FEATURE EXTRACTION OF THE FOREARM MOVEMENT USING ELECTROMYOGRAPHY

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Abstract

Electromyography is a technique for determining muscle activity levels. When a muscle contracts, an action potential is created and propagates across the muscle fibers. Electromyography involves the connection of electrodes to the skin and the measurement and plotting of the electrical activity of muscles. Since there was not much research involving the usage of Python in EMG feature extraction and pattern recognition, the aim of this study to the feature extraction of forearm movement from individuals who were post-stroke and also healthy individuals was proposed using Python. Next, several existing EMG feature extraction methods were proposed; Time Domain features and Frequency Domain Features. Time Domain features consist of Variance (VAR), Root Mean Square (RMS), Integrated EMG (IEMG), Wavelength (WL), and Zero Crossing (ZC). Frequency Domain Feature consists of Mean Frequency (MNF) and Median Frequency (MDF). A number of features are robust across different kinds of noise and most of the TD and FD features are superfluity and redundancy, thus the reduction of computational time caused by redundant features is achieved.

Keywords: Electromyography, Feature Extraction, Post-Stroke

1 Introduction

Surface electromyography (sEMG) has been utilized in research, healthcare, and other disciplines such as ergonomics and brain-machine interfaces for many years [1]. sEMG established itself as a tool for measuring, analyzing, diagnosing, and controlling muscle contractions (motor) in humans. sEMG is one of various approaches and technologies accessible to scientists and professionals across a range of disciplines, including neurology, rehabilitation, kinesiology, and biomechanics [2]. sEMG electrodes are used to record the action potentials of muscle fibres in muscle bundles beneath the skin. Surface electrodes provide a non-invasive approach for EMG signal extraction. However, because the EMG surface signal is stochastic, it is more difficult to examine than other well-known bio-electrical signals (e.g., electrocardiogram, ECG; electrooculogram, EOG; and galvanic skin reaction, GSR) [3]. The pattern recognition process is often based on derived values from the initially received data, which are referred to as features. These features are then utilized to train classifier algorithms, which predict the classes of new but comparable sets of data. Following the selection of the desired features, these features are extracted from segmented raw EMG data by segmenting the data into overlapping windows, and these windows are split into training, validation, and testing sets.

2 Literature Review

2.1 History of EMG

Luigi Galvani, an Italian physicist and biologist who taught obstetrics at the University of Bologna from the 1770s onwards, discovered "animal electricity" when he hung the fresh body of a dead frog on a copper hook with a steel wire during a rainstorm and witnessed muscular contraction. When his helper touched the motor nerve with an electrostatically charged scalpel, he saw that an electrostatic charge given to a nerve causes muscle contraction. Carlo Matteucci replicated Galvani's experiment and validated his discovery in the 1840s. Later, the introduction of the galvanometer resulted in the identification of an electric signal flowing on the muscle surface during contraction, which opened up a new vista in a human electrophysiological study [4].

Guillaume Benjamin Duchenne invented electrodes and simulation equipment in the 1850s and utilised these to discover that distinct muscles could be innervated by delivering an electric signal to certain surface spots [4]. Electromyography (EMG) became clinically acceptable after the introduction of the string galvanometer, the cathode ray tube, and other safety devices. The Nobel laureates Joseph Erlanger and William Osler found that the conduction velocity of nerve fibres is proportional to their physical diameter. Fritz Buchthal developed microelectrodes in the twentieth century to capture the action potential of each muscle fibre.

During WWII, Martin Glover Larrabee worked at Framingham Hospital, where he and his co-workers collected compound muscle action potential (cMAP) from the muscular surface. Meanwhile, George Dawson worked on signal averaging and photographic superimposition techniques, as well as recording sensory nerve action potentials (SNAPs) [4]. Then, Edward Lambert established the first electromyography (EMG) laboratory at the Mayo Clinic in the United States in 1943.

Erik Stålberg later explored the electrical signal velocities via muscle fibres. He also discovered normative mean jitter values in several muscles, which led to the electromyography (EMG) of a single fibre, making it easier to identify abnormalities in neuromuscular transmission. The first commercial EMG equipment for neuromuscular problem diagnosis was invented in 1948 by three scientists named James A. Fizzel, James Golseth, and Herbert Jasper [5].

