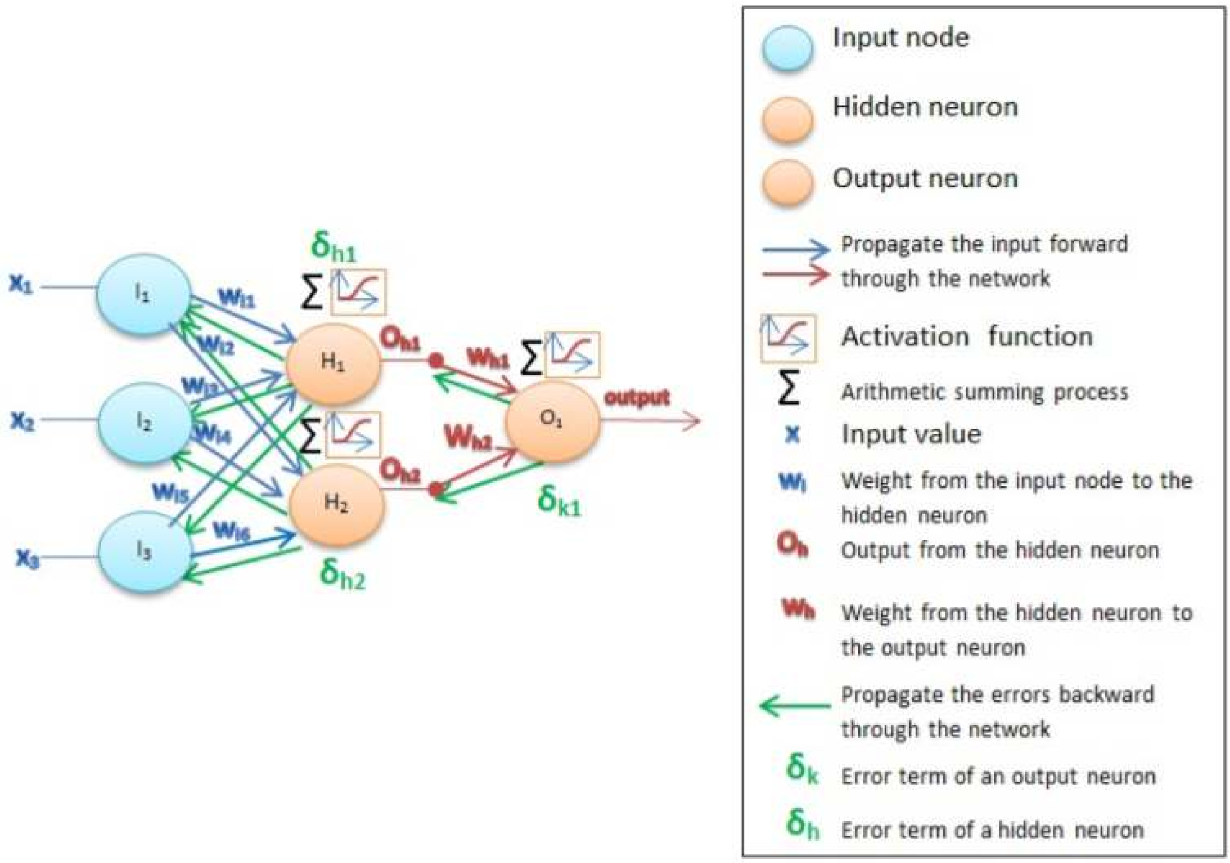


Figure 3. 5:A feed-back network (Rechy-Ramirez & Hu, 2015)

3.1.1 Learning process of Neural Network

The human brain perceives and senses the external world with its sensory organs and shapes their behavior by interpreting information since birth. With experience, the brain develops and the input-output relationship is largely shaped. But with the unexpected event or input, output also will be surprise because of the person has no experience for that situation. Learning process is similar to human brain in Neural Network. First, inputs are received from the outside world during the learning period and outputs are generated by passing the activation function. The error rate is calculated by comparing each stud with the previous output and the error is attempted to reduce to zero so to reach the desired output with the help of various existing learning algorithms. The main work done in this step is to update the weights for the desired output. If the weight values calculated by Neural Network reach the targeted output value in response to the inputs given by, the Neural Network stores these weight values. After the training is completed, inputs that are not given to the network during learning are given and the real output approach is analyzed with the output of the Neural Network. If Neural Network takes a close approach to the given test sample, the network has learned. If more than enough sample input is given to neural network during training, Neural Network memorizes it not learn. Prediction speed and the learning performance can often be increased by preparing and processing the data. Preparation and processing of the data is divided into four main steps they are sampling, normalizing, dividing and windowing.

-Data Processing: The sampled data is characterized by the sampling size and the sampling rate. The sampling size is the size of the informational index used in prediction. While the sampling rate is the rate of which raw information is examined. The sampling size is a significant factor in the guessing accuracy of prediction models (Johansson & Nafar, 2017).

-Normalization: The reason of doing normalization lies in the removal of differences among the signals gained from various subjects at various time but from the same muscle. This procedure is finished by separating the signal by a reference value taken from the same muscle taken the signal is perused by the same electrode configuration. By normalizing the data, it is scaled to values fitting for the prediction model. When the prediction depends on a few input factors, autonomous normalization of each factor guarantees that bigger value input factors do not excessively influence the prediction, decreasing the prediction errors (Johansson & Nafar, 2017; Oweis et al., 2014).

-Dividing: To build a Neural Network the data must be separated into a few subsets, in particular a training data set that is utilized to build up the prediction model, a validation data set is utilized to avoid over fitting issues and to choose when to end the training process. A test data set is utilized to assess the estimating capacity of the prediction model. There is no certain rule for the division of data, but to accomplish better estimating performance it is significant that separate all subsets according to basic system. Generally, the training data set contains a large portion of the data. Some standard rates are 70% for training versus 30% for validation and testing, 80% versus 20% and 90 versus 10% also we can divide the small part too, into validation and testing. With that way the result of the model will be more reliable (Johansson & Nafar, 2017). In this study 70% training 15% validation set and 15% test set dividing rate is chosen because of compare the result with similar studies.

-Windowing: Data is windowed by choosing a window size. Window size decides the number of data points that comprise progressive inputs toward the model, by which the subsequent output value will be predicted. A small window size may bring about inadequate amount of input data to catch a pattern in the data while a bigger window size my yield a too complex pattern. Also bigger window size causes to longer training process (Johansson & Nafar, 2017).

Learning Process Steps:

- ***Sample Collection**:* Collection of necessary examples for network learning and testing. Chosen examples should cover all aspects of the event and there should not be any situation that is not introduced to the network. The samples in the training set are sent to the network one by one during the learning phase and the network is trained.

- ***Determination of structure of network:*** The structure of the network to be created for the event to be learned is determined. Thus the number of inputs, hidden layers, process elements in each hidden layer, output are learned.

- ***Determination of learning parameters and selection of weights:*** Network learning coefficient, addition of process elements and activation functions, momentum coefficient are determined in this step and the initial values of the weights are assigned. Usually assign random values in the start, and then network determines the appropriate values during learning.

- ***Giving the selecting samples from the learning set to the network:*** The network starts learning, and samples are shown particular arrangements to the network for change weights by the learning rule.

- ***Advanced calculations during learning:*** The output values of the network are calculated for the presented input.

- ***Comparing the actual output with the expected output:*** The error values generated by the network are calculated in this step.

- ***Changing weights:*** Changing weights by using the recalculation method to reduce the error.

- ***Complete learning:*** Network performance is measured by showing examples on the test set. The success against the examples network has never seen shows real performance of the network. If that performance is acceptable, we can say learning is finished.

The weight values for first input sample are random at first and weights change as samples are shown to the network to reach the desired values. Desired weight values are not known at first. Therefore, it is not possible to interpret and explain the behavior of Neural Network. Initial weight values, structure of network, parameters of the network, representation of the data to the network and formulation of samples can be changeable to reach better accuracy. The best way to show the network's learning is to draw the error chart. If the error is plotted on each iteration, it can be observed that the error has fallen over time. It appears that the error will not decrease further after certain iteration. It means that learning has stopped for this network and no better result can be found (Çayıroğlu, 2008).

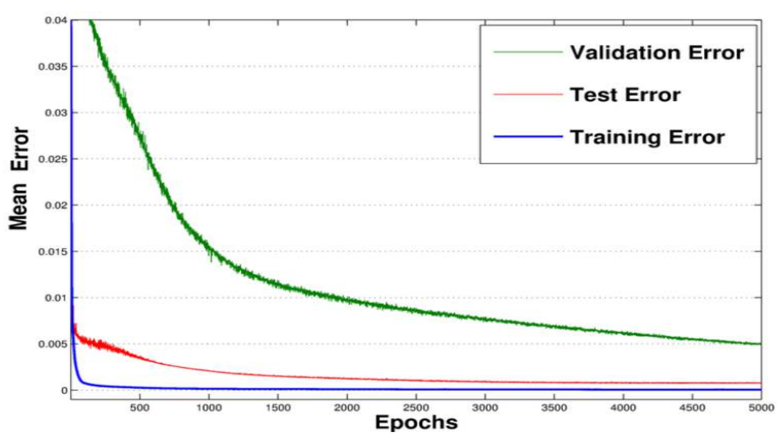


Figure 3. 6: Graph of mean error by number of epochs (Gaspar, 2011)

3.2 Convolutional Neural Network (CNN)

The Convolutional Neural Network is a significant architecture of deep learning that is an alteration of standard Neural Network for handling multiple arrays of data, for example, pictures, signals and languages. There are three basic thoughts behind how CNN works, including local receptive field, shared weights, and pooling. In the Convolutional layer, channels are convolved with patches of input such that an individual filter has same learning weights for all patches. The dot product of filters with patches is gone through the activation unit, and the size of output is decreased by means of pooling. In the end fully connected layer is used to connect output of pooling layer (Rehman et al., 2018).

