Hand Gesture Classification Using Features of Multivariate Synchrosqueezing Transform Based Time-Frequency Matrix

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by

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This is to certify that we have read the thesis **Hand Gesture Classification Using Features of Multivariate Synchrosqueezing Transform Based Time-Frequency Matrix** submitted by **Lütfiye Sarıpınar**, and it has been judged to be successful, in scope and in quality, at the defense exam and accepted by our jury as a MASTER'S THESIS.

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- Where I have quoted from the work of others, the source is always given. This thesis is entirely my own work, with the exception of such quotations.
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Abstract

Hand gesture recognition is a procedure for the classification of meaningful hand gestures for human-computer interaction. Surface electromyography (sEMG) is frequently used in hand gesture classification studies as it carries intrinsic information related to intended gestures. This thesis study presents the comparison of classification success of features extracted from TF matrices and features extracted from TF matrices by the NMF method. TF matrices were obtained by applying MSST to 250 ms four-channel sEMG signals. A publicly available dataset containing surface EMG (sEMG) signals of 40 subjects performing 10 hand gestures, was used. In this study, the four joint time-frequency (TF) moments; mean, variance, skewness, and kurtosis of TF matrix and non-negative matrix factorization (NMF)- based features, which are kurtosis, skewness, standard deviation, sparsity and discontinuity, were proposed as features for hand gesture recognition. The distinguishing power of the feature variables for the tested gestures was evaluated according to their p values obtained from the Kruskal-Wallis (KW) test. It was founded that mean, variance, and skewness properties were statistically significant, while kurtosis was less important for the discrimination of hand sEMG signals of hand gestures. In terms of NMF-based features, discontinuity with the smallest p-value found as the most significant feature for the classification of studied hand gestures. In the last part of the study, machine learning-based classification algorithms are applied to determine the effect of statistical analysis on classification success. Many ML-based classification methods, including SVM, NB and ANN, have been used for the determination of classification success in hand gesture recognition of the two feature sets.

Looking at the classification results, NMF-based features achieved higher classification accuracy than TF moments. However, the obtained classification performance still needs improvement. For this reason, it is seen that different features obtained from MSST matrices, whose effects on EMG-based hand gesture classification are investigated in this thesis, can be developed by using different feature combinations or models. In line with these results, it is predicted that MSST-based features may not be an alternative to hand movement classification with further research.

Keywords: Multivariate Synchrosqueezing Transform, joint time-frequency moments, electromyography, Kruskal-Wallis test, hand gesture recognition, machine learning

Çok Değişkenli Senkron Sıkıştırma Dönüşümüne Dayalı Zaman-Frekans Matrisinin Özelliklerini Kullanarak El Hareketi Sınıflandırılması

Öz

El hareketi tanıma, insan-bilgisayar etkileşimi için anlamlı el hareketlerinin sınıflandırılmasına yönelik bir prosedürdür. Yüzey elektromiyografisi (sEMG), amaçlanan hareketlerle ilgili içsel bilgileri taşıdığı için el hareketi sınıflandırma çalışmalarında sıklıkla kullanılmaktadır. Bu tez çalışmasında, zaman-frekans (TF) matrislerinden çıkarılan özellikler ile TF matrislerinden Negatif Olmayan Matris Çarpanlarına Ayırma (NMF) yöntemiyle çıkarılan özelliklerin sınıflandırma başarısının karşılaştırılması sunulmaktadır. TF matrislerini elde etmek için 4 kanallı sEMG sinyaline Çok Değişkenli Senkron Sıkıştırma Dönüşümü (MSST) uygulandı. Çalışma on el hareketini gerçekleştiren kırk deneğin yüzey EMG (sEMG) sinyallerini içeren halka açık veri seti ile gerçekleştirildi. Çalışmada dört ortak TF momenti; TF matrisinin ortalaması, varyansı, çarpıklığı, basıklığı ve NMF methodu ile çıkarılan basıklık, çarpıklık, standart sapma, süreksizlik ve seyreklik el hareketi tanıma da kullanılmak üzere öznitelik olarak önerilmiştir. Test edilen jestlere ait özellik değişkenlerinin ayırt edici gücü Kruskal-Wallis (KW) testinden elde edilen p değerlerine göre değerlendirilmiştir.El hareketlerine ait sEMG sinyallerini ayırt etmede ortalama, varyans ve çarpıklık özelliklerinin istatistiksel olarak anlamlı olduğu, basıklığın ise daha az önemli olduğu belirlendi. NMF tabanlı özellikler incelendiği zaman el hareketlerinin sınıflandırılmasında istatiksel olarak en anlamlı özelliğin süreksizlik olduğu tespi edildi. Çalışmanın son bölümünde istatistiksel analizlerin sınıflandırma başarısına etkisini belirlemek amacıyla Makine Öğrenmesi (ML) tabanlı sınıflandırma algoritmaları uygulanmıştır. Sınıflandırma sonuçlarına bakıldığında NMF methodu ile çıkarılan özniteliklerin TF momentlerine göre daha yüksek sınıflandırma doğruluğu elde ettiği görülmektedir.

Bununla birlikte, elde edilen sınıflandırma performansının hala iyileştirilmesi gerekmektedir. EMG tabanlı el hareketi sınıflandırmasına etkileri araştırılan MSST matrislerinden elde edilen farklı özelliklerin, farklı özellik kombinasyonları veya modelleri kullanılarak geliştirilebileceği görülmektedir. Bu sonuçlar doğrultusunda ileri araştırmalarla MSST tabanlı özelliklerin el hareketi sınıflandırmasına alternatif olabileceği öngörülmemektedir.

Anahtar Kelimeler: Çok Değişkenli Senkrosıkıştırma Dönüşümü, ortak zaman-frekans momenti, elektromiyografi, Kruskal-Wallis testi, el hareketi tanıma, makine öğrenmesi

I dedicate my thesis to my mother and sister, the two most powerful women in my life

Acknowledgment

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Finally, as always, I would like to present my grateful and deepest love to my family, who has always provided support and encouragement while researching and writing this thesis, and to my little nephew, Eymen Aras AYGÖREN, who has been my source of motivation.

November – 2023 Lütfiye SARIPINAR

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List of Abbreviations

ACC	Accuracy
ANN	Artifical Neural Nerwork
APSO-MKNN	Augmented Partial Swarm Optimization and Modified K-Nearest Neighbor
ASM	Approximate String Matching
CWT	Continuous Wavelet Transform
CLA	Classification Learner App
EMG	Electromyography
FD	Frequency Domain
GT	Gabor Transform
HMI	Human Machine Interfaces
IF	Instantaneous Frequency
IA	Instantaneous Amplitude
İKÇÜ	İzmir Kâtip Çelebi University
KW	Kruskal Wallis
k-NN	K-Nearest Neighbor
LSTM	Long Shortterm Memory
ML	Machine Learning
MSST	Multivariate Synchrosqueezing Transform
NB	Naïve Bayes
NMF	Non-negative Matrix Factorization
ORCID	Open Researcher and Contributor ID
PCA	Principal Component Analysi
RF	Random Forest
sEMG	Surface Electromyography
SD	Standard Deviation

SFM	Spatial Fuzzy Matching
SST	Synchrosqueezing Transform
STFT	Short Time Fourier Transform
SVD	Singular Value Decomposition
SVM	Support Vector Machines
TD	Time Domain
TF	Time Frequency
TFA	Time Frequency Analysis
TFD	Time Frequency Domain
TP-DWT	Ternary Pattern and Discrete Wavelet Transform
TFM	Time Frequency Matrix
TFR	Time Frequency Representation
WT	Wavelet Transform
1D	One-dimensional
2D	Two-dimensional

List of Symbols

Ω_k^b	Instataneous Frequency
A_k^i	Instataneous Amplitude
Ω_k^{multi}	Multivariate Instataneous Frequency
A_k^{multi}	Multivariate Instataneous Amplitude
$T_k^{multi}(\omega,b)$	Multivariate Time-Frequency Coefficients
t^n	Temporal Time Frequeny Moment
ω^m	Spectral Time-Frequency Moment
W	Base Vector
H	Coefficient Vector
S_w	Sparsity Base Vector
S_H	Sparsity Coefficient Vector
D_w	Discontinuity Base Vector
D_H	Discontinuity Coefficient Vector
k	Number of samples
N	Sum of sample size
$\mathcal{P}(X\|Y)$	Posterior Probability
$\mathcal{P}(Y\|X)$	Possibility of Y given X
$\mathcal{P}(X)$	Prior Probability of X
$\mathcal{P}(Y)$	Marginal Probability of Y
p	P value
δ	Dirac Delta Function

Chapter 1

Introduction

1.1 Hand Gesture Recognition

Communication has changed from being only between humans to a new form between humans and machines. Humans use the keyboard, mouse, and touchpad to communicate with machines. The limited possibilities offered by the existing methods have revealed the need for a new method. Hand gestures are the most effective method used to establish communication between machines and humans. Hands are the most efficient communication tools in the body for controlling motion-based devices and using the device with high performance. Hand gestures convey feelings and thoughts, reinforce information conveyed in verbal communication, and establish interaction with objects. Hand gesture recognition, which allows people to interact with smart devices in intuitive ways, is a procedure for the classification of meaningful hand gestures for human-computer interaction. The primary purpose of hand gesture recognition is to create a way of interaction between computers and humans by making the computer more open to user needs and providing meaningful information transfer (Côté-Allard et al., 2019).

Hand gesture recognition system has a wide real-life application area such as intelligent prostheses, control of rehabilitation devices, sign language translation, exoskeletons, human-robot interaction, control of rehabilitation devices, chatbots, natural language processing, control of virtual reality and electric wheelchairs, and many other areas. In hand gesture recognition-based studies, studies are usually carried out on intelligent systems that work with commands from humans (Jaramillo-Yánez et al., 2020; Shuo et al., 2020). Although these applications work with different systems, they were essentially developed to provide interaction between humans and machines. The main purpose of these systems, which assist human movements and actions, is to ensure effective communication between them(Jabbari et al., 2020).