2.2 EMG

Electromyography is abbreviated as EMG. It is the examination of electrical impulses generated by muscles. EMG has grabbed the interest of biological researchers due to its potential for identifying EMG patterns [6]. Motor unit action potential trains are generated as a result of this continuous activation. The EMG signals are formed by the superposition of these trains from the concurrently operating motor units. EMG can be detected actively with electrodes injected into muscle tissue or indirectly with surface electrodes mounted above the skin in most cases.

Surface Electromyography (sEMG) is widely recognized in the health sector due to the ease with which electrodes are applied to the patients under examination and the short time it takes to assess the signals. The sEMG signal may be used to determine muscle motor functioning since the amplitude and other features of the signal obtained are directly connected with muscle activity [7]. Because of its ease of use and lack of invasiveness, the sEMG is more common. The EMG detector, on the other hand, collects signals from multiple motor units at the same time, particularly if it is placed on the skin surface, causing various signals to interact.

2.3 Anatomy of the Forearm

Muscle contractions are studied using EMG data. In order to perform feature extractions in this study, raw EMG data from the forearm must be retrieved. As a result, the forearm anatomy theory is revisited. Humans are divided into three categories. There are three types of muscle: skeletal, smooth, and cardiac. Skeletal muscles are the muscles that allow the bones to move. The experiment involving forearm movement is carried out in this study. As a result, the kind of muscle employed in this study will be the Flexor carpi radialis and Extensor carpi ulnaris muscle of the
forearm.

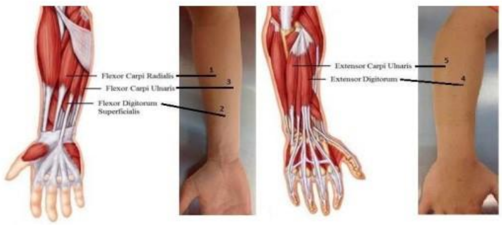

Figure 1: Only two Forearm muscles were used in sEMG acquisition (1) Flexor Carpi Radialis and (5) Extensor Carpi Ulnaris [8].

2.4 Feature Extraction

Feature extraction is the process of converting raw signal data into a useful data structure by filtering out noise and emphasizing significant information [9]. To improve performance in the classification of biological signals, feature extraction and dimension reduction are necessary. In addition, feature extraction is used to extract features from the original signal in order to achieve accurate classification. The most important element of biomedical signal classification is feature extraction since if the features aren't chosen carefully, the classification performance might decrease [10].

Time-domain feature extraction includes Variance (VAR), Integrated Electromyography (IEMG), Root Mean Square (RMS), Zero Crossing (ZC), and Waveform Length (WL). The time domain characteristics are assessed as a function of time. The time-frequency domain features extracted from EMG data are Median Frequency (MDF) and Mean Frequency (MNF). Frequency domain characteristics are commonly utilized to diagnose neurological disorders and muscular fatigue. Normally, this feature extraction is accomplished by the examination of the EMG signal spectrum.

2.5 Previous Studies

2.5.1 Individual hand motion classification through EMG pattern recognition: Supervised and unsupervised methods [11].

(Castiblanco et al. 2016) have stated that “In order to detect and categorize hand movements, Electromyography (EMG) signals are employed in electronic devices with biofeedback control. Due to various EMG signals between individuals which made it. difficult to discern movement in these systems, numerous pattern recognition approaches have been introduced to tackle this difficulty. In response to the prior issue, the current research analyses the performance of K - means and Support Vector Machine (SVM) approaches in identifying five different hand movements. As a result, two classification methods were used: the first method consisted of identifying the motions separately. The second one classified all five motions using a decision tree-based technique. In addition, the impact of signal normalization on classification performance is examined in this article. As a result, The SVM classifier yielded a success rate of 92% in the bulk of the tests in both strategies. K means, on the other hand, indicates 55% for the first approach and 75% for the second. In both tests, the SVM classifier outperformed the K means with an error rate of less than 9%. When the EMG data are normalized and a window size of 0.3 seconds is used, the classifier's accuracy improves.