One significant feature of CNN that separates it from other machine learning calculations is its capacity to pre-process the data by itself. In this manner, you may not spend a lot of assets in data pre-preparing. During start, the filters may require hand building yet with progress in preparing; they can adjust to the learned features and create filters of their own. Therefore, CNN is continuously evolving with development in the information (Team, 2019).

CNN networks are simply neural networks that use convolution in place of general matrix multiplication in at least one of their layers. This method helps the network to definition in more practical manner. For instance, unlike the linear arrangement of neurons in a normal Neural Network, CNN have a general structure of three dimensions; length, width and height.

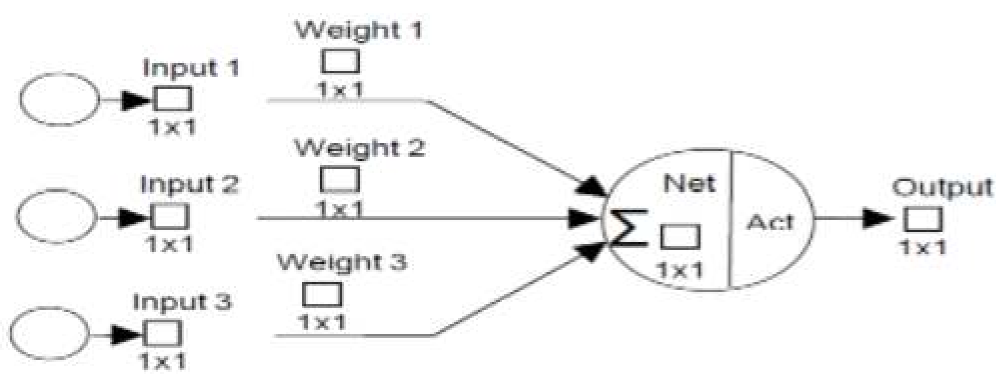


Figure 3. 7: Normal Neural Network structure: Scalar inputs multiply with scalar weights and all parameters are in scalar form (Ghrairi, 2019)

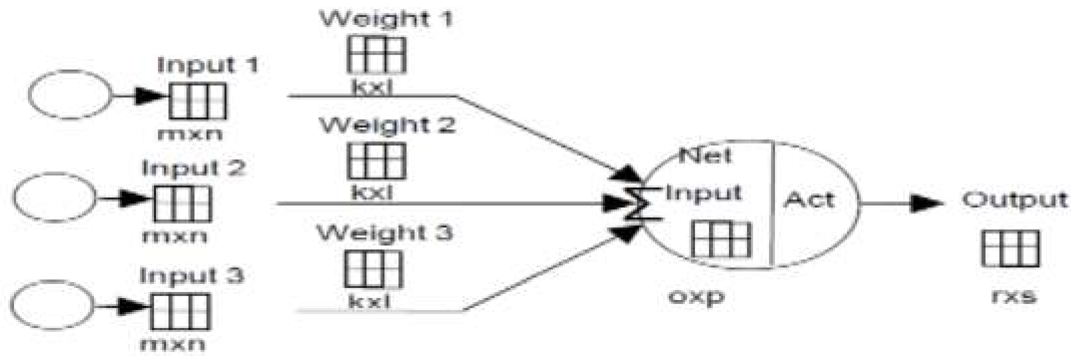


Figure 3. 8: CNN structure: The Convolutional process runs on matrix weights and matrix inputs. All parameters are matrices (Ghrairi, 2019).

CNN consists of multiple stacked layers to create a complex architecture for classification problems. These layers are convolution layers, pooling layers, activation function layers and fully connected layers. Typically, the purpose behind these layers is to create property maps of the input, reduce the dimensions of the intermediate layers, reshape and simulate in fully connected layers. Before these layers input should be prepared for better accuracy. High input size can increase memory requirement, training time and test time per image but also it increases the success of the network.

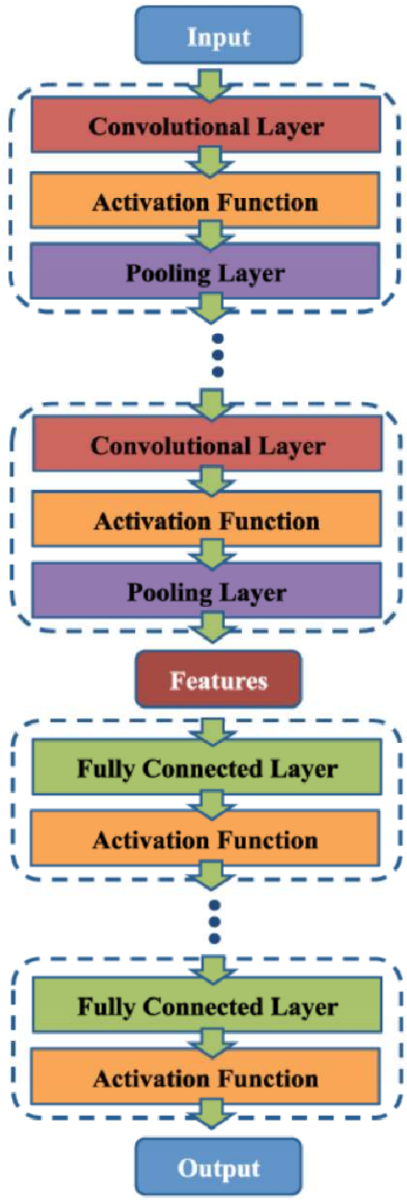


Figure 3. 9: A general CNN architecture

3.2.1 Convolution Layer

Primary function of a convolution layer, extract features from input data. Convolution is a mathematical operation of two functions. In the CNN concept, the convolution process simply involves multiplying with the kernel function and shifts it on the main data. For each window in sliding, the sum of the elements multiplication gives the result of that window. The windows are shifted across the entire image, the output of the convolution process called the feature map is produced.

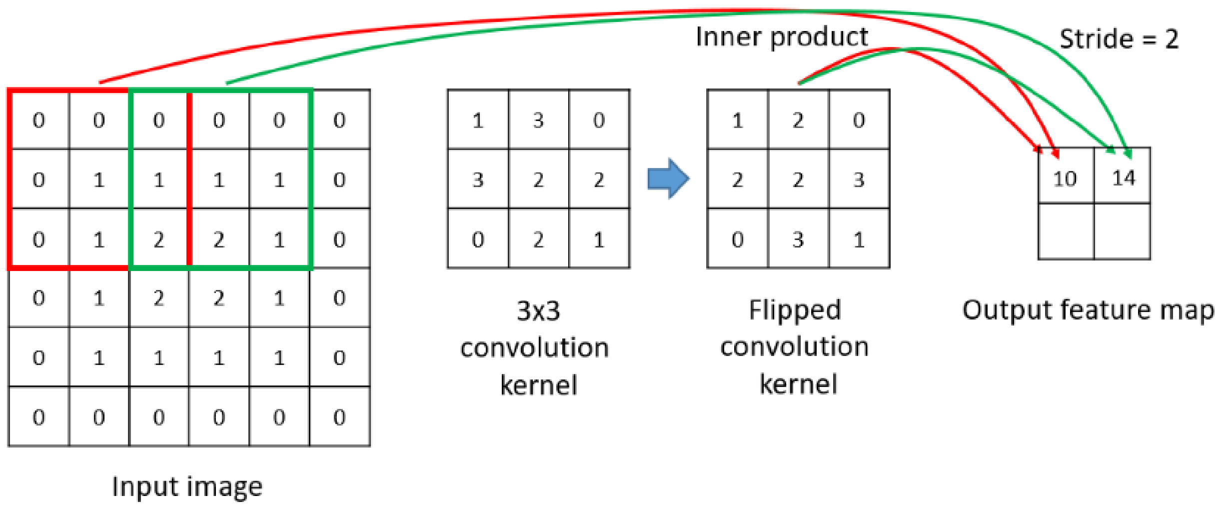


Figure 3. 10: Demonstration of two-dimensional convolution (Ayyüce Kızrak, 2018)

In the Convolutional Network terminology, the first contention to the convolution is generally referred to as the input and the second contention as the kernel. The output is called as the feature map. In machine learning applications, the input is generally a multidimensional array of data and the kernel is generally a multidimensional array of parameters that are adjusted by the learning calculation. The commutative properties of convolution increase because kernel has flipped according to the input. The main motivation behind to flip the kernel is to obtain the commutative property (Ian Goodfellow, Yoshua Bengio, 2018). When there is a correlation between the kernel and the input, the resulting feature map appears to have higher values in these areas. The regions have no similarity they have lower values in the feature map.

In the convolution processes of CNN, there are three design issues to consider: size of the kernel, kernel number and stride number. These parameters have an impact on the form of output data, memory usage and required time. The kernel size determines the input of the each neuron so it is same with the exit of the convolution layer. The size of the kernel represents the weights of the model. For example, if the size of the kernel is 3x3, its output has link to 9 different nodes in the input layer. If the kernel size is too small, it cannot extract enough features. On the other hand, larger kernel size increases the computational complexity. The stride parameter determines the stride size of the kernel shift. If the step is more than one, the width and height of the output will be significantly reduced (Ian Goodfellow, Yoshua Bengio, 2018).