Here, signals that carry information about movement and recorded by the EMG method are generally used. The signals received from the muscles responsible for creating movement in the body are the most preferred signals. The EMG method has more information about the movement than the other methods because the generation of EMG signals is based on physiological processes occurring in skeletal muscles. The EMG measures the electrical signal created by the contraction and relaxation of the muscle that performs the movement. Therefore, the EMG method is the most preferred method in generating the dataset for hand gesture recognition studies(Lee et al., 2021).

1.2. sEMG Signal and Analysis

Electromyography is the discipline that enables the detection, analysis, and use of the electrical signal produced by the contractions of the muscles. EMG signals, which can be obtained using different approaches, have a wide range of applications such as disease diagnosis, limb assit, physiological training, control and rehabilitation processes. The location of the electrodes and the application areas of EMG are shown in Figure 1.2 (Gao et al., 2022). EMG data is divided into noninvasive and invasive, respectively, depending on whether the electrode used to record the signals is placed on the skin surface or invasively within the muscle (Qi et al., 2019).

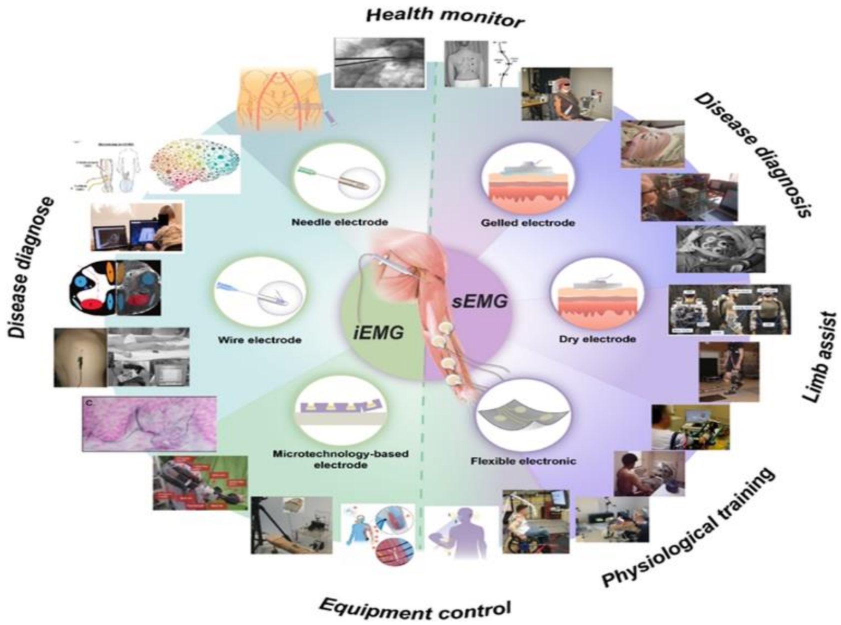

Figure 1.2: The representation of frequently used EMG electrodes and EMG applications(Gao et al., 2022)

While surface EMG (sEMG) is recorded noninvasively from the skin surface, intramuscular EMG (iEMG) signals are measured invasively inside the muscle with the help of a needle or wire. Being noninvasive and easy provides the acceptance of surface electrodes as the ideal method. Additionally, sEMG method provides repeatability and distinguishability for different movements (Milosevic et al.). sEMG examines the sensing, elaboration, and uses of the sEMG signal, measured by non-invasive electrodes from skeletal muscles. The sEMG method measures the bio-electric potential produced by the current obtained from muscle fibers' ionic flow (Webster, 2006). sEMG signals, measured by contraction and relaxation of skeletal muscles, have sufficient information about gestures to generate the input information of intelligent systems. sEMG-based gesture recognition systems are evaluated as promising techniques for improving Human Machine Interaction (HMI). By courtesy of these systems, which allow classification to be entrusted to automatic learning, the need for a full physiological understanding of motor functions is eliminated, and more successful results are obtained. Therefore, sEMG is frequently used in hand gesture classification studies as it carries intrinsic information related to intended gestures (Chen et al.). The biosignals recorded by the sEMG method ensure sufficient information for hand gestures; thus, they are an ideal way to realize gesture-based studies. Therefore, using the sEMG method recorded dataset is preferred in the current study. sEMG signals contain noises and sounds coming from the environment or internal organs. Therefore, preprocessing and cleaning must be performed before using sEMG signals to obtain the relevant information in the most accurate way. Processed signals, free of unnecessary information, are more advantageous than raw sEMG signals(McManus et al., 2020).

After the pre-processing process, various analysis methods are applied to the signals to analyze them more deeply and obtain various information. Analysis of EMG signals can be done from different domains such as time domain (TD), frequency domain (FD) and time-frequency (TF) domain. TD has a simpler calculation process and shows the change of the signal over time. FD shows the distribution of the signal energy in the frequency range. In the literature different time-frequency analysis (TFA) methods exist to represent the signal in TFD(Ahsan et al., 2011).

1.3 Time- Frequency Analysis

TF analysis (TFA) methods, which allow a comprehensive examination, are often preferred in the processing of biomedical signals. TFA methods, which enable signals to be represented in the TF domain, are used to obtain signal energy's distribution on the TF domain(Too et al., 2019). They have a time-varying spectrum and are named TF representations (TFR). In this way, it becomes possible to examine the frequency spectrum in a certain time interval or the change of the signal in a certain frequency range over time. In TFA, the signal is characterized on the T versus F axis that shows the variation of frequency over time and provides nonstationary information of EMG signals. TFA method enables determination of when multiple signal frequencies are available by computing a spectrum at specific time intervals. In this way, a better analysis of the signal's frequency spectrum is provided(Huang et al., 1998; Roy et al., 2020).

TFA methods frequently preferred can be listed as Short Time Fourier Transform (STFT), Wavelet Transform (WT), Gabor Transform (GT), and Continuous Wavelet Transform (CWT). Synchrosqueezing Transform (SST) is an effective TFA method that generates a focused and condensed representation of signals in the time-frequency domain (TFD). In this study, Multivariate Synchrosqueezing Transform (MSST) was applied as a TFA technique to obtain TFM from sEMG signals. (Ahrabian et al., 2015; Jabbari et al., 2020).

1.4 Machine Learning Approach

Machine learning (ML) approach is frequently preferred in EMG-based gesture classification studies. Feature extraction is required to classification with ML algorithms. A function of measurements that represent the quantifiable model of the image or object is described as feature. The features that constitute the input information of classification algorithms enable the data to be represented more effectively(Kawanabe, 2012). ML algorithms make predictions by finding the correlations based on the training.

While the prediction performances increase directly to the data quality used in the training stage, the prediction capabilities improve more data as they are used. Therefore, data collection and processing of data require particular attention in the development of ML model(Halevy et al.). Machine learning has two main phases, and the first one is model generation.

In model generation, the algorithm is trained on the transmitted data and generates data representation to use later to predict new outputs. The second step, which involves transmitting the unseen data to the trained model and evaluating the correctness of the obtained output, is called inference. Obtained outputs are used to enhance or rebuild the learning model. The learning stage requires memory and high computational sources with increased data complexity (Wolpert & Macready, 1997). ML models are often preferred because they provide low computational cost, high speed and classification success. Many ML-based classification methods, including Support Vector Machine (SVM), Naïve Bayes (NB), K-Nearest Neighbours (KNN), Random Forest (RF) and Artifical Neural Networks (ANN) have been used for the determination of classification success in hand gesture recognition.

1.5 Literature Review

There are many studies in the literature on multi-channel sEMG signal-based hand gesture recognition and classification, and a few of these studies will be included in this section.

Li et al. worked with 4-channel sEMG in their study, where they suggested a new method to increase the success of gesture recognition. In the first step, they applied S-transform on sEMG signals to increase the details of signal time-frequency characteristics. They divided the TFM output of the ST into 16 sub-matrices throughout the time and frequency axes. Then, they applied multiscale singular value (SVD) decomposition to all sub-matrices to obtain the time-frequency joint features. In the study carried out with nine different gestures, the classification obtained with the Deep Belief Network (DBN) method resulted in high accuracy (%93.33) (Li et al.). Bargellesi et al. (Bargellesi et al., 2019) used a random forest-based wearable motion recording sensor for hand gesture recognition system.

They collected gesture features at various times to measure hand gestures and applied feature extraction procedures to evaluate gestures with different durations and data. The experimental evaluation depends on the gestures dataset from a gesture pool. Tuncer et al.(Tuncer et al., 2020) used sEMG and machine learning in their proposed study to automate the control of prosthetic hands. The method includes a novel ternary pattern and discrete wavelet (TP-DWT) based iterative feature extraction. TP-DWT is a hybrid feature extraction method that uses TP, DWT, and statistical moments together. In the proposed method, 4 different situations were analyzed: classification with traditional classifiers, channel concatenation,2-level feature selection process based feature selection and the TP-DWT network- based feature extraction. The study's results have proven that the proposed method increases the success of sEMG signal recognition. In the study, the highest accuracy rate was obtained with the KNN algorithm of 99.14%. Cho et al.(Cho et al., 2018) developed an interface based on basic personal training to increase the accuracy of gesture recognition in contactless interfaces. In the proposed interface, gestures must be learned directly by each user. The study, which evaluated the recognition of five hand gestures with minimum error, recommends a computer-assisted surgical technique. It was found that the gesture recognition accuracy calculated with SVM and NB classifiers increased by 10% with the self-training method.