2.5.2 Combined Influence of Forearm Orientation and Muscular Contraction on EMG Pattern Recognition[12].

(Khushaba, 2016 et al.) stated that the accuracy of EMG categorization was investigated using a variety of contemporary time- and frequency-domain EMG characteristics. Twelve subjects with intact limbs and one participant with bilateral transradial (below-elbow) amputation were recruited. They conducted six different wrist and hand movements at three different degrees of muscle activity and in three different forearm orientations. The results demonstrated that a classifier trained on features that measure the angle of muscle activation patterns, rather than their amplitude, outperforms other feature sets across a range of contraction intensities and forearm orientations.

2.5.3 Featureless EMG pattern recognition based on the convolutional neural network [13].

(Too, 2019 et al.) the research addressed the feature extraction problem by offering a featureless EMG pattern recognition technique that does not require any features. The raw EMG signal was first converted to a time-frequency representation using (TFR) a spectrogram. To categorize the data, the TFRs or spectrogram images are instantly loaded into a convolutional neural network (CNN) for classification. Two CNN models were described for automatically extracting features from spectrogram images, obviating the need for human feature extraction. The proposed CNN models were evaluated using EMG data from the publicly accessible NinaPro database.

2.5.4 A Review on Electromyography Decoding and Pattern Recognition for Human-Machine Interaction [14].

(Simão, 2019 et al.) the article conducts a review of the literature on electromyography (EMG) signal pattern identification and its applications. The EMG technology is introduced, and the most critical parts of designing an EMG-based system, such as signal collection and filtering, are addressed. With varying degrees of effectiveness, EMG-based systems have been used to operate upper- and lower-limb prostheses, electrical gadgets, and machinery, as well as to monitor human behavior. Nonetheless, present systems remain insufficient and are frequently abandoned by their users, necessitating additional study. Apart from controlling prostheses, EMG technology enables the development of machine learning-based devices capable of recognizing the intention of able-bodied users and so paving the way for novel human-machine interaction (HMI) modalities.

2.5.5 Muscle Activity Distribution Features extracted from HD sEMG to perform Forearm pattern Recognition [15].

(Nougarou, 2018, et al.) proposed a more intuitive control of a robotic arm used by some of the disabled by using an efficient pattern recognition system based solely on forearm surface Electromyographic (sEMG) data. HD sEMG, unlike simple sEMG, can produce muscle activity pictures with different spatial distributions depending on forearm movement. The recognition method locates nine forearm movements with high classification accuracy based on these parameters (99.23 %). The findings show the potential of the suggested recognition system and its good performance-complexity trade-off in terms of a number of learning data, image resolutions (spatial filtering), and the number of sub-images.

3 Methodology

3.1 Preparation

1. For reference, the subject's weight, height, and hand length are measured and documented.
2. Subjects are sat in an armchair with their forearm supported and fixed in a single position to eliminate the effect of variable limb postures on the produced EMG signals.
3. Scrub the electrode patch regions with a paper towel or alcohol swab to remove excess skin oil and moisture. Hair is removed.

Figure 2: The placement of the red and green electrodes on flexor carpi radial muscle.

Figure 3: The placement of the red and green electrodes on the extensor carpi ulnaris muscle.

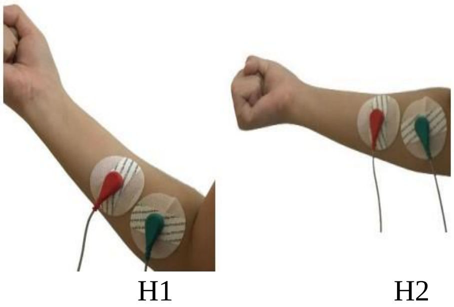

Figure 4: Forearm flexion (H1), and hand contraction 2 (H2)

To train the pattern classification algorithm, the trial consists of a session with five seconds repeats for each selected movement. To minimize muscular tiredness that might impact the EMG data generated, each effort is done individually. Extensor carpi ulnaris and Flexor carpi radialis are the muscles where the electrode pads were placed. The analog voltage data of the EMG signals acquired by Muscle Sensor v3 is saved using CoolTerm software. According to each move, the data is recorded in Microsoft Excel.

3.2 Data Collection

The experimental design was established for data collection. This covers the type of data being gathered, the location or body part being measured, the sensor device to be used, and the processing processes to be used, among other factors. Then it's time to construct an ethical screening application that has been granted permission to collect data from human bodies. This requires a good understanding of the research. The data collection process began after the application was approved. The experiment was carried out after choosing a suitable less distracting place and constructing the necessary equipment for the recording method.