3.2.2 Pooling Layer

The purpose of the pooling layer is to reduce the number of parameters and calculation in the network. This reduction process is defined as pooling and is done in two different ways. One is maximum pooling and the other is average pooling. While performing this operation, a rectangular window is scrolled over the input and operations are performed according to the type of pooling to be performed.

Maximum Pooling chooses activation with the largest value in the rectangular window and places them in the center.

Mean pooling calculates the average value from the activations inside the window and places it in the center.

Figure

Figure 3. 11: Representation of Max pooling and Average pooling.

The Figure represents the pooling process where the 4x4 input size and 2x2 sub-sampling. This 4x4 input is divided into four 2x2 matrices. The max pooling method is gives the maximum value of four values in the 2x2 matrix as an output. However, the average pooling method gives the mean of the four values inside the 2x2 matrix pool. If the output value is calculated as a fraction, it is rounded to the nearest integer (Ghrairi, 2019).

3.2.3 Activation Functions in Convolution Neural Network

Activation functions are numerical conditions that determine the efficiency of a neuron system. Activation functions; used when transmitting the output value in neurons in one layer to the next layers. In order to decide whether this output value will be transmitted to other layers, a threshold value must be determined. Because of the information in an artificial nerve cell value may be in the range (+∞,-∞) and neuron may not know the limits of the true value. Therefore, activation functions are needed to decide whether the neuron should be active or not. So it can be controlled the output value produced by a neuron and it can be seen able that neuron is active or not from outside. Since CNN are mostly used in nonlinear classifications also an activation function is usually chosen as a nonlinear function (Ser & Bati, 2019). In Section 3.1 general activation functions of Neural Network are explained. In this section some special activation functions for CNN will be examined.

Softmax Activation Function: Softmax function calculates the probabilities distribution of the event over ‘n’ various events. In general, this function will calculate the probabilities of each target class over all possible target classes. Later the determined probabilities will be useful for deciding the objective class for the given data.

The fundamental advantage of using Softmax is the output probabilities range. The range will be 0 to 1, and the total of the considerable number of probabilities will be equivalent to one. If the Softmax function utilized for multi-classification model it returns the probabilities of each class and the target class will have the high probability.

The equation processes the exponential of the given input value and the sum of exponential values of all the values in the input. After that, the ratio of the exponential values is the output of the Softmax function (Polamuri, 2017).

$$F(X_i) = \frac{exp(X_i)}{\sum_{j=0}^{k}(X_j)} \quad , \qquad i = 0,1,2, \dots . k \tag{16}$$

Rectified Linear Units (ReLU) Activation Function: ReLU is a nonlinear function. The output value can be between 0 and +∞. When using the sigmoid function, almost all neurons of the network are activated in some way. So it is logical to use less neuron, since the calculation is costly. ReLU enable more efficient use of the network where some neurons are not activated during random start-up and the cost of computing become less.

$$y = \max\ (0, x) \tag{17}$$

A problem with the ReLU function may be the calculation gradient and update weights, the values of the horizontal line do not respond to the gradient and a significant part of the network is not updated during back propagation. This problem is called 'dying ReLU'. This problem can be partially solved with Leaky ReLU (Ghrairi, 2019).

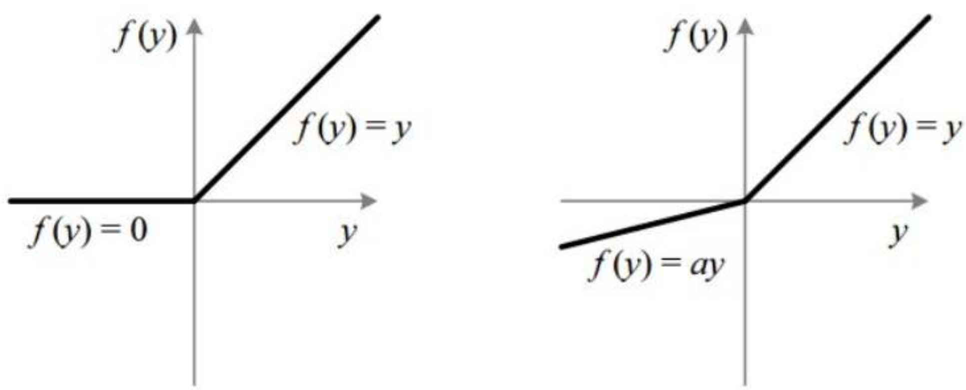


Figure 3. 12: ReLU vs. Leaky ReLU

Leaky ReLU has a small slope for negative values, instead of altogether zero. For instance, Leaky ReLU may have $y = 0.01x\ when\ x < 0$. Also it speeds up training and more balanced. Range of the leaky ReLU is $-\infty\ to + \infty$.

3.2.4 Fully Connected Layer

The fully connected layer is used and created mainly as the last layer of a CNN. In this layer, each input neuron is connected to each output neuron. There is a separate weight associated with each connection and separate bias value for each output neuron. Neurons in a fully connected layer have full connections with all activations in the previous layer, as seen in regular Neural Networks. The main purpose of this layer is to set the goal that can be considered as classification with mathematically add up the weight comes from previous layers via matrix multiplications. In short way in this layer, all feature elements fed by the previous layer are used to calculate output property.

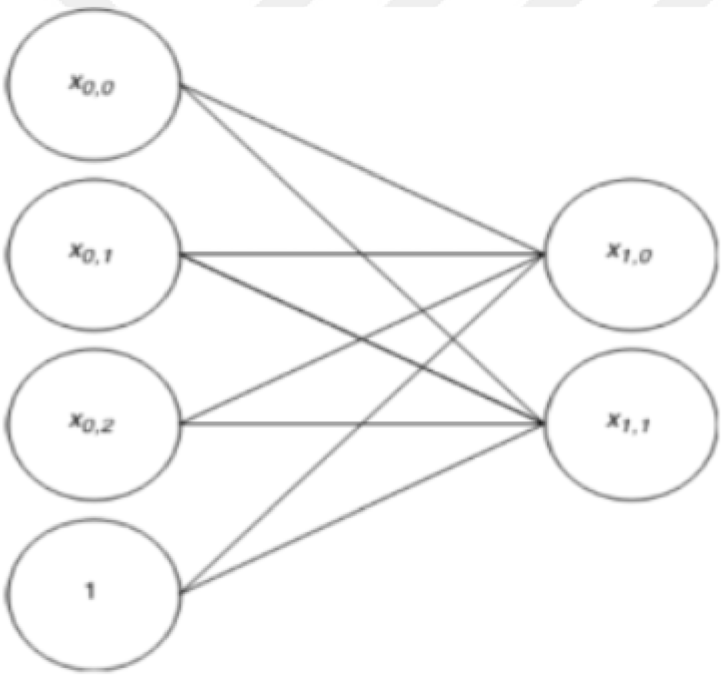


Figure 3. 13: Example of Fully Connected Layer

The forward transmission of a fully connected layer is calculated using equation 18,

$$z = f\ (x \times \theta + b) \tag{18}$$

where, x is the input matrix with one sample per row, θ is the weight matrix, $\times$ is the matrix multiplication operator, b is the line vector with bias values, f is the activation function and z is the matrix that contains the activation of the output neurons (Ghrairi, 2019).

CHAPTER 4
CLASSIFICATION OF EMG SIGNALS

This chapter describes the main contribution of the thesis. After introducing the data set, preparation of data samples for classification was explained in the first section. Then, preparing data for classifier is described. Finally experimental design and results are given. For all these applications MATLAB R2018b is used.

4. 1 Preparing Data Set and Application

The data set taken from University of California Irvine Machine Learning Repository is used in this thesis study. This data set contains signals of different people grapping different objects. It is aimed to detect these gripping movements with the surface electrodes attached to the forearm. Three surface EMG electrodes is used for getting signal, two of them in Flexor Capri Ulnaris and Extensor Capri Radialis and the reference electrode in the middle, to accumulate data about the muscle activation.

For the data collection five subject of a similar age around 20 to 22 year old were asked to repeat the six movements, which can be considered as fundamental hand movements. The speed and power were deliberately left to the subject's will (Sapsanis et al., 2013). Figures of movements are shown in Figure 4.1.