Zhang R et al. (Zhang et al., 2022) proposed two machine learning-based methods to define and characterize hand gestures recorded by multichannel sEMG. To determine the sex differences' effect on muscles, they used time features as input for gesture recognition. After feature extraction, statistical analysis was performed with one-way ANOVA. The success of gender differences on classification results was determined with SVM, k-NN and ANN classifiers. The study results showed that gender differences could improve classification results significantly, and the sex label-added ANN algorithm performed the most accurate success (98.4% accuracy). Tavakoli et al.(Tavakoli et al., 2018) studied to identify four gestures with information obtained from a wearable double surface EMG sensor placed on the flexor and extensor muscles of the forearm. In the study, SVM threshold and locking gesture were used to examine rejection tolerance of unwanted gestures. The system, which has the ability to recognize 5 gestures, presented a classification accuracy higher than 95% for a trained user.

Shair et al.(E. F. Shair, 2020) examined the problem experienced in prosthetic movements controlled by EMG signals. They proposed the approach of using time-frequency distribution obtained from sEMG signals measured during finger gestures to control the myoelectric system. The study, based on ten individual and combined finger gestures, analyzes presented a comparison of three machine learning algorithms (SVM, KNN, and Ensemble Classifier). It was conlcuded that the study could provide insight into traditional prosthesis control principles. Zhang et al.(Zhang et al., 2018) proposed an EMG armband that recognizes human gestures based on physiological characteristics to eliminate the failure tolerance of gestures. The aim of the study was to examine the hand gesture recognition system without wearing-independent the EMG armband. They estimated device placement using the temporal location of the armband's wearing position. High recognition accuracy was achieved in the study carried out with RF on the progression and tracking of movements. Mane et al.(Mane et al., 2015) proposed a new technique for classifying single-channel sEMG signals and determining low-level hand movement. They used Wavelet nalysis and ANN to provides EMG-based feature extraction and classification in appropriate time-frequency range, respectively. The study examining palm-closed, palm-open, and wrist extension movements resulted in high accuracy of palm-open motion for all subjects.

Alonso et al.(Alonso et al., 2020) performed the string matching technique to enable real-time analysis of hand gestures. They captured the trajectories of hand joints using the K-means technique and encoded them as strings of characters. The main goal of the study was increase the precision of various gestures by determining the amount of clusters. The sequences were analyzed with Approximate String Matching (ASM) based classifier. Experimental results demonstrated that the proposed method is effective in terms of identifying different gestures and memory allocated. Li et al. (Li et al., 2020) proposed a new method based on spatial fuzzy matching (SFM) with jump motion for the hand gesture recognition. In the proposed method, spatial information matched and fused by the SFM algorithm to generate a fused gesture dataset. For gesture matching, help was taken from the analysis of the fused gesture dataset, which contains the categorized form of gesture frames. As a result of the study, it was concluded that the proposed method can be used for decision making in machine learning-based studies.

In the study (Motoche & Benalcázar, 2018) carried out with the aim of creating a real-time sensitive hand gesture recognition model, sEMG signals were measured by the Myo armband. The proposed model, which completes the recognition of each class in 5 repetitions and is trained for each user, works with a sliding window approach. The study, which included two different feature extractions: pre-processed signal values and results obtained from many functions, resulted in high recognition accuracy in the classification carried out with a three-layer ANN. Tai et al. (Tai et al., 2018) suggested Long Shortterm Memory (LSTM) based new appraoach for the hand gesture recognition. The proposed approach does not require additional devices and allows storing gesture images without needing a database. In the experimental study conducted with the prototype created for performance evaluation, it was observed that proposed model could detect effective movement even in consecutive continuous movements. Moreover, Shi et al.(Shi et al., 2018) generated a bionic hand controlled by sEMG - based pattern recognition system. The study aimed to create a prototype that would identify hand postures and control the produced bionic hand based on analyzed sEMG signals. They used k-NN to measure the hand gesture recognition and imitation success of the sEMG pattern recognition system in four hand postures. The proposed system, which provides high classification accuracy (over 80%) in the study, was able to fill the gap between the features of sEMG signals and the postures of the bionic hand.

Gupta et al.(Gupta et al., 2012) tested a real-time database of hand images of twenty five different people for hand gesture recognition. In the program, which can recognize ten static hand gestures in real time, gestures are classified according to shape-based features. The study, which used skin color segmentation to eliminate the possibility of misperception, recognized hand gestures faster and achieved a high recognition rate. Jalab et al.(Jalab & Omer, 2015) researched four special gestures consisting of play, forward, reverse and stop in their proposed interface to control the media player. In the procedure, a new image containing the subject's hand boundaries was created by segmentation applied to the image captured from the webcam. Then, hand shape features were extracted to detect hand gestures and an ANN was applied to determine classification success. The study that proposed a computer vision algorithm resulted in a classification success of 95%.

Wahid et al.(Md Ferdous et al., 2018) investigated the success of ML algorithms that were not specifically trained in recognizing different hand gesture subjects independently of each other and proposed a new method to develop gesture accuracy. They worked with features extracted from the original EMG signals, features obtained by normalizing the signal to the maximum peak value, and features obtained by normalizing it to the AUC-RMS value. The study, which compares many machine learning classifiers (RF, NB, SVM, SVM) has proven that the proposed method increases the classification accuracy. In the study where 3 different hand gestures were examined, the highest recognition accuracy was obtained with the RF algorithm and features normalized to the AUC-RMS value. Pisharady et al.(Pisharady & Saerbeck, 2015) described a review of studies focusing on vision-based hand gesture recognition over the past sixteen years. The study presented quantitative and qualitative comparisons of algorithms in methods using RGB and RGB-D cameras. Quantitative comparison was provided with the different features of the algorithm and the 13 measures used in the evaluation. In addition, the study includes more than two dozen open-access hand gesture datasets.

Moin et al.(Moin et al., 2021) studied with a wearable sEMG biosensing system to recognize and classify hand gestures. This system, hyperdimensional computing-based, provides real-time gesture classification and adaption to variable conditions. The system allows many functions such as data collection, ML-based training, and classification performed on a single device. The results of the study showed that 13 hand gestures belonging to two participants were classified with 97.12% accuracy on the first try.

Kumar et al.(Kumar et al., 2023) studied to eliminate the sEMG signal's redundant information and develop the hand gesture recognition system's effectiveness and sensitivity. In the study using Augmented Partial Swarm Optimization and Modified K-Nearest Neighbor (APSO-MKNN) PCA was applied to reduce the dimensionality of the dataset. In the proposed model, muscle activity patterns associated with hand gestures were analyzed forhand gesture recognition and focused on their translation into actionable commands for computer systems.

1.6. Purpose of the Study

The main goal of this master thesis is to analyze the significance of features extracted from sEMG signals to be used in the classification of hand gestures. In the study, two different feature sets were studied: the first four order moments of TFM obtained by applying MSST to sEMG signals and the features obtained by applying NMF to TF matrices. This study was presented the implementation of MSST-based features for the first time to analyze and classify them for hand gesture classification. The distinguishing power of the feature variables for the tested gestures was evaluated according to their p values obtained from the Kruskal-Wallis (KW) test. In the conclusion part of the study, comparison of machine learning-based classification accuracies and classification algorithms was presented.

Chapter 2

Materials and Methods

In this study, ML-based approaches were applied to classify hand gestures using sEMG signals. Features extracted from TFA were used for input information of ML algorithms. Multivariate Synchrosqueezing Transform (MSST) is used as a TFA method. In the study, two separate feature sets were studied: the first four order moments of TFM obtained by applying MSST to sEMG signals and the features obtained by applying NMF to TF matrices. The distinguishing power of the feature variables for the tested gestures was evaluated according to their p values obtained from the Kruskal-Wallis (KW) test. In the last part of the study, Machine Learning - based classification algorithms were applied to determine the effect of statistical analyzes on classification success.

2.1 sEMG Dataset

The study realized with a publicly available sEMG dataset (Ozdemir et al., 2022) generated using the proper numbers of channels, gestures, and participants. In the study, 40 healthy participants (20 males, 20 females) performed ten hand gestures, the most basic in daily life. In the experiment, each individual performed ten hand gestures in 5 repetitions during the 6 seconds.   During the experiment, which was carried out in a quiet environment, participants were not allowed to use metal objects, buckles, belts, mobile phones or earrings in order not to affect the measurements. Data were collected from muscles near the skin surface to eliminate noise from the external environment or internal organs. Quality signals were obtained with the 4-channel electrode system placed on four different surface muscles. The data set recorded from the forearm has a sampling rate of 2 kHz. The processed gestures are demonstrated in Figure 2.1 (Ozdemir et al., 2022).

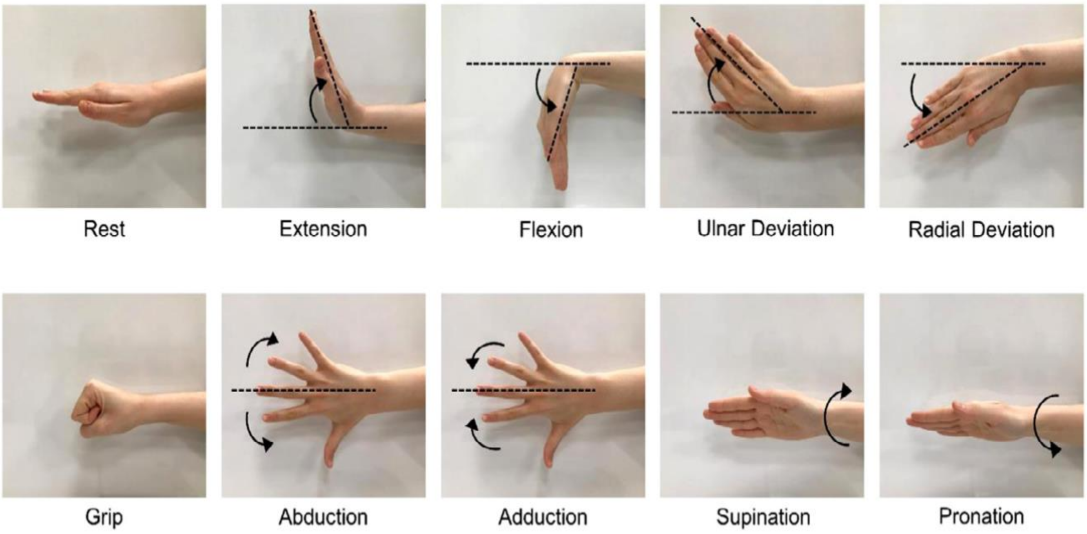

Figure 2.1: The tested ten hand gestures (Ozdemir et al., 2022)

During the experiment, the participants performed ten hand gestures with 6 s duration, and 4 s resting periods between gestures. Each cycle starts with a 4-second resting period and during the 6 second each gesture is performed once for. There are 4 s rest periods between gestures to emphasize the transitions between movements. Figure 2.2 (Ozdemir et al., 2022) shows the recording timeline of the dataset. One cycle takes 104 seconds with a 30-second rest period between each cycle. Hence, each participant completed 5 repetitive cycles in a total of 640 seconds.