The goal of this study is to look at the relationship between forearm EMG signals in a relaxed state, hand contractions, and forearm flexions. The data will be used for signal processing and analysis, as well as for pattern recognition. A non-invasive approach is used to obtain EMG signals from human upper forearm muscles. Two volunteers are used in a series of studies to acquire EMG data for varied hand angles and movements. The participants are a post-stroke participant (58 years old) and a healthy participant (24 years old), both of whom are men. Before the study, all subjects were given an oral briefing and given the opportunity to give their informed consent. This data collection includes the following four experiments:
i) EMG signal extraction from forearm muscles in relaxed posture;
ii) EMG signal extraction from forearm and upper arm muscles giving
hand contractions.
iii) EMG signal extraction from forearm flexion.

4 Result and Discussion

4.1 The Result from Data Collection

As stated previously, data was collected from two individuals over the course of 5 sessions. Five repetitions of the specified movements made up a session. The individuals were told to relax in between motions for a few seconds and to make each movement as natural as possible. The amount of force exerted by the individuals during arm movements was neither restricted or measured in any way. One is a healthy subject (24 years old) and another one is a post-stroke subject (58 years old).

During the data collection process, the signal was recorded during basic hand movements. Note that the signal that is measured are signals that have been filtered and rectified by the EMG muscle sensor v3. Since the Arduino IDE built-in serial plotter and monitor do not allow for data to be written to a file right away, the CoolTerm serial monitor program is used for the output to be taken into a text file, then sent the data to Microsoft Excel to produce the EMG signal below.

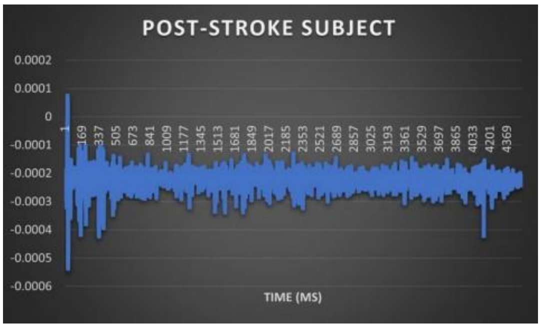

Figure 5: The EMG signal taken from post-stroke subject

Figure 6: The EMG signal taken from a healthy subject

4.2 Feature Extraction for Time Domain

Referring to the figures below, the amplitude of the input signal is used to compute time-domain characteristics. With certain limits, the resulting numbers provide a measure of the waveform amplitude, frequency, and duration.

In this stage, a 58-year old post-stroke subject and a 24-year-old healthy subject performed 5 sessions per day for 3 separate days for each of two movements, flexing and contracting the hand, using 1 sensor for receiving data. The total duration of each measurement is 4 secs with 100 samples per sec, i.e. delay (10) (100Hz), having six characteristics of the raw signal: maximum value, absolute average, waveform length, number of slope changes, Willison Amplitude, and standard deviation.

Based on figure 7, Variance is the average of the square values of the variable's deviation. The red line is the signal which is already extracted from the original signal (blue line) by implementing the Time Domain (TD) features; The variance of EMG (VAR) is a useful characteristic that reflects the strength of the EMG signal. Figure 8 shows the results of where the Root Mean Square (RMS) is modeled as an amplitude modulated Gaussian random process, with the RMS being associated with constant force and non-fatiguing muscular contractions. Feature extraction using the RMS approach is fairly popular. Because it is computationally efficient and speedy while retaining important data. From figure 9, Integrated EMG (IEMG) is a pre-activation indicator for muscle activity that is commonly used. It's the area under the rectified EMG signal's curve. The sum of the absolute values of the EMG amplitude can be used to approximate IEMG. The Waveform Length (WL) in figure 10 is the total length of the waveform over the segment, which is another improvement of the IEMG feature. Zero crossing (ZC) is a time-domain measure of frequency information in the EMG signal. The ZC computation for signals incorporates additional criteria in addition to the confidence of whether the signal passed through zero or not, because at the moment of signal extraction, in many instances, ambient or line noise is also read.