1) Cylindrical: for holding cylindrical tools
2) Tip: for holding small tools

3) Hook: for supporting a heavy load
4) Palmar: for grasping with palm facing the object
5) Spherical: for holding spherical tools
6) Lateral: for holding this, flat objects

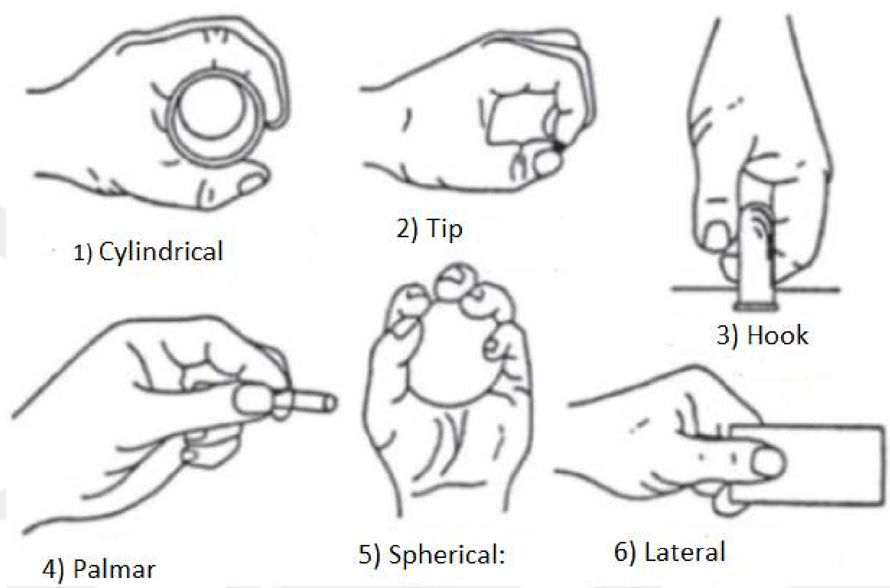


Figure 4. 1: Six hand movements used in the data set (Ayaz, 2018)

For every movement, the subject was asked to perform it for six seconds and the entire system was repeated 30 times for every fundamental movement. In the end, for each subject a total of 180 of 6 second long 2- channel EMG signals were recorded. The data is recorded at a sampling rate of 500 Hz. The signals were band-pass filtered using a Butterworth Band Pass filter, with a low and high cutoff frequency at 15 Hz and 500 Hz respectively and a notch filter at 50 Hz to get better information from signal without noises.

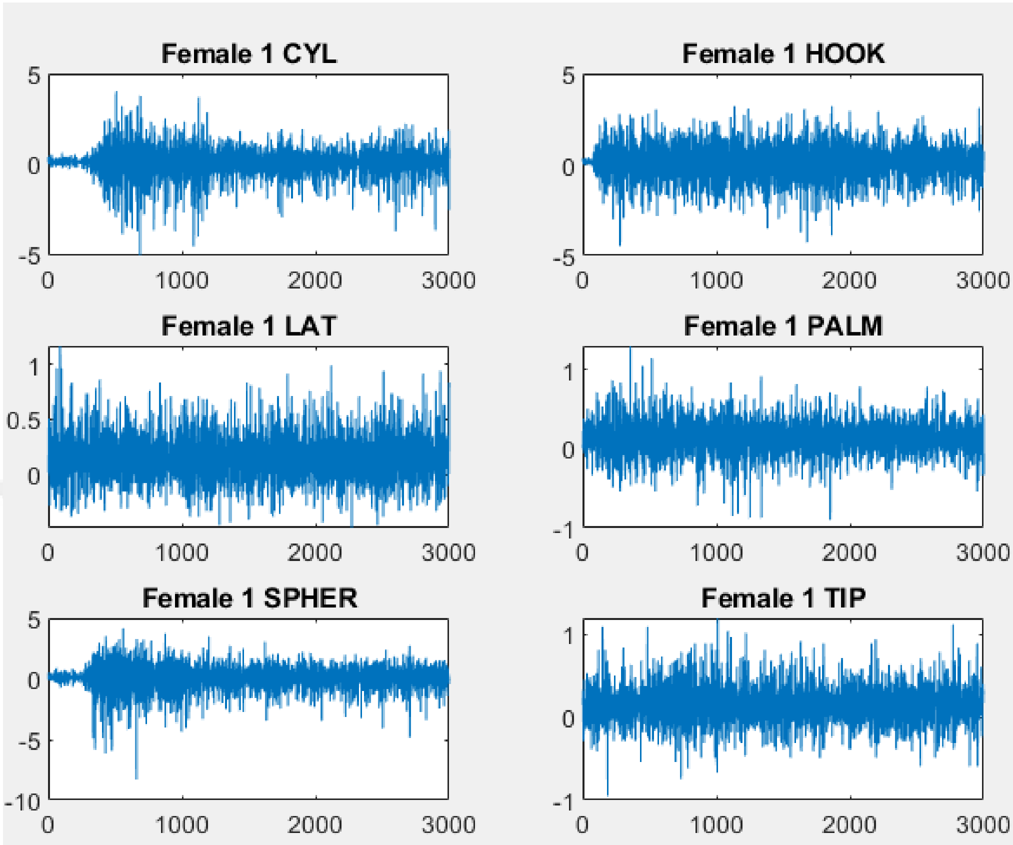


Figure 4. 2: First attempts for different movements EMG signals from Female 1

So as to concentrate just on section where the muscle is contracted, the sliding window approach is applied. Windowing technique can be applied as adjacent or with overlapping. The signal is divided into windows with the finish of the past window is associated with the following window in the adjacent windowing. For the overlap windowing, piece of the past window and next is overlapped. In this thesis, 300 msec (150 data point) is chosen for window size and slide that window 30 data point until the end as described in (Sapsanis et al., 2013).

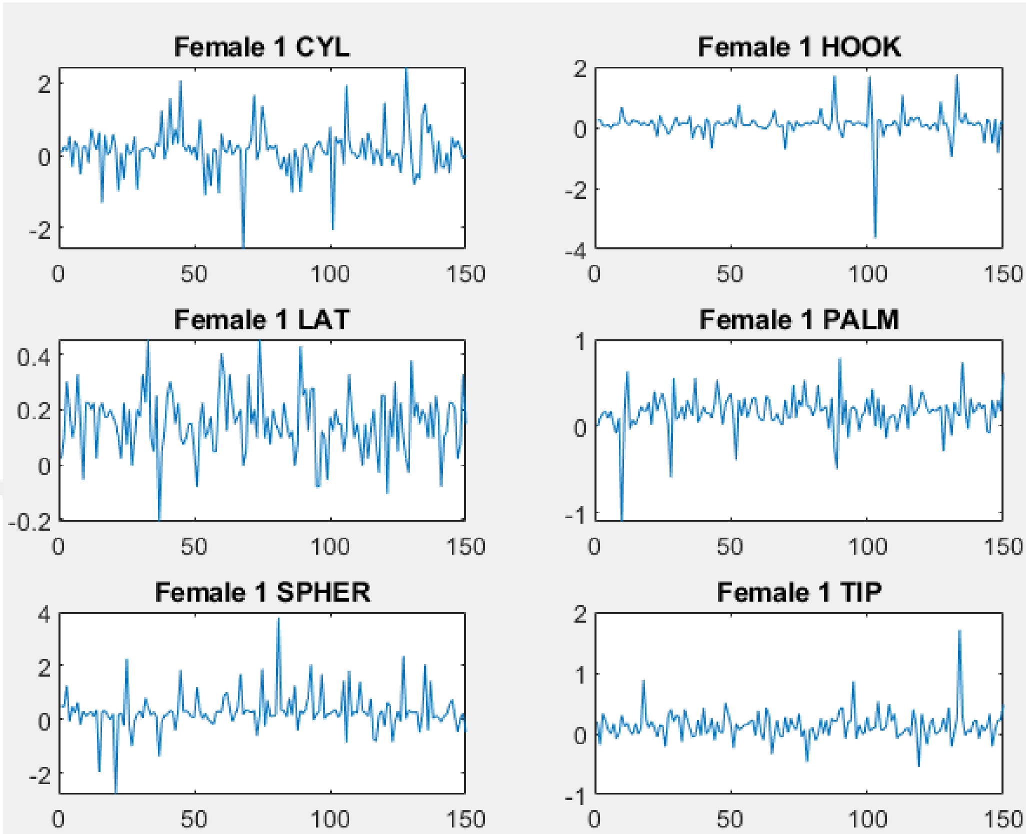


Figure 4. 3: First separated window from Female 1

Windowing is applied to the EMG signal that comes from both channels for each individual. According to the purpose of thesis the same movements from a different person are combined and adding each others to create Data matrix. In the end, Data matrix of 2x150x86400 is obtained so 86.400 window samples generated with length of 150.

Data matrix contains six different hand movements from 5 different people but classification will focus only movements rather than the person who does the movement. Therefore, Data has six different moments; every 14.400 data points refer different hand movements. Class categorical matrix is created to define classes of hand movements. Class matrix has size 1x150x86400.