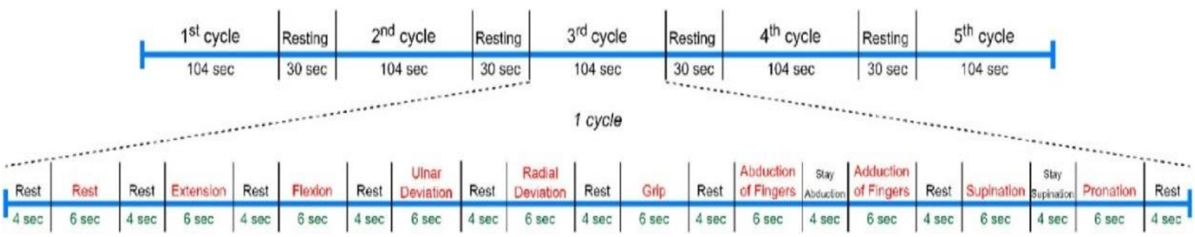

Figure 2.2: Experimental recording timeline(Ozdemir et al., 2022)

2.2 Preprocessing

The data collection process was completed with four channel MP36 model Biopac EMG system. With the help of this system, the collection, preparation, and analysis of signals were applied simultaneously. After data collection, preprocessing step is applied to prepare data for further analysis. The main goal of preprocessing is to enhance the quality of raw data.

2.2.1 Filtering

sEMG signals affected by noise from the surrounding environment or biological signals from neighboring muscles or internal organs. In order to remove irrelevant information in the sEMG signal, filtering is practiced to the signal and accurate information about the relevant movement is obtained(Küçük et al., 2019). There are several preprocessing methods, and in the current study, bandpass filters were applied. All the signals were filtered with the sixth-order Butterworth band-pass filter (5-500 Hz) and second-order Notch filter (50 Hz) were applied with the BIOPAC software during the experiment. In this way, signals cleared of noise become ready for the next process(Subhedar & Mankar, 2019). The Figure 2.3 (Ozdemir et al., 2022) shows that an example drawing of sEMG signals filtered with BIOPAC software of 10 gestures recognized in this study.

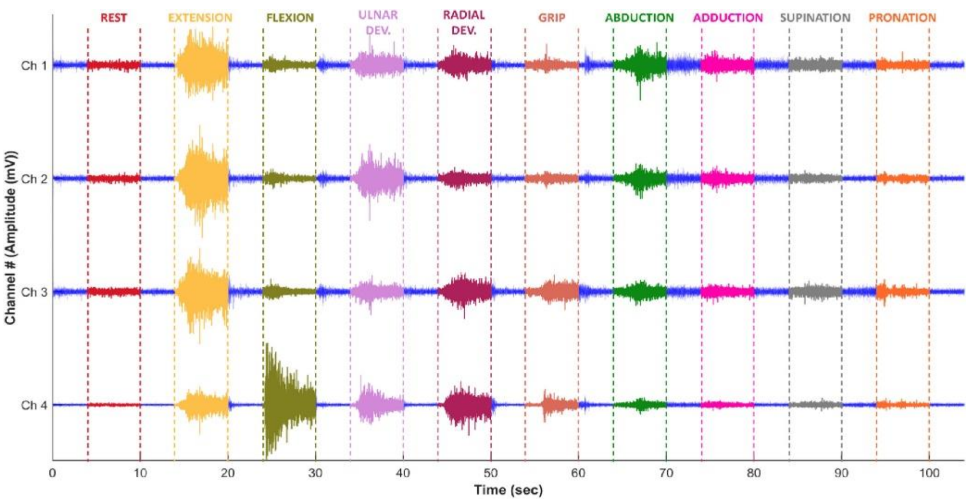

Figure 2.3: The plot of 4-channel filtered sEMG signals of ten hand gestures(Özdemir et al., 2022b)

2.2.2 Segmentation

Segmentation, which represents the time zone when the muscle contracts and rests, is applied to remove only the necessary and information-carrying regions from the signal. Additionally, segmentation enables the duplication of data in the data set, and in this study, segmentation was performed with overlapped sliding window. The process of the overlapped sliding window application, which aims to capture the features in the meaning part of the signal, can be seen Figure 2.4 (Ozdemir et al., 2022). To obtain new features, the window is slided along the data points, and this continues iteratively until the final data point. Each window is called a segment, and segment's length and its shift parameters are critical to obtain successful classification results. In here, low segment may cause excessive unnecessary values, while high segment values may cause the loss to capture the interested part of the signal(Keogh et al.).

After filtering, 250 ms gesture were moments extracted from the 6 s signals applying overlapped sliding window. In addition, as a common approach, 1 s ’transient-states’ at the beginning and end were removed from the 6 s segment, and the middle 4 s was taken as the ’steady-state’ to make a sliding window. The signals in this period are evaluated due to the approach that these periods when the muscles remain in the maximum state of contraction are the basic sEMG of the relevant gesture. Besides, this method provides the prevention of potential delays that may occur at the beginning and end of transitions(Moin et al., 2021). At the end of this process, there was a total of 76 sEMG segments for each 4 s signal. As a result, filtered and segmented sEMG signals are obtained from the collected raw dataset. In this way, it is aimed to obtain more reliable and meaningful results.

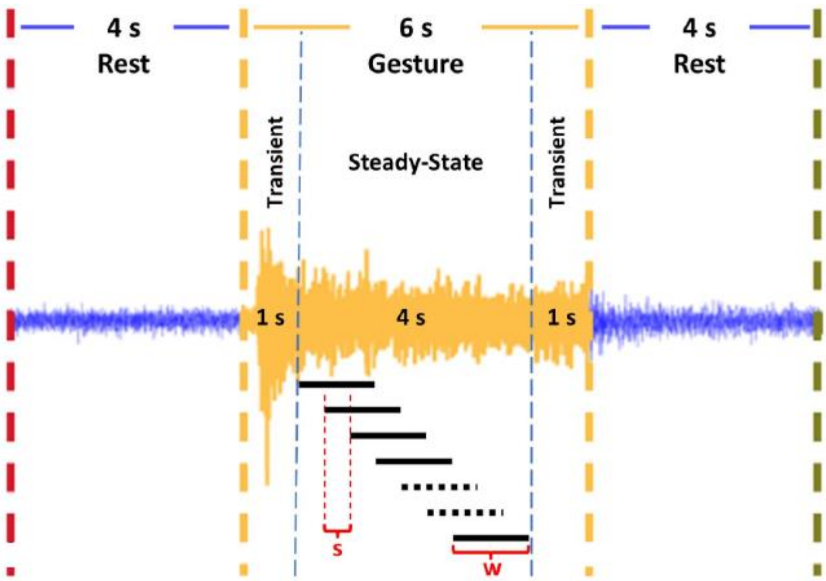

Figure 2.4: Demonstration of overlapped sliding window process(Özdemir et al., 2022a)

2.3. Multivariate Synchrosqueezing Transform

The Continuous wavelet transform-based post-processing technique, Synchrosqueezing Transform (SST), produces a focused and condensed representation of nonstationary and nonlinear signals in the time-frequency domain (TFD). The SST method provides the reconstruction of the signal while enhancing the TF resolution and production a highly localized TF representation of signals. SST technique's purpose is to separate the signals into constituents which have time-varying oscillatory properties. To seperate into components, the energies of the TF approach need to be reassigned. In this way, coefficients' subsequent energies are concentrate around the IF curves of the modulated oscillations. The reassignment phase constitutes significant localization of signal components in the TFD. Also, TF algorithms need multivariate extensions. To overcome these, a compact TFR of multi-channel signals requires to be created. In this study, Multivariate Synchrosqueezing Transform (MSST) method an extension of the SST, is proposed to generate TFR of multichannel signals (Ahrabian et al., 2015; Ozel et al., 2019).

MSST method characterizes the TFR as a single oscillatory structure that catches the properties of the multivariate signal. MSST produces a focused and condensed representation of signals from standard components provided by different channels in TFD. Actually, MSST method separates the TF domain into parts to identify the common data oscillations that include multi-channels with multivariate signals (Subhedar & Mankar, 2019). MSST method enables to identify common oscillations of the data that contains multi-channels with multivariate signals by applying many SST operations in succession.

Implementation of MSST requires several steps to follow. Firstly, SST is implemented for each data channel to specify channel frequency band and instantaneous frequencies (IF)

1. The first step of the process begins by implementing SST to each N-channel multivariate signal channel x(t). At this section, SST coefficients represented by $T_n(\omega, b)$ are procured for each channel.

2. A set of sections through the frequency axis is determined for the TF domain. Every instantaneous frequency $\Omega_k^n(b)$ and instataneous amplitude $A_k^i(b)$, for each frequency bin k, are calculated by Equation (1.2) and Equation (2.2), respectively.

$$\Omega_k^n(b) = \frac{\sum_{\omega \, \epsilon \, \omega_k} |T_n(\omega, b)|^2 \omega}{\sum_{\omega \, \epsilon \, \omega_k} |T_n(\omega, b)|^2} \tag{2.1}$$

$$A_k^n(b) = \sqrt{\sum_{\omega \, \epsilon \, \omega_k} |T_n(\omega, b)|^2} \tag{2.2}$$

3. The next step is calculating multivariate instantaneous frequency $\Omega_k^{multi}(b)$ and amplitude $A_k^{multi}(b)$ by Equation (2.3) and Equation (2.4), respectively.