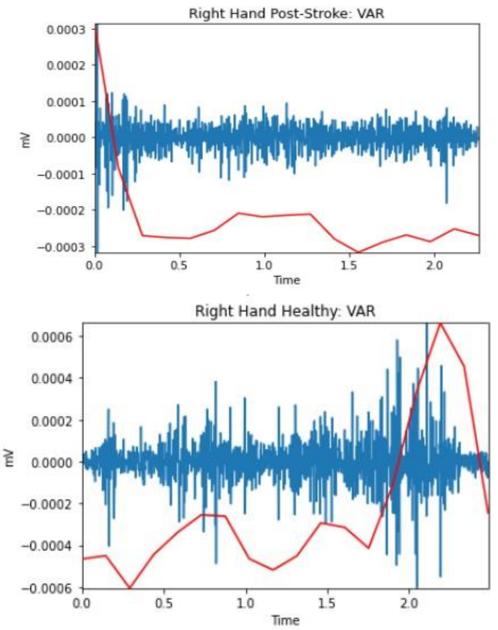

Figure 7: Time-domain feature extraction for Variance (VAR) for both subjects

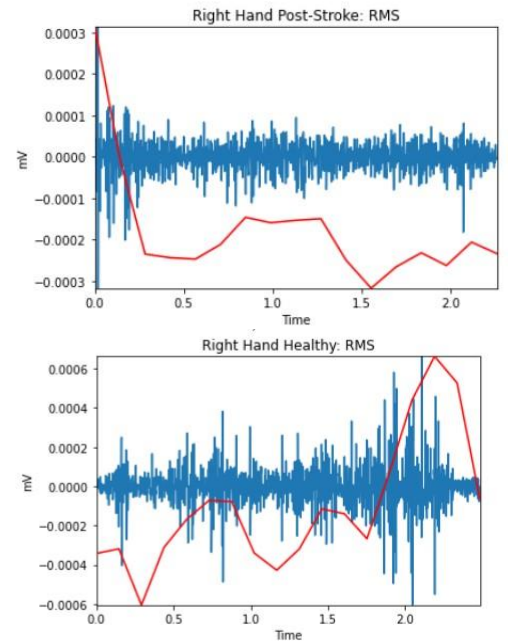

Figure 8: Time-domain feature extraction for Root Mean Square (RMS) for both subjects.

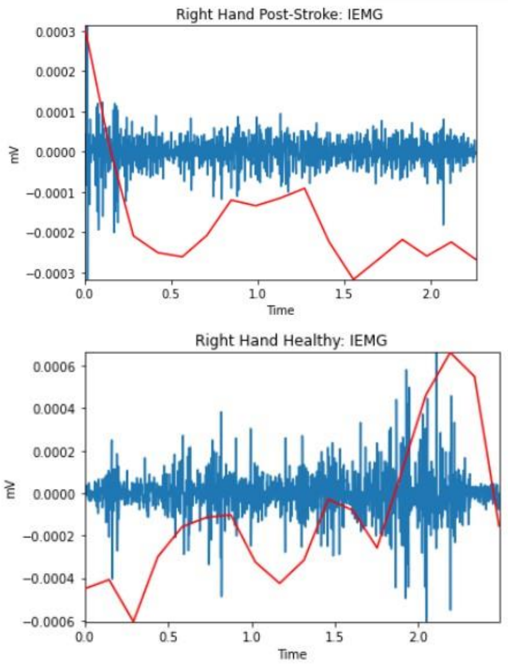

Figure 9: Time-domain feature extraction for Integrated EMG (IEMG) for both subjects.