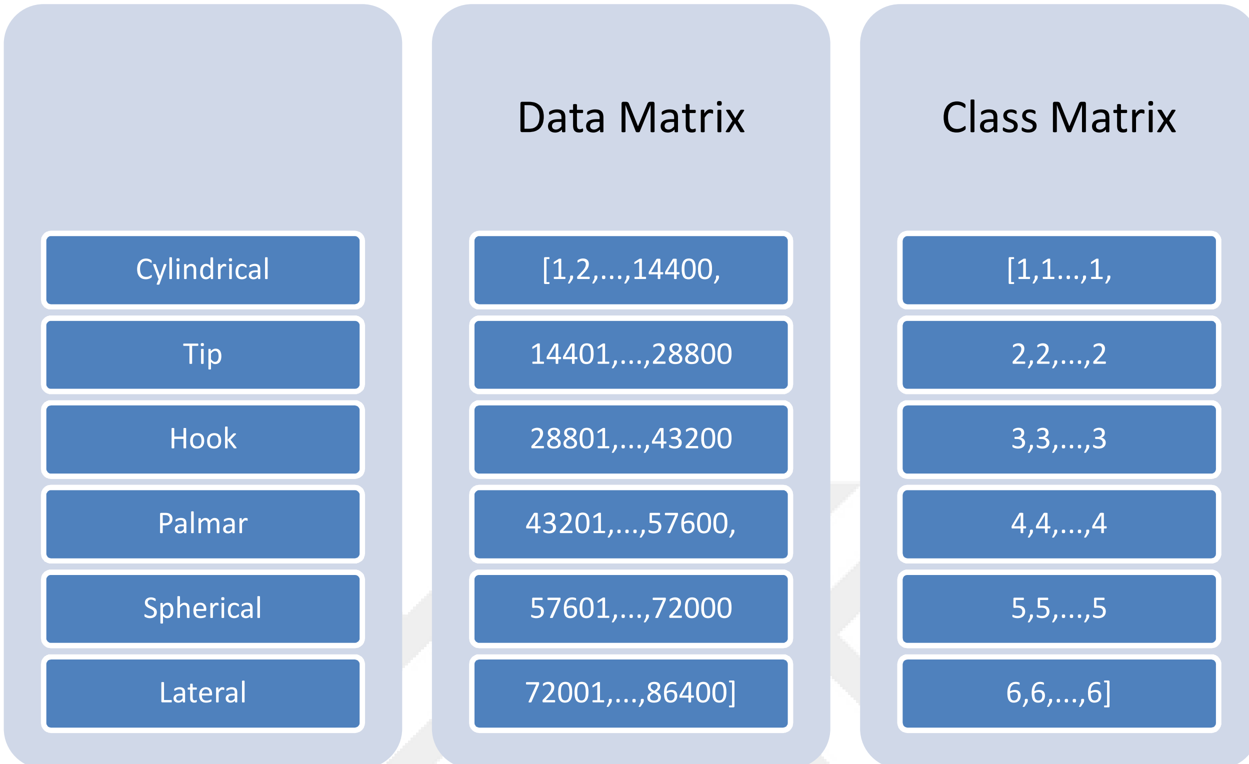


Figure 4. 4: Structure of data set and classification set

4.2 Cross Validation and Dividing the Data Set

After the creating Data and Class, next process is dividing them into Train, Validation and Test matrices as mentioned in Section 3.1.1. While dividing the data set, cross validation is applied to make Neural Network more reliable.

There is a risk of over fitting on the test set because the parameters can be changed until the network performs optimally. So information about the test can leak into the model and assessment measurements no longer report on generalization performance. To prevent this issue, one more piece of the data set can be held out as 'validation' set. Training continues on the training set when the examination is done on the validation set, and the network seems to be effective, final evaluation can be done on the test set.

However, this method not that suitable for if the number of sample is less, other way to prevent over fitting is cross validation. A test set should be waited for final evaluation, but the validation set is not require for this method. In k-fold cross validation, the training set is split into k smaller sets, then fit the model utilizing the k-1 folds and validate the model utilizing the remaining kth folds. Scores and errors are noted for each training. Repeat this until each k-fold serve as the test set. Finally, average of the recorded scores should be calculated as a final result.

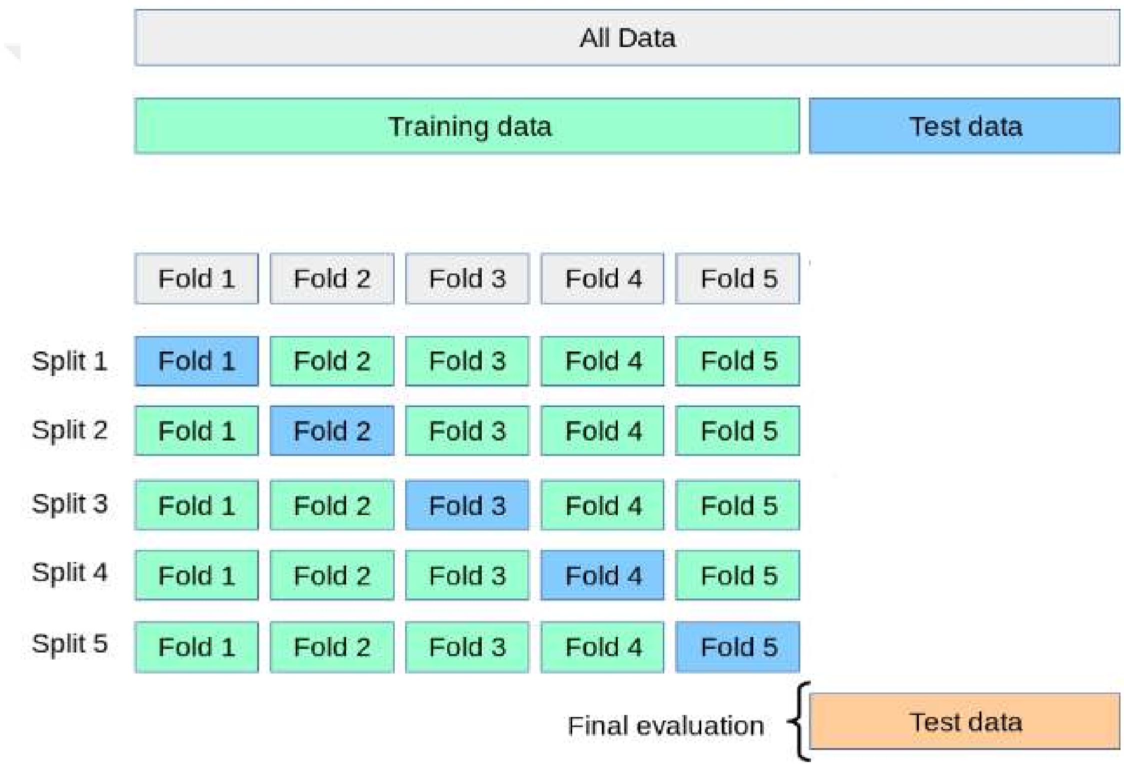


Figure 4. 5: Visualization of Cross-Validation.

In this thesis both method will be tried. Firstly, data set is split into %70 Training set, %15 Validation set and %15 Test set, 60480 samples are used for training. For cross validation k is chosen as 5.

After dividing operation, several different feature extraction methods like EMD, RMS and FFT are applied to see changes in the classification accuracy.

Figure 4.6 and Figure 4.7 shows IMFs of hook movement and lateral movements, respectively.