Ω_k^{multi} and A_k^{multi} are calculated by using a combination of frequency band k, joint instantaneous frequency, and instantaneous frequencies through the N channels.

$$\Omega_k^{multi}(b) = \frac{\sum_{n=1}^{N}(A_k^n(b))^2 \Omega_k^n(b)}{\sum_{n=1}^{N}(A_k^n(b))^2} \tag{2.3}$$

$$A_k^{multi}(b) = \sqrt{\sum_{n=1}^{N}(A_k^n(b))^2} \tag{2.4}$$

4. Each frequency band's joint instantaneous amplitude and frequency are obtained. Thus, multivariate TF coefficients $T_k^{multi}(\omega, b)$ for each oscillatory scale k are determined. $\mathrm{T}_k^{multi}(\omega, b)$ is represented as

$$\boldsymbol{T}_k^{multi}(\omega, b) = A_k^{multi}(b)\delta\left(\omega - \Omega_k^{multi}(b)\right) \tag{2.5}$$

and δ demonstrates the Dirac delta function.

With the MSST method, the 4-channel sEMG signal is represented by a single TF matrix, ensuring that all channel information is preserved. Figure 2.5 demonstrates the TFRs of extension and flexion features obtained from MSST of the 250 ms signal segment. The figure proves that different gesture power distributions of TFR are different. Thus, we suggest using different properties of the TF matrix as a feature to distinguish the hand gestures(Ahrabian et al., 2015; Ozel et al., 2019).

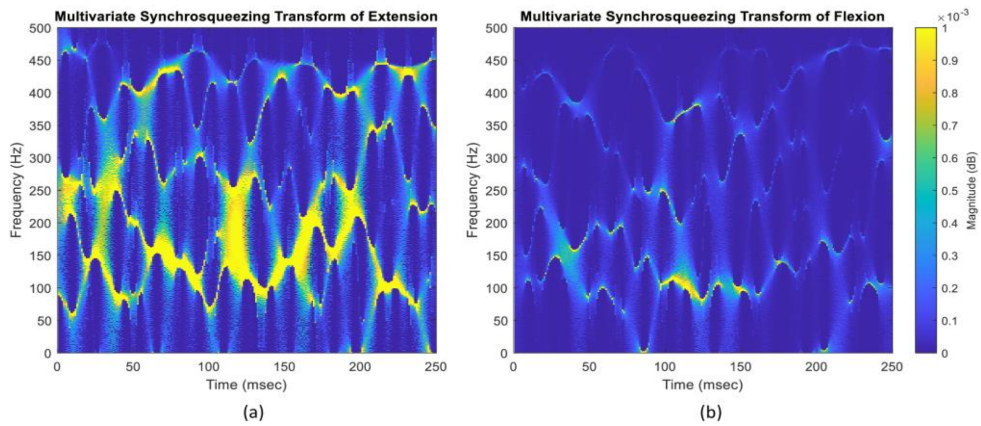

Figure 2.5: An example of Multivariate Synchrosqueeizng Transform of a) Extension, and b) flexion movement gestures, respectively.

2.4 Feature Extraction

A function of measurements that represent the quantifiable model of the image or object is described as feature. Features are obtained in the feature extraction step, which is performed before the classification step. Feature extraction is one of the basic steps in ML based classification studies and aims to represent the signal in the most informative minimal form. Feature extraction, the ideal way of collecting relevant, helpful information from included signals, eliminates redundant parts and interferences. Feature extraction is applied in machine learning algorithms to avoid increase the complexity of application and processing cost by raw data. The extracted features, which form the input information of ML classifiers, affect the gesture recognition system's performance (Jaramillo-Yánez et al., 2020; Qi et al., 2020; Valdivieso Caraguay et al., 2023). Additionally, features can enable the capture of hidden patterns that may not be noticeabled in a single data point.

Feature extraction is an indispensable process to obtain patterns in studies carried out with EMG signals that have noisy property and very low amplitude. The raw data processing is realized with mathematical functions. There are several different EMG feature extraction techniques in the literature. These methods are divided into 3 main parts: time domain (TD), frequency domain (FD), or time frequency (TF) domain(Boostani & Moradi, 2003; Ozel et al., 2019). TD features, which are frequently preferred in detecting muscle activation, have low complexity and computational cost. Besides, FD features are preferred in studies of detection of muscle fatigue. The spectral properties of nonstationary real-life signals change over time. Therefore, processing of signals individually in the TD or FD does not provide adequate information. Additionaly, this makes it difficult to determine the relationship between the signal's time and frequency properties. Time frequency domain (TFD) features, which include the combination of frequency and time information, provide a more accurate representation of signals. TFD features present the detailed analysis of alteration of signal's frequency components over time. In this way, sEMG signals are represented more properly by TFD features(Karheily et al., 2022). TFD features, which show the change of frequency over time, provide advantages in studies carried out with non-stationary signals such as sEMG signals.

All the TFD features are not directly used in classification algorithms as including all points would trigger the dimensionality problem. Therefore, to obtain good results from classification, small representative features containing relevant information need to be extracted from TFDs(Akan & Karabiber Cura, 2021; Boashash et al., 2015). The interpreting the TFD as a TF matrix (TFM) and extracting features from the TFM has been proposed as an alternative way for hand gesture classification, recently(Rabin et al., 2020).

2.4.1 TF Moments

TF matrices were obtained by applying MSST to 250 ms four-channel sEMG signals. In our study, the TF matrix's four statistical parameters, variance, skewness, kurtosis, and mean, are selected as features to represent each hand gesture pattern. In a two-dimensional (2D) TF matrix, $T(\omega, t)_{MxN}$, M and N represent frequency resolution and the number of samples in EMG, respectively. The selected features were associated with the first four order moments, and Equation (2.6) was used to calculate.

$$\langle t^n \omega^m \rangle = \iint t^n \omega^m P(\omega, t) dt d\omega \qquad (2.6)$$

In the Equation (2.6), P (t, f) represents probability distribution of TF matrix, P(t) represents the marginal distribution, n and m represent the order of time and the order of frequency, respectively. In the formula of the mean calculated by the Equation (2.6), $\langle t^n \rangle$ and $\langle \omega^m \rangle$ represent the first temporal and spectral time-frequency moments. It specifies the first-order joint moment (mean) of coefficient $\langle T(t, \omega) \rangle$ the time-frequency distribution of x. The variance, skewness, and kurtosis are calculated by taking the second, third, and fourth moments, respectively(Loughlin et al., 2000). After the features extraction step, feature selection applied to choose the distinctive features from different hand gestures.

2.4.2 Non-Negative Matrix Factorization

Non-Negative Matrix Factorization (NMF) a part-based matrix decomposition method, disintegrates a nonnegative matrix into matrix factors. The NMF algorithm, starting with random values, recursively modifies them to decrease a cost function (Ghoraani & Krishnan, 2011). The matrices obtained by the NMF method for feature extraction from time-frequency distributions have a dimensionally and structurally simpler structure than the original matrix. It provides the preserving of the nonnegative nature of inputs which in some cases is important for obtaining meaningful physical interpretation (Boashash et al., 2015). The NMF method is applied to obtain non-negative data in the form of linear and parts-based representations. To obtain a low-dimensional approximation with the NMF method, the input data must be non-negative. The NMF method certainly necessitates that matrices W and H have non-negative entrances and this means that data can only be defined using additional components. As a result, the attained decomposition matrix can state the real matrix only by the linear combination of addition without extraction.

When the NMF technique is applied to a non-negative matrix A, two matrices with lower ranks, represented by W and H, are obtained.

$$A \sim \tilde{A}_{NxM} = W_{RxL} H_{RxM} = \sum_{r=1}^{R} \omega_r h_r \tag{2.7}$$

In the Equation (2.7), the base vectors representing the frequency structure of each component and the coefficient vectors representing the temporal structure of each component are represented by W and H, respectively. The decomposition parameter represented by R generally depends on the application (Degirmenci et al., 2022).

2.4.2.1 NMF-based Feature Extraction

NMF, also defined as feature extraction or dimensionality reduction technique, is generates decreased representation of the original data. (Subhedar & Mankar, 2019). We applied NMF to reduce TF matrix representation (TFM) ' s dimensionality and obtain meaningful information.

In the T_{MxN} representation obtained by applying MSST to the X signal, M represents the frequency resolution and N represents the number of samples, respectively. TF decomposition comprises two sets of vectors expressed by W and H, as shown in the Equation (2.7). Base matrix represented by W supplies information on the TFM's frequency structure, and the coefficient matrix represented by H supplies information on TFM 's temporal structure (Karan et al., 2021). In this study, first factor, r=1, used to provide more concentrated representation and reduce model size significantly. In our study, kurtosis, skewness, standard deviation, sparsity and discontinuity are proposed as features extracted from NMF vectors.

The calculated base W= {W_1, W_2,….W_M} and coefficient H= {H_1,H_2,….H_N} components of sparsity are defines as given Equation (2.8). The base and coefficient vectors of sparsity are represented by S_H and S_w, respectively.

$$S_w = \log_{10} \frac{\sqrt{M} - \frac{\sum_{j=0}^{M-1} w_j}{\sum_{j=0}^{M-1} w_j^2}}{\sqrt{M} - 1} \tag{2.8}$$

$$S_H = \log_{10} \frac{\sqrt{N} - \frac{\sum_{j=0}^{N-1} h_j}{\sum_{j=0}^{N-1} h_j^2}}{\sqrt{N} - 1} \tag{2.9}$$

The other feature, discontinuity's base and coefficient vectors are represented by D_W and D_H, respectively.

$$D_w = \log_{10} \sum_{j=1}^{M-1} \left(w_{j+1} - w_j\right)^2 \tag{2.10}$$

$$D_H = \log_{10} \sum_{j=1}^{N-1} (h_{j+1} - h_j)^2 \tag{2.11}$$

The base and coefficient vectors of other NMF-based features can also be considered in this way.