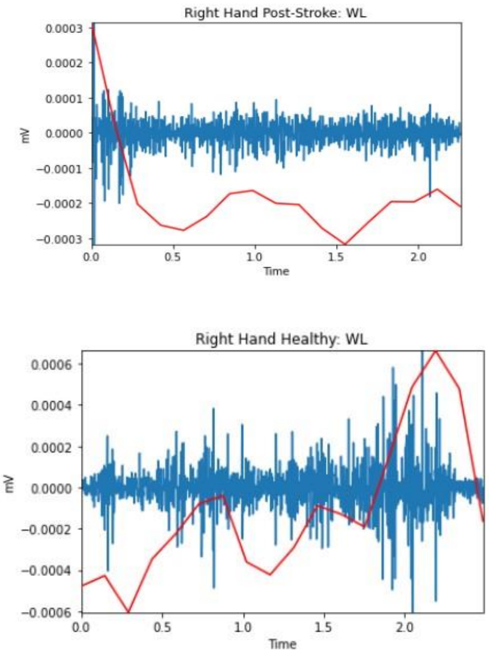

Figure 10: Time-domain feature extraction for Wavelength (WL) for both subject

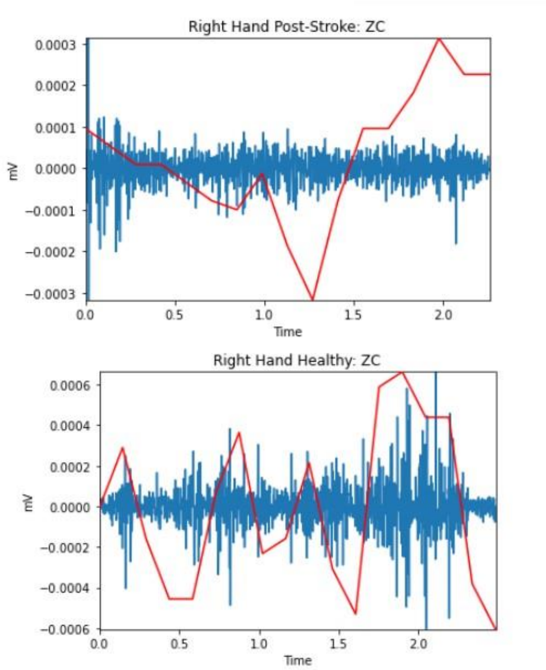

Figure 11: Time-domain feature extraction for Zero Crossing (ZC)

4.3 Feature Extraction for Frequency Domain

Based on figure 12 and figure 13, shows the difference between the signals which has undergone the Frequency Domain series feature (red line) and the original signal (blue line). Given the fact that muscle fatigue causes a downward shift in the frequency spectrum of the EMG signal, MNF and MDF have been lauded as the gold standard for muscle fatigue evaluation with surface EMG data. MNP can be utilized as a muscle tiredness indicator, despite the fact that EMG signal amplitude is rarely employed to diagnose muscle fatigue. MNF has the robustness tolerance of white Gaussian noise and power line interference.

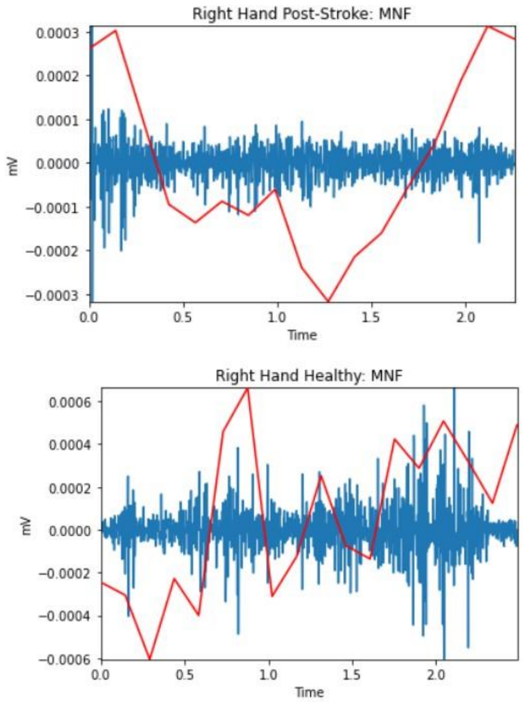

Figure 12: Frequency domain feature extraction for Mean frequency (MNF)

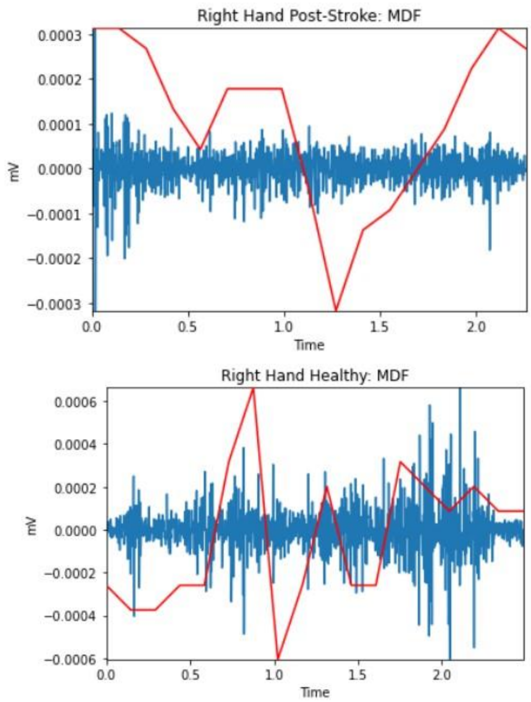

Figure 13: Frequency domain feature extraction for Median frequency (MDF)