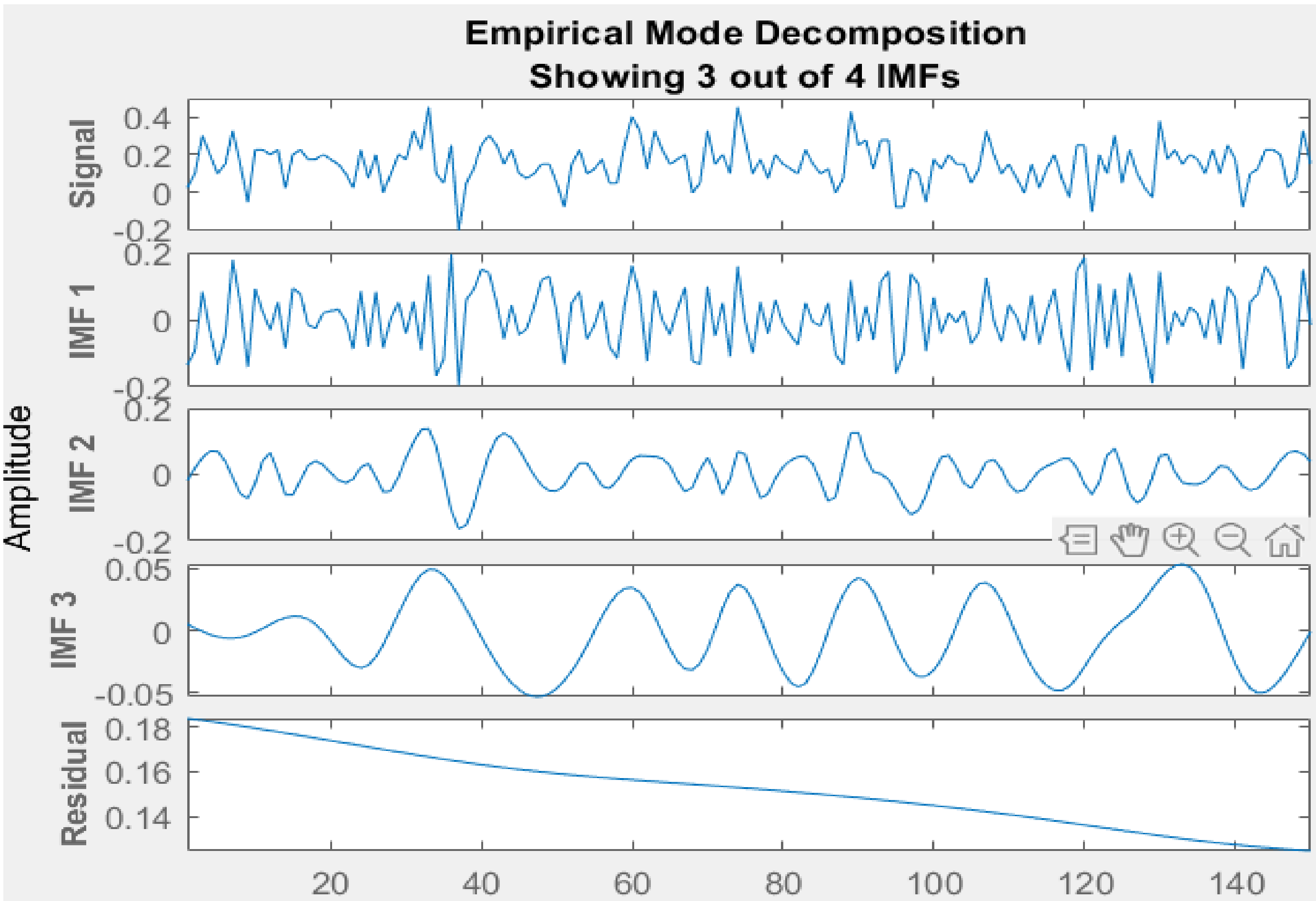


Figure 4. 6: First three IMF of the Hook movement

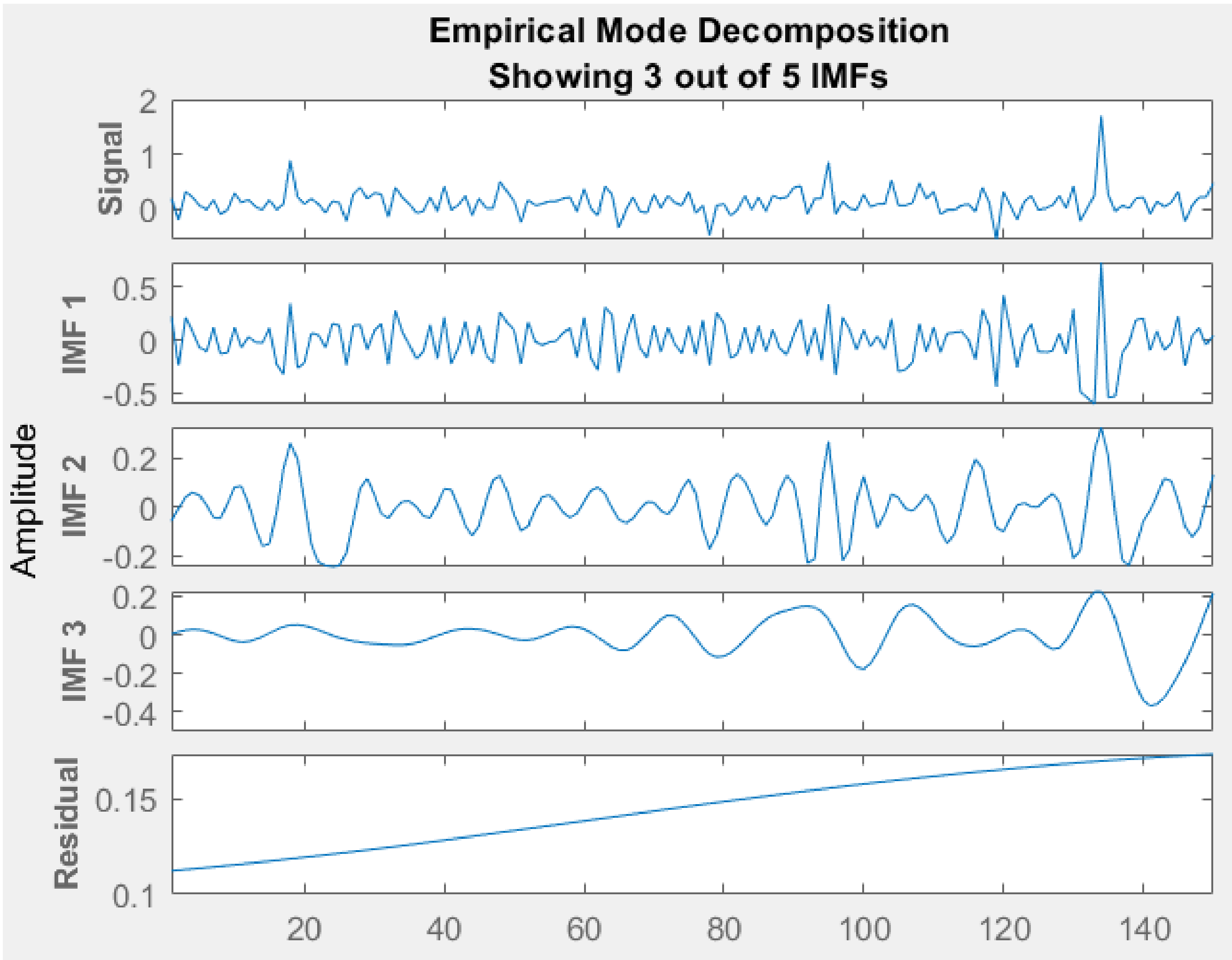


Figure 4. 7: First three IMF of the Lateral movement

In this way, the original signal $x\ (t)$ is eventually decomposed into a sum of IMFs plus a residual term. Therefore, EMD energy entropy can describe fault characteristics and afterward recognize the fault types.

Fast Fourier transfer Method is applied to see changes in frequency domain. To use FTT function in MATLAB library length of signal and frequency domain are calculated.

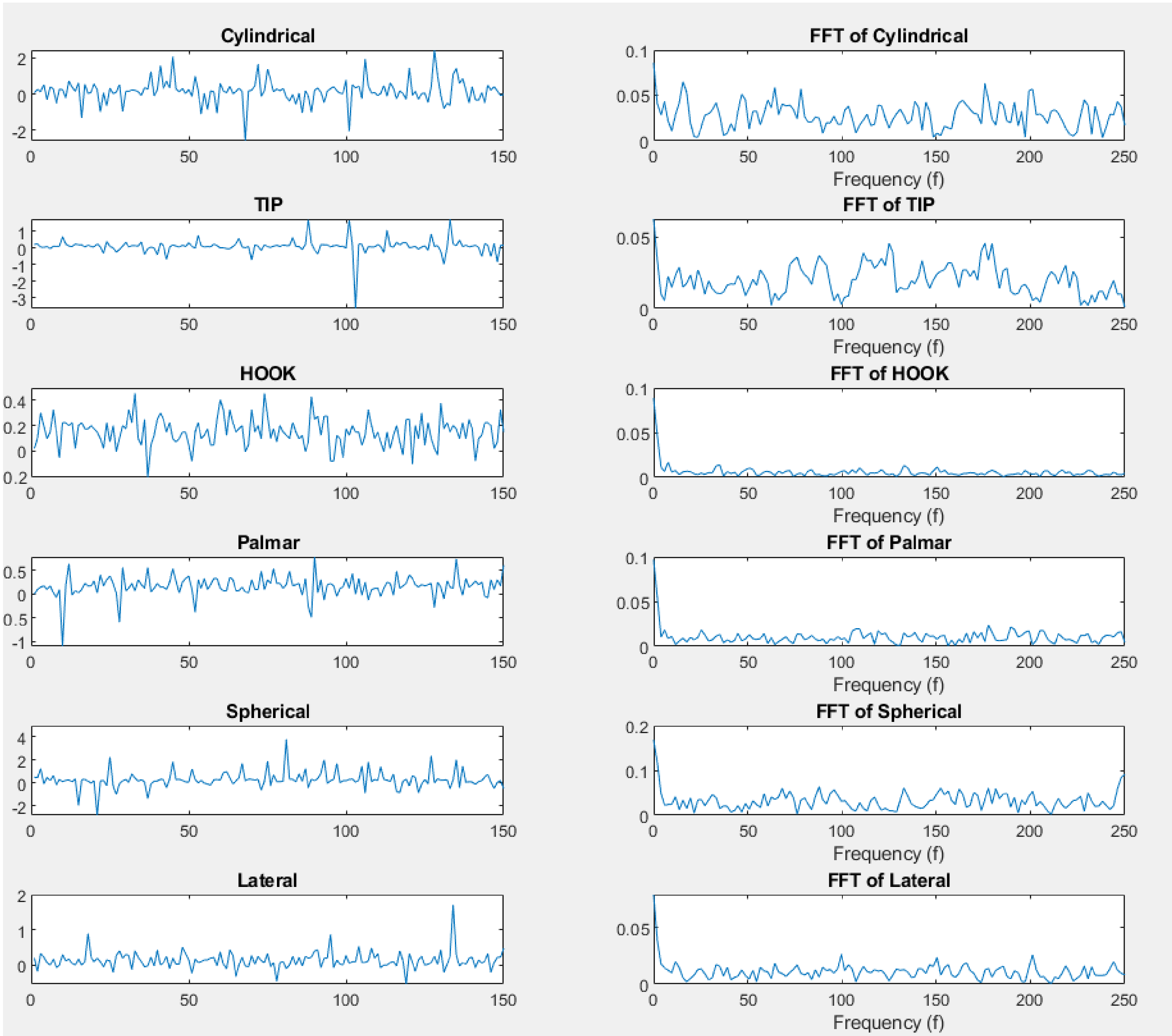


Figure 4. 8: Original windowed signals and FFT of each signal

Also Root Mean Square function is applied to signal to see differences between movements as described in Section 2.3