2.5 Statistical Analysis

In the current step, statistical analysis is applied to select the most distinctive features. In our study, we used the Kruskal-Wallis (KW) test, which is one of the statistical analysis methods used in hand gesture classification studies. KW test is used to determine whether two or more samples are originate from the same population. In the KW test, probability values are calculated by using sequencing information to test the distinguishing power of features. The KW test is used when all samples in each population have the same continuous distribution (Loughlin et al., 2000; Ostertagov¨¢ & Ostertag, 2013).

The KW test is the non-parametric equivalent of the parametric one-way ANOVA test and does not require normal distribution within the group. Thus, it is accepted as a more comfortable, flexible, powerful, and easy-to-use technique. KW test doesn't make hypotheses about normality. However, it admits the assumption that the observations in each group come from populations with the same distribution pattern and that the samples are random and independent(Guo et al., 2013; Maniruzzaman et al., 2020).

Examining the statistical properties of the features reduces feature set's dimensionality and thus resulting in a quicker and more precise model. In this way, the classification model is developed with only the statistically significant features (Fatimah et al., 2021). The evaluation principle of the KW test is to analyze the differences according to the mean ranks to determine whether they are likely to have come from samples from the same population. The KW test, which compares the medians of groups of data in terms of X, uses the ranking information of the data instead of numerical values to calculate the test statistics. To implement KW test, data for all samples are sorted into ascending order in a combined set disregarding which sample the values belong to. Then, ranks are assigned to the sorted data points and different ranks are collected for each sample. In this way, each sample's own rank sum is obtained and the formula calculates the H statistic.

$$H = \frac{12}{N(N-1)} \sum_{i=1}^{k} \frac{R_i^2}{n_i} - 3(N+1) \tag{2.12}$$

In the formula, the number of samples and the sum of sample sizes for all samples (total number of observations) is represented by k and N, respectively. While the ith sample's number of observations and the sum of ranks in the ith sample is represented by n_i and R_i, correspondingly (Mishra et al., 2016; Ostertagov¨¢ & Ostertag, 2013; Tcheslavski & Gonen, 2012). The statistical significance is represented by p values. Whether the p-value of the relevant features is more significant or less than the reference p-value is associated with the separability of the features. If the p value of the variable is close to zero, the groups can be separated from each other regarding the variable. Practically, an appropriate threshold value is chosen and the variables having a p value lower than the threshold are accepted statistically significant.

In our study, statistical significance was examined with the KW test for two separate feature sets: features obtained from TF moments and NMF-based features. In the study, we applied the KW tests to inter-subject and intra-subject scenarios for each feature set. In the intrasubject scenario, the statistical analyses were implemented on data formed by combining different numbers of subjects separately. In the inter-subject scenario, statistical analysis was applied to the whole data set to specify statistical significance between every feature. In practice, we applied statistical analysis with the KW test and considered the features having $p < 0.001$ as statistically significant (Fatimah et al., 2021; Loughlin et al., 2000; Ostertagov¨¢ & Ostertag, 2013).

2.6 Machine Learning

Machine learning-based classification can be defined as the process of dividing data into categories. The input information of the algorithm is created with raw data or feature matrices. In the study, filtering and segmentation processes were applied to the raw sEMG dataset before obtaining TF matrices with MSST method. Classification is performed with the toolboxes found in the Matlab algorithm. Matlab, which has a wide range of applications, offers many classification models. Many machine learning methods in the Classification Learner Application (CLA) were used for the classification of ten hand gestures.

In the beginning, the dataset is divided into two as training data and testing data. Classifier algorithms need a sufficient amount of training data to achieve satisfying accuracy of gesture. Before ML algorithms are trained, feature selection process is performed to decrease dimensions and obtain highest performance. Also, Principal Component Analysis (PCA) is performed to features and it is ensured that the features have the least variance. Data must be normalized before these steps. The purpose of normalization is to prevent the creation of diceptive components from different data scales. The data is rescaled between 0 and 1 with normalization(Kawanabe, 2012). We performed z-score normalization to ensure that every feature is involved with an appropriate effect.

Feature selection ensures that the feature is retained or exactly removed. Dimensionality reduction generates new variables from present variables to reduce the variables number. Principal components generated by PCA include a specific amount of information from original variables. The working principle of PCA is the representation of multidimensional data with lesser features by catching the basic features of the data. In this way, the dimensionality of the prediction space is reduced(Halevy et al., 2009; Kisa et al., 2022). After the training, the test part is applied to compare the accuracy of the network structures. In this study, dataset is divided into 70% training and 30% testing.

2.6.1 Support Vector Machine

In the Support Vector Machine (SVM) model, which solves the classification problem by converting it into an optimization problem, calculating processes are decreased and a solution is obtained in a shorter time compared to other methods(Osowski et al., 2004). SVM, one of the supervised machine learning algorithms, uses a separating hyperplane to perform classification. The hyperplane (H), a discriminative surface, separates the data set linearly and performs the classification. The nearest points of the two classes, called support vectors, are used to obtain the optimal hyperplane. Support vectors, maximum margin and separating hyperplane can be seen in the Figure 2.6 (JavaTPoint). Maximizing margin distance is used to identify the classification decision boundaries. The margin of the training data is maximized by the optimal separation hyperplane, and the training samples closest to the optimal hyperplane represent the support vectors.

In the processing, a hyperplane is obtained which has the maximum distance between the hyperplane and the nearest data point by the classfier. Linear SVM can categorize or classify data with the help of a single straight line, while the kernel SVM classifies nonlinear data by adding features to higher dimensions. Linear SVM allows labeled data to be matched into a vector space, thus separating each class from each other by wide gaps. In nonlinear classification, the kernel trick proposed by Scholkopf is used to enable SVM. The kernel trick matches the input information onto a high dimensional feature space to enhance the gap between classes(Fatimah et al., 2021; Liu & Wang, 2018). In our study, we used linear, cubic and quadratic kernels to classify hand gestures.

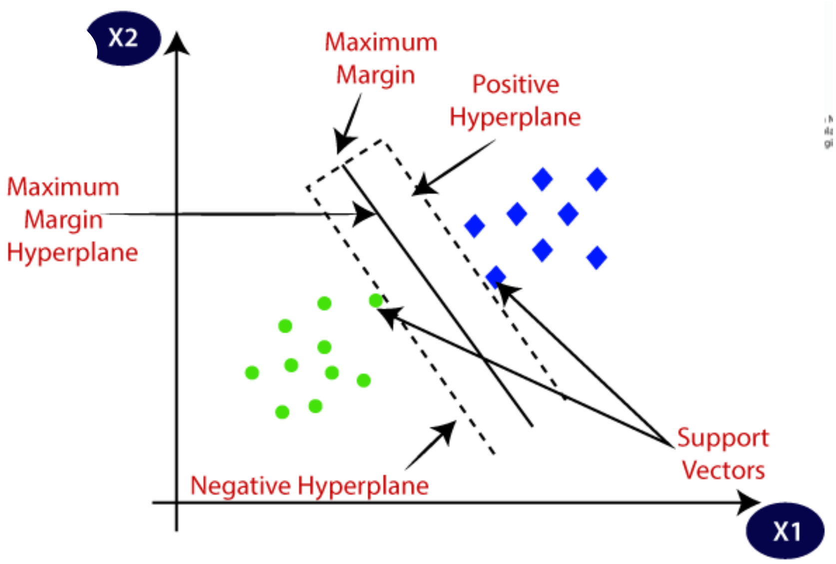

Figure 2.6: Demonstration of classification of data using SVM(JavaTPoint)

2.6.2 K-Nearest Neighbours

K-Nearest Neighbours (KNN) algorithm, which belongs to the instance-based supervised learning class, classifies the input data as the closest training examples. K, which represents the number of evaluated neighbors, is selected through cross-validation and has a much smaller value than the sample size number. The majority of votes of k training neighbors is considered for the classification of test data. An example of the classification made with the KNN algorithm is given in Figure 2.7 (KDnuggets).

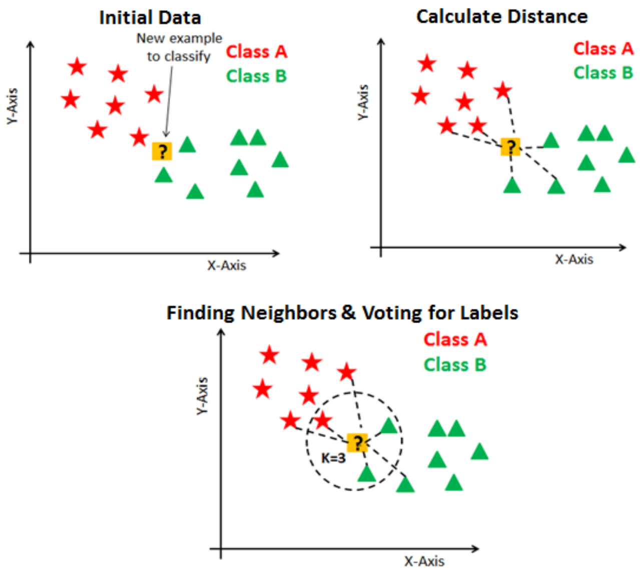

Figure 2.7: An example classification with KNN algorithm(KDnuggets)

The classification principle of the model is based on the nearest neighbor approach. The algorithm, which assumes that data belonging to the same class are close to each other, has several metrics to calculate the distance between points in the graph (Harrison). Some of the distance functions found in literature are given in Equation (2.13), Equation (2.14) and Equation (2.15). The most preferred Euclidean distance function is included in Equation (2.14).