5 Conclusion

The main purpose was in this paper was to feature extraction of basic forearm movements and the construction of the application. Several features were chosen from Time Domain and also a few features from Frequency Domain. Variance (VAR), Root Mean Square (RMS), Integrated EMG (IEMG), Zero Crossing (ZC), Mean Frequency (MNF), and Median Frequency (MDF) are the seven optimal features included in this study. A number of features are robust across different kinds of noise and most of the TD and FD features are superfluity and redundancy, thus the reduction of computational time caused by redundant features are achieved.

6 References

1. Manzur, H., & Alvarez-Ruf, J. E. (2020). Surface electromyography in clinical practice. A perspective from a developing country. Frontiers in Neurology, 11, 1236.
2. Medved, V., Medved, S., & Kovač, I. (2020). Critical appraisal of surface electromyography (sEMG) as a taught subject and clinical tool in medicine and kinesiology. Frontiers in Neurology, 11.
3. Padmanabhan, P., & Puthusserypady, S. (2004, September). Nonlinear analysis of EMG signals-a chaotic approach. In The 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (Vol. 1, pp. 608-611). IEEE.
4. Kazamel, M., & Warren, P. P. (2017). History of electromyography and nerve conduction studies: A tribute to the founding fathers. Journal of Clinical Neuroscience, 43, 54-60.
5. Treidler, S. (2020). Overview of electromyography and nerve conduction studies. MedLinkNeurology.
6. Too, J., Abdullah, A. R., & Saad, N. M. (2019). Classification of hand movements based on discrete wavelet transform and enhanced feature extraction. Int. J. Adv. Comput. Sci. Appl, 10(6), 83-89.
7. Chandrasekhar, V., Vazhayil, V., & Rao, M. (2020, July). Design of a real-time portable low-cost multi-channel surface electromyography system to aid

neuromuscular disorder and post-stroke rehabilitation patients. In 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC) (pp. 4138-4142). IEEE.

8. Roell, J., Sikula, J., & Desai, J. (2015). Real-time individual finger movement of a Mecha TE robotic hand using human forearm EMG signals through hardware-software communication. Sch. J. Eng. Technol, 3, 252-257.
9. Spiewak, C., Islam, M., Zaman, A., & Rahman, M. H. (2018). A comprehensive study on EMG feature extraction and classifiers. Open Access Journal of Biomedical Engineering and Biosciences, 1(1), 1-10.
10. Subasi, A. (2019). Chapter 4-Feature Extraction and Dimension Reduction, Practical Guide for Biomedical Signals Analysis Using Machine Learning Techniques.
11. Castiblanco, C., Parra, C., & Colorado, J. (2016, August). Individual hand motion classification through EMG pattern recognition: Supervise and unsupervised methods. In 2016 XXI Symposium on Signal Processing, Images and Artificial Vision (STSIVA) (pp. 1-6). IEEE
12. Khushaba, R. N., Al-Timemy, A., Kodagoda, S., & Nazarpour, K. (2016). Combined influence of forearm orientation and muscular contraction on EMG pattern recognition. Expert Systems with Applications, 61, 154-161.
13. Too, J., Abdullah, A. R., Saad, N. M., Ali, N. M., & Zawawi, T. T. (2019). Featureless EMG pattern recognition based on convolutional neural network. Indonesian Journal of Electrical Engineering and Computer Science, 14(3), 1291-1297.
14. Simão, M., Mendes, N., Gibaru, O., & Neto, P. (2019). A review on electromyography decoding and pattern recognition for human-machine interaction. IEEE Access, 7, 39564-39582.
15. Nougarou, F., Campeau-Lecours, A., Islam, R., Massicotte, D., & Gosselin, B. (2018, October). Muscle activity distribution features extracted from HD sEMG to perform forearm pattern recognition. In 2018 IEEE Life Sciences Conference (LSC) (pp. 275-278). IEEE