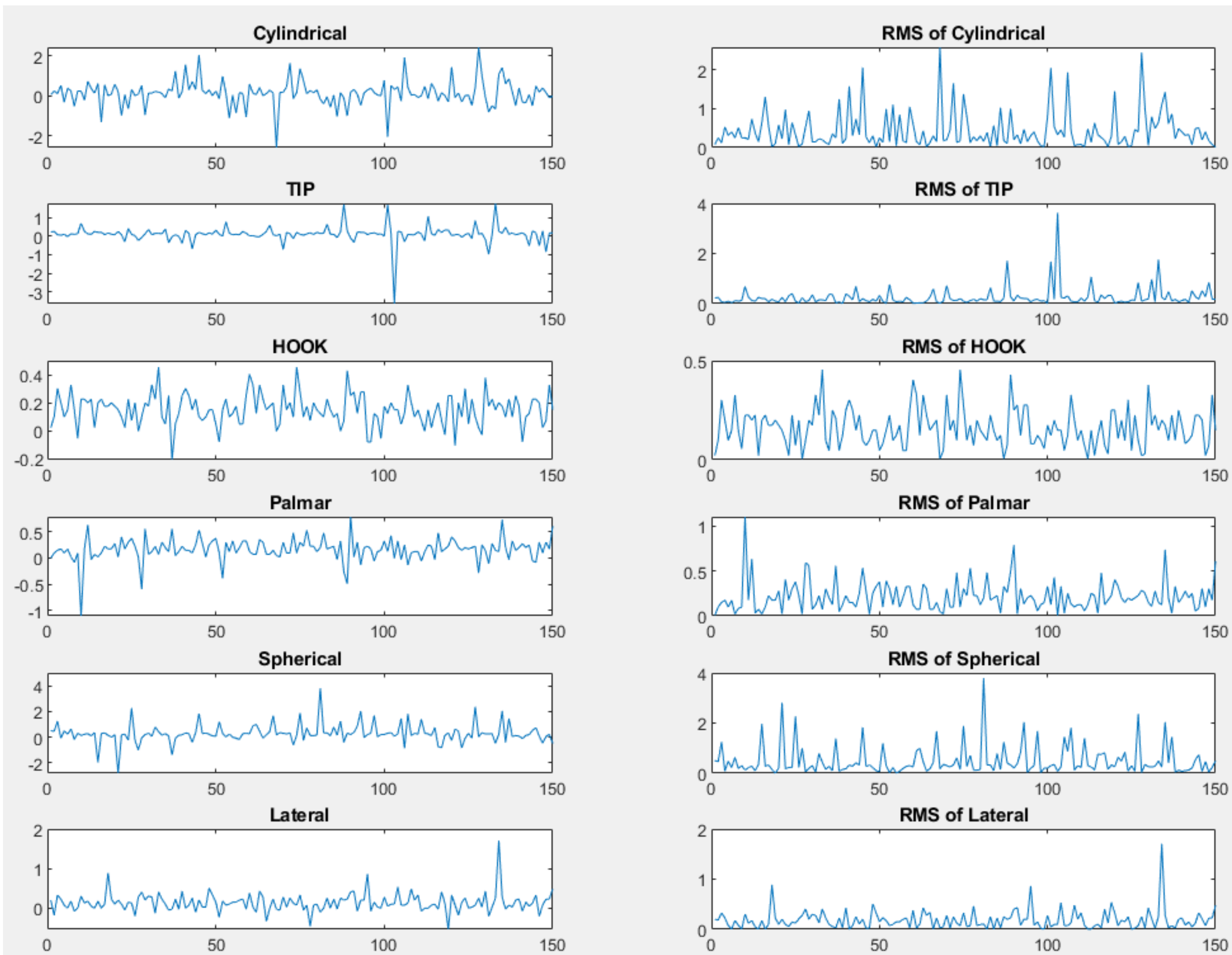
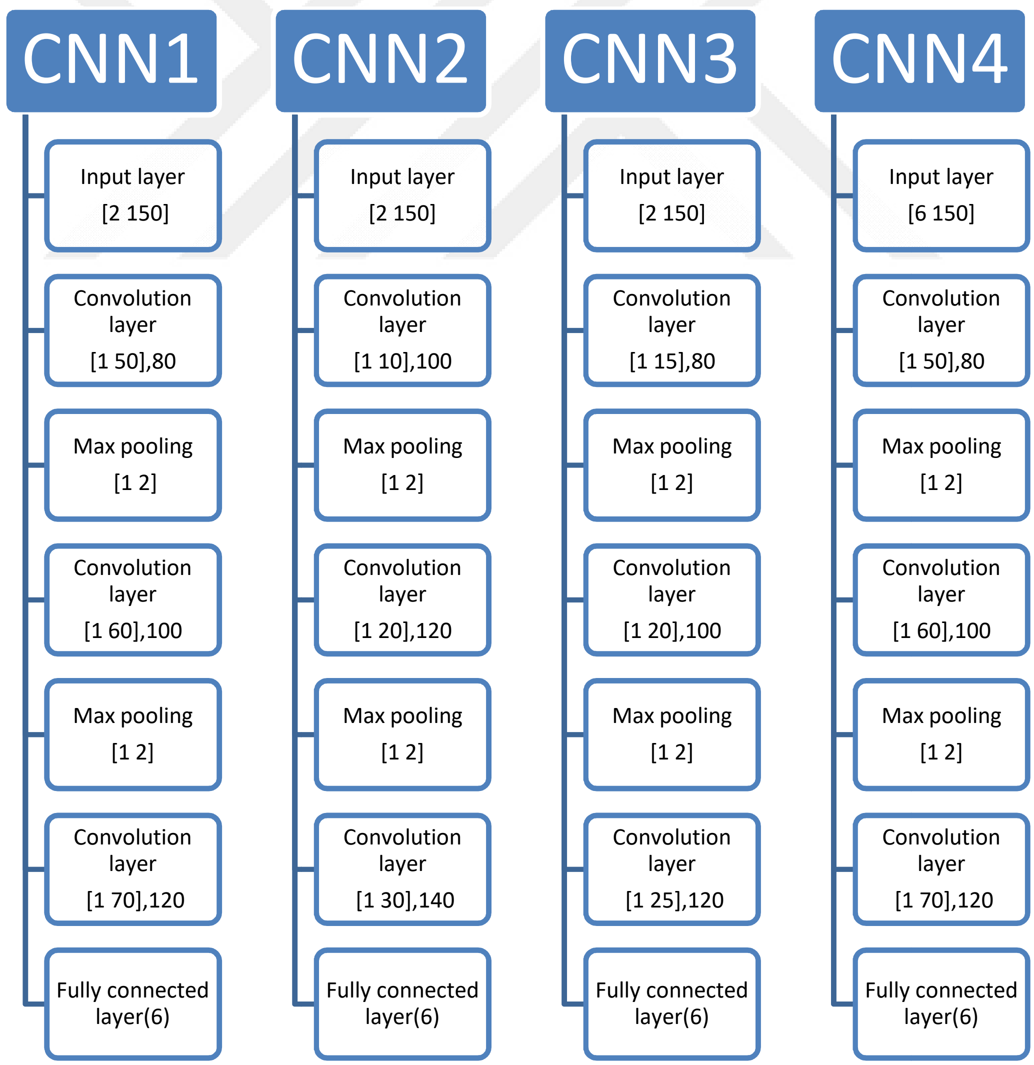


Figure 4. 9: Windowing signal and RMS of each signal.

4.3 Experiment and Results

The general structure of CNN is given in Section 3.2. In this section experiment methods and result will be given. Firstly, CNNs will be examined in 4 main groups according to the input signals for better explanation. Afterwards their accuracy with the cross validation and normal separation methods will be given.

- CNN1: The raw signal with 150 ms windowing.
- CNN2: FFT of the raw signal.
- CNN3: RMS of the raw signal.
- CNN4: IMFs of the raw signal.



Input Layer: This layer is where the input size specified. Size is [2 150] for CNN1, CNN2 and CNN3 because data is coming from 2 channel and [6 15] for CNN because for every data from each channel there are 3 IMF.

Convolutional Layer: In the Convolutional layer, the first argument represents filter size; training function uses this filter while scanning along the input data. The second argument is the quantity of filter with that size, which is the quantity of neurons that associate with the same part of the input.

Max Pooling Layer: The max pooling layer is doing down-sapling and returns the maximum values of rectangular area of input which specified by the argument.

Fully Connected Layer: This layer combines all the features learned by the past layers. The last fully connected layer combines features to classify the signal. So the size of the last fully connected layer should be same with the number of classes as shown in last page. Number of classes are 6 for this study.

The optimum values of the number of layers and parameters were obtained heuristically in Network architecture. There are batch normalization layer and RELU layer after every Convolutional layer, finally after fully connected layer there are softmax layer. These layers are described in Section 3.2.3.

After choosing Network architecture, training options should be specified. Stochastic gradient descent with momentum (SGDM) is chosen to train the network with an initial learning rate of 0.01. Maximum number of epoch is chosen as 6, an epoch means full training cycle on the whole training data set and the data is shuffled in every epoch. Some trail parameters and results are given in table 1.

Table 1: Some trails for choosing optimum values.

Number of CNN	Convolution layer	Max pooling	Training option	Learning rate	Epoch	Result
CNN1	[1 12],10 [1 12],10 [1 12],10	2	Sgdm	0.01	4	75.72%
CNN1	[1 20],20 [1 20],20 [1 20],20	2	adam	0.001	6	75.39%
CNN2	[1 50],50 [1 50],60 [1 50],70	2	Sgdm	0.01	9	69.16%
CNN2	[1 50],50 [1 60],50 [1 70],50	2	Sgdm	0.01	6	65.81%
CNN3	[1 50],50 [1 50],60 [1 50],70	2	Sgdm	0.01	6	86.09%
CNN3	[1 20],80 [1 30],100 [1 40],120	2	Sgdm	0.01	6	87.48%
CNN4	[1 15],30 [1 25],40 [1 35],50	2	sgdm	0.01	6	81.94%
CNN4	[1 20],50 [1 30],60 [1 40],70	2	Sgdm	0.01	6	86.54%

Network accuracy is followed from the monitor during training section with validation frequency with 30 iterations. The network trains on the training data and calculates the accuracy on the validation data.