Manhattan: $$\sum_{i=1}^{k}|xi - yi| \tag{2.13}$$

Euclidean: $$\sqrt{\sum_{i=1}^{k}(xi - yi)^2} \tag{2.14}$$

Minkowski: $$\left(\sum_{i=1}^{k}(|xi - yi|)^q\right)^{1/q} \tag{2.15}$$

The calculated distances between the present input and each training sample are lined in ascending order (Fatimah et al., 2021; Liu & Wang, 2018). KNN, which does not have a model including a training pattern, aims to arrive the closest model by comparing it with all existing models for training. In this way, KNN does not need extra time for training the model and requires more time when working with large data sets(Mehla et al., 2020).

2.6.3 Random Forest

An ensemble classifier model, which called as Random Forest (RF), combines numerous decision trees' performances to classify or determine the variable's value. The working principle of RF is based on generating numerous decision trees in the training phase and receiving the class labels only that have the majority vote. Regression trees are created as many as the number of feature subsets by RF and each tree produces a classification results. The working principle of the RF algorithm is shown in detail in Figure 2.8 (ScalerTopics, 2023). The classification result is based on the majority voting. RF enhances tree diversity to prevent different tree correlations. To provide this, RF uses different training data subsets formed by bagging. The bagging technique randomly resamples the original training data by applying replacement, and thus, some of the data are not used, while some are used more than once. As a result, a classifier is obtained with increased prediction accuracy, stability, and tenable to small changes(Ahmad et al., 2018; Rodriguez-Galiano et al., 2015).

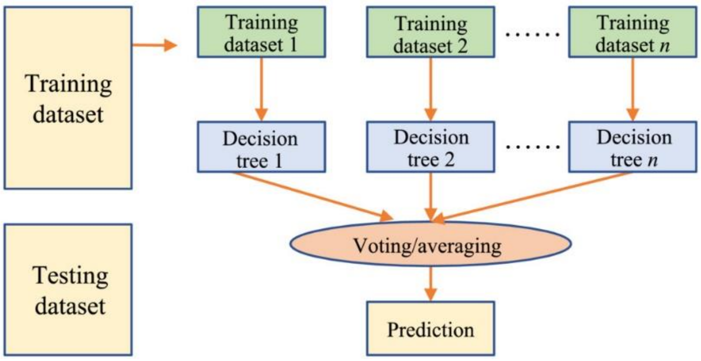

Figure 2.8: Representative demonstration of the operation of the RF algorithm(ScalerTopics, 2023)

2.6.4 Artificial Neural Network

Artificial Neural Network (ANN) is an information processing model often preferred in non-parametric and nonlinear classification studies. The structural organization of this model consists of multiple processing neurons working in parallel with each other. Interconnected each neuron works on the principle of processing the data it receives at the input and creating output data.

In a neural network, the placed units in layers are connected with hidden layers to provide a one-way information flow from the input to the output unit. In the algorithm, which aims to find a weight set close to the desired output vector for each input vector, the received signal is distributed from input units to the hidden layers. The data coming to the input layer is collected in the hidden layer after being multiplied by the weight, and the transfer function is used to obtain the output from them(Baxter et al., 2001). The working principle of the ANN algorithm is shown in detail in Figure 2.9 (GeeksForGeeks.org,2023). The training phase of this model consists of selecting the structure, initializing weights, selecting regularization parameters to avoid overfitting and learning rate [32, 35].

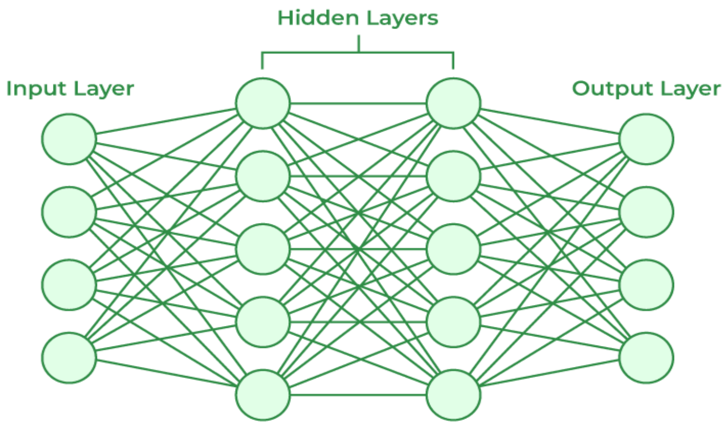

Figure 2.9: Representative representation of the ANN model (GeeksForGeeks.org, 2023).

2.6.5 Naive Bayes

Naïve Bayes (NB), one of the classification algorithms, classifies data according to probability principles. NB assumes that the presence of a particular property in a class does not depend on the presence of any other feature. It assigns the most probable class to a given sample given its feature vector. All of these properties are considered independently, even if the properties are dependent on each other or on the presence of other properties.

NB is a simple to perform, robust, and computationally efficient classifier that is often very successful in practice despite its unrealistic assumption of independence. The working principle of the NB algorithm is shown in detail in Figure 2.10 ((Tech&Tales, 2023). When classifying new data, probability operations are performed on the trained data, and classification is made according to the probability value by making presentations to the system(Karlik, 2014; Ma et al., 2016).

$$P(A\backslash B) = \frac{P(B\backslash A)P(A)}{P(B)} \tag{2.16}$$

In the Equation (2.16) generated using Naive Bayes probability for the NB classifier, $\mathcal{P}$(A|B) represents the posterior probability. The possibility of B given A is represented by $\mathcal{P}$(A|B) in the Equation (2.16).

$\mathcal{P}$(A) represents the prior probability of A, and no information about B is included when calculating it. The marginal probability of B, represented by P(B) in the Equation (2.16), acts as the normalization constant(Yadav et al., 2023).

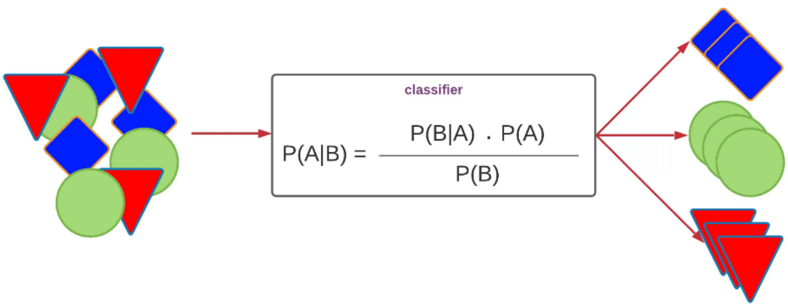

Figure 2.10: Basic demonstration of Naive Bayes(Tech&Tales, 2023)

Chapter 3

Results and Discussion

This study compares the classification success of features extracted from TF matrices and features extracted from TF matrices by the NMF method. In the study, both feature sets were analyzed in terms of statistical significance using KW rankings, and the effect of statistical analysis on classification success was investigated. Firstly, 250 ms gesture were moments extracted from the 6 s signals applying overlapped sliding window. In addition, as a common approach, 1 s ’transient-states’ at the beginning and end were removed from the 6 s segment, and the middle 4 s was taken as the ’steady-state’ to make a sliding window. At the end of this process, there was a total of 76 sEMG segments for each 4 s signal. TF matrices were obtained by applying MSST to 250 ms four-channel sEMG signals. Thanks to the MSST method, the 4-channel sEMG signal is represented by a single TF matrix, which provides to preserve the whole information of all channels. In Figure 2.5, TFR’s of extension and flexion resulted from MSST of 250 ms segment of the signal are shown, respectively. As shown in Figure 2.5, different gestures have different power distributions in their TFR’s which leads us to use the distinct properties of the TF matrix as a feature for distinguishing the hand gestures. For this aim, four features, i.e. mean, variance, skewness, and kurtosis are computed and separated into 10 groups according to the tested hand gestures. In the second feature set, the base and coefficient vectors extracted from the TF matrix with the NMF method were proposed as features. Ten features are figured, i.e., base and coefficient vectors of skewness, kurtosis, discontinuity, standard deviation and sparsity. Before statistical analysis, z-score feature normalization was applied to four TF moment and ten NMF-based features. In the statistical analysis, the features with $p < 0.001$ are considered statistically significant(Motoche & Benalcázar, 2018).

All processes of the study were carried out in MATLAB® environment. We performed the KW tests for two feature sets in the inter-subject and intra-subject scenarios. In the inter-subject scenario, the whole data set was examined to determine statistical significance between every feature. In the intrasubject scenario, the data of a different number of the subjects were combined and the statistical analyses were performed separately.

3.1 Statistical Analysis Results

Firstly, the analysis results of TF momets are given. The statistical analysis results of the inter-subject scenario are shown in Figure 3.1. The p values for mean, variance, skewness, and kurtosis were obtained as 5.9155e-16, 2.5985e-20, 1.2819e-16 and 1.0664e-07, respectively. The variance with the smallest p value is found as the most significant feature for the classification of tested hand gestures. Moreover, 45 binary combinations of 10 gestures for each feature were tested and some of the lowest and the highest p values were also shown in Figure 3.1. The ranges (minimums and maximums) of p values are obtained as [1.2692e-07, 1] for mean, variance, and skewness, and [4.2652e-07, 1] for kurtosis. For the mean, the best significance value was obtained as 1.2692e-07 between flexion and radial deviation, and there was no significant difference between grip and adduction gestures. For the variance and skewness, the best significance value was obtained as 1.2692e07 between flexion and ulnar deviation, flexion and radial deviation. There were no significant differences between the radial deviation and abduction gestures in terms of variance as well as the supination and pronation gestures in terms of skewness. The flexion and abduction gestures differentiate in terms of kurtosis $p = 4.2652e-07$ significantly, whereas the adduction and pronation gestures do not differentiate. The flexion gesture has the most different signal pattern in the tested gestures(Kıymık et al., 2005). TFR matrix of flexion represents this property by generating the most significantly different features.