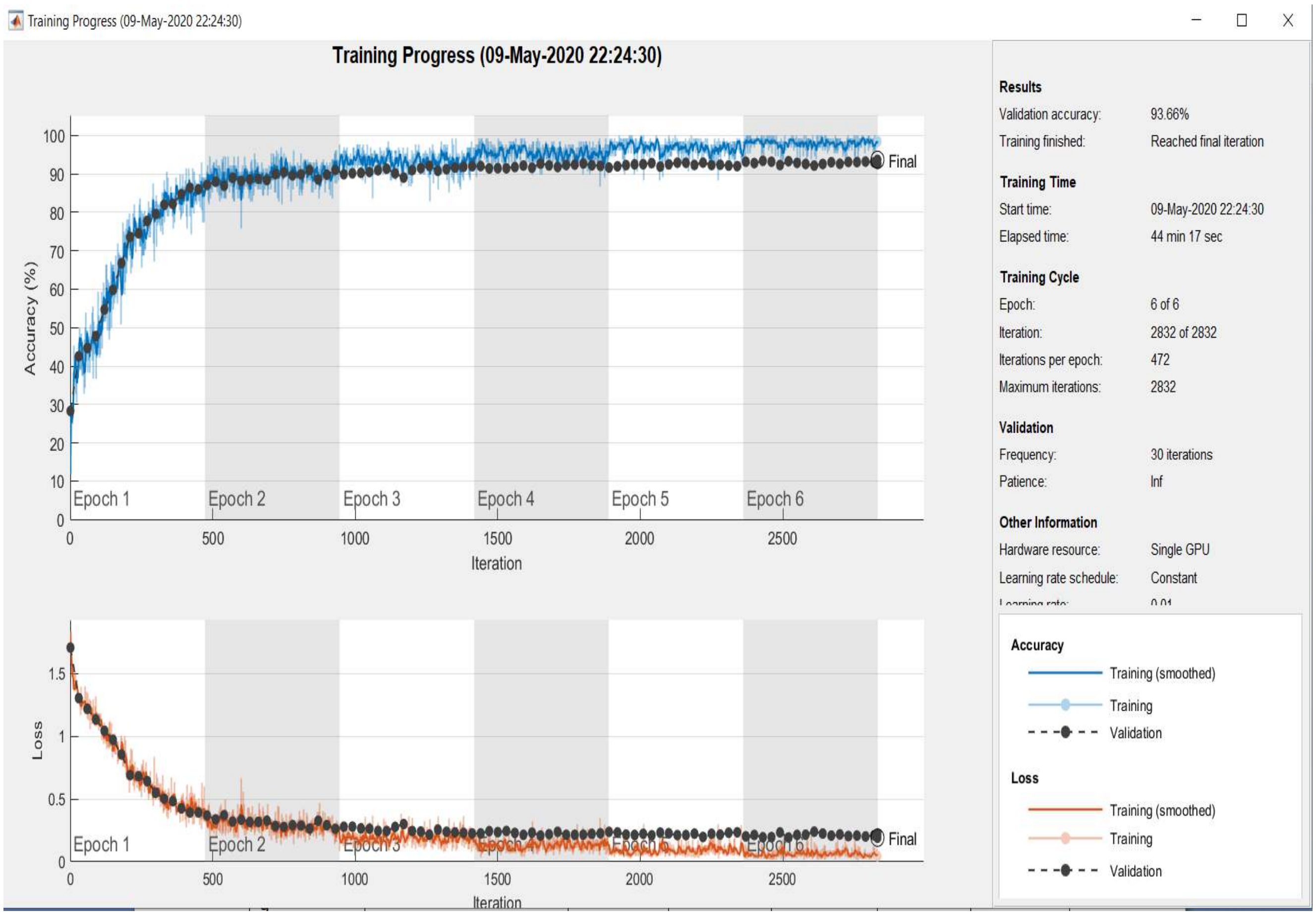


Figure 4. 10: Result of CNN4

A confusion matrix is used to visualize the performance of a network. On the confusion matrix, the rows shows the predicted class and the columns relate to the true class. The diagonal cells show the observations that are correctly classified. The off-diagonal cells show to incorrectly classified observations. Both the quantity of observations and the level of the total number of observations are shown in every cell. With confusion matrix we can see the number and percentage of the true and false predictions for each class.

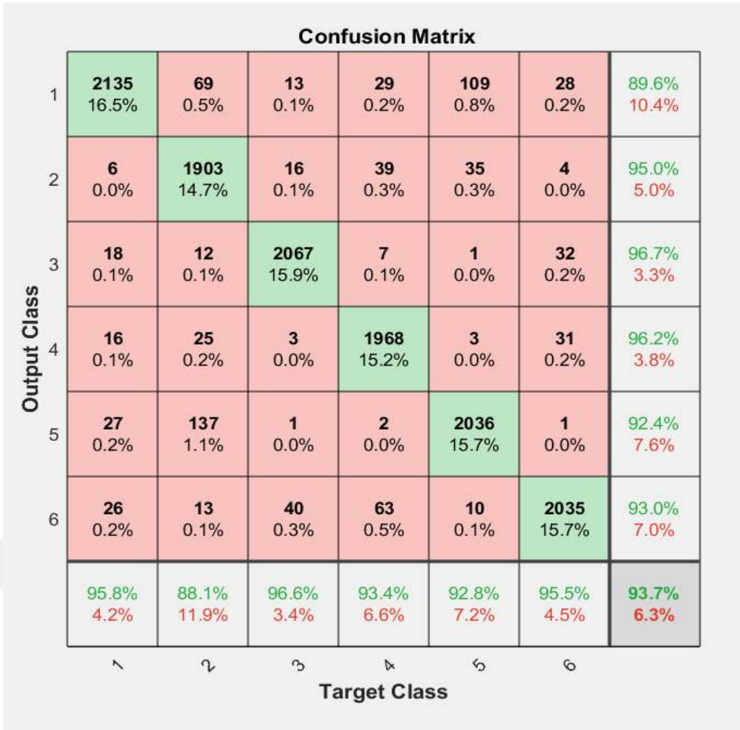


Figure 4. 11: Confusion matrix of CNN4.

The results of CNNs trained with 70% train set, 15% validation and 15% test set are given in table 2.

Table 2 : Results of Convolutional Neural Networks.

Dividing	Validation accuracy	Test Accuracy
CNN1	91.50%	91.57%
CNN2	69.16%	68.54%
CNN3	88.76%	87.80%
CNN4	**93.66%**	**93.70%**

CNN1:The signal with 150 ms windowing, CNN2:FFT of the signal, CNN3:RMS of the signal, CNN4:IMFs of the signal.

After constructing the network parameters, 5-fold cross-validation is applied to have more accurate simulation results. The results of CNNs trained with k=5 cross validation Test set are given in Table 3.

Table 3 : Final results of Convolutional Neural Networks

Dividing	Average Test Accuracy
CNN1	90.62%
CNN2	67.30%
CNN3	88.59%
CNN4	**95.90%**

In first step CNN1 and CNN4 accuracy was not so different but with cross validation we get more reliable results so we can say that EMD increase the success of classification. The lowest accuracy was taken from CNN2, because the frequency values of the movements are close to each other so the FFT method is not efficient for this study. The results show that CNN is a promising classifier even the raw signal is applied to the classifier. Also, it has been observed that EMD method creates better classification accuracy.

CHAPTER 5
CONCLUSION

Many machine learning algorithms such as deep learning algorithms have been designed and successfully applied to solve EMG classification problems. In this thesis, Convolutional neural network is used to increase classification success without doing feature extraction from data. CNN has better generalization capability than any other network mode with deep feeding architecture and a layer that is fully connected in its structure. The main reason for using CNN in this study is that, CNN greatly reduces the number of features required for training and complex artificial neural network and classic neural network models can sometimes be more difficult to design than CNN. The disadvantage of CNN for this study is the large number of data required for training and the length of training time, but rapid results were obtained from the test set provided after training was completed so that it can be used as real time classification.

According to the results of this study, CNN has been successfully in classifying EMG signals. Received signals are trained with four different CNN according to the difference of input signals and two different preprocessing methods are applied to these four CNN. When the appropriate parameters were set, the success rate of the windowed signal in the test set increased to 91.57%. When FFT is applied to this signal, the success rate has decreased to 68.54%. As it can be understood, the frequency ranges of the chosen hand movements have not enough difference for classification. Similarly, when RMS was applied to the signal, the success rate decreased to 87.80% due to the loss of negative part of the signals. However when applying EMD to this signal and inserted into CNN, the best success rate was achieved with 95.90%. Thus it has been seen that using the IMFs of the signal for classification gives better results.

Classification of the EMG signal is known to assist in the development of bionic hands as well as to identify clinical diagnoses. The methods used in this thesis were tried to contribute to increase the classification success and performance of the EMG signal. It is thought that the results obtained will contribute to new studies.

In future, CNN based classification can be try on real time classification applications or accuracy can be increased with other deep learning architectures, also arrangements can be made for clinical diagnoses, and it can be used to control bionic arms.

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