The mean, variance, skewness, and kurtosis of flexion have the lowest p values in all analysis combinations.

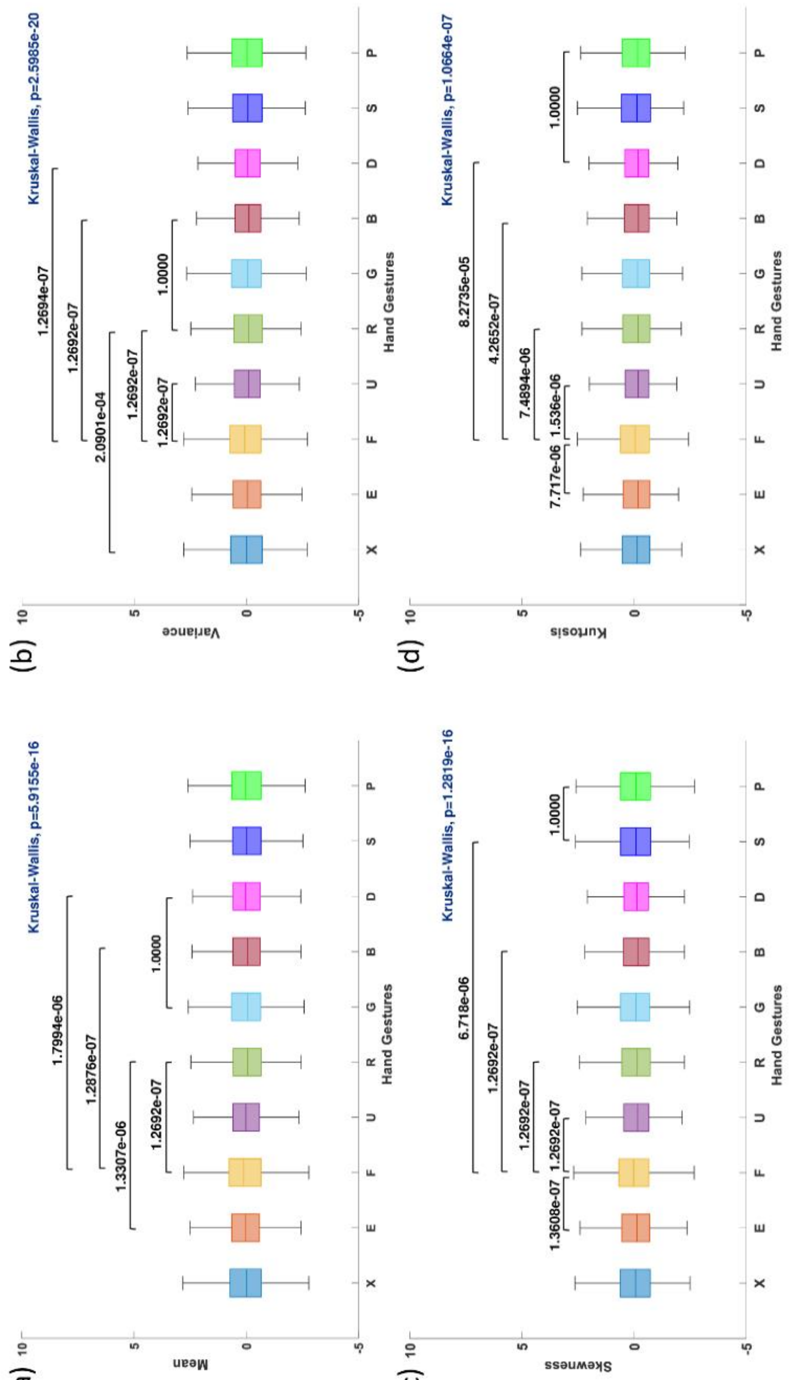

Figure 3.1: The box plots and the highest and lowest p values of each feature for all subjects a) mean, b) variance, c) skewness, and d) kurtosis, respectively (X: Rest, E: Extension, F: Flexion, U: Ulnar Deviation, R: Radial Deviation, G: Grip, B:fingers abduction, D: fingers adduction, S: supination, and P: pronation).

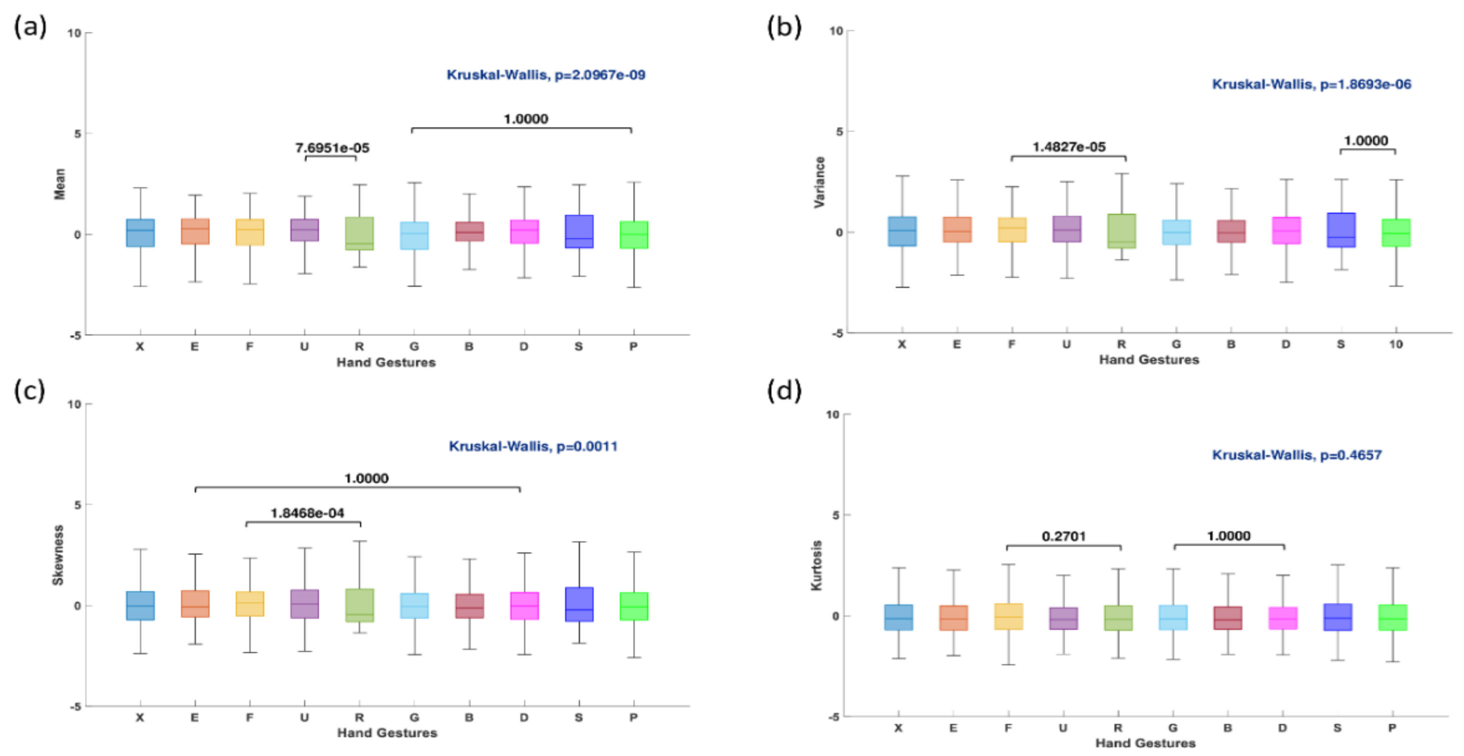

Figure 3.2: The box plots and the highest and lowest p values of each feature for 5 subjects: a) mean, b) variance, c) skewness, and d) kurtosis, respectively (X: Rest, E: Extension, F: Flexion, U: Ulnar Deviation, R: Radial Deviation, G: Grip, B: fingers abduction, D: fingers adduction, S: supination, and P: pronation).

Intra-subject scenario was carried out to evaluate the effect of the number of data and subjects on the p value. The statistical significance of the four features for each of the 40 subjects was investigated separately and it is observed that p value of all features is bigger than 0.001 for ten hand gestures groups. The average p values of the mean, variance, skewness, and kurtosis were found 0.7231, 0.7841, 0.9034 and 0.9820, respectively. The same analyses were performed with combination of 2-subject, 3-subject and 4-subject data and the same statistical inference was obtained. The statistical significance of mean, variance, and skewness begins when the data of 5 subjects were analyzed and their p values decreased to 2.0967e-09, 1.8693e-06, 0.0001, respectively, as seen in Figure 3.2. The kurtosis needs the data of 30 subjects to be significant statistically.

Secondly, the analysis results of NMF-based features are given. The results of the inter-subject scenario are demonstrated in Figure 3.4. The p values of coefficient vectors for skewness, kurtosis, discountunity, sparsity and standard deviation were calculated as 3.91157e-05, 0.0072, 1.92104e-208, 0,0016 and 2.71292e-05, respectively. The discontinuity with the smallest p-value is the most significant feature for the classification of studied hand gestures. Also, Figure 3.4 includes the lowest and the highest p values, which resulted from testing the 45 binary combinations of 10 gestures for each feature. The obtained p values ranges for skewness, kurtosis, standard deviation, discountinuity and sparsity are [1.92104e- 208, 1]. In terms of sparsity, while the grip gesture showed a significant difference with rest, extension, ulnar deviation, abduction, and supination. The other hand gestures did not differ significantly from each other. For the kurtosis, a significant difference was obtained only between adduction and supination. For the standard deviation, the best significance differences were obtained between supination and grip, radial deviation ve flexion, ulnar deviation ve flexion, rest ve grip gestures. In terms of skewness, flexion gesture was significantly different from pronation, adduction, abduction, grip, radial deviation, ulnar deviation, extension, rest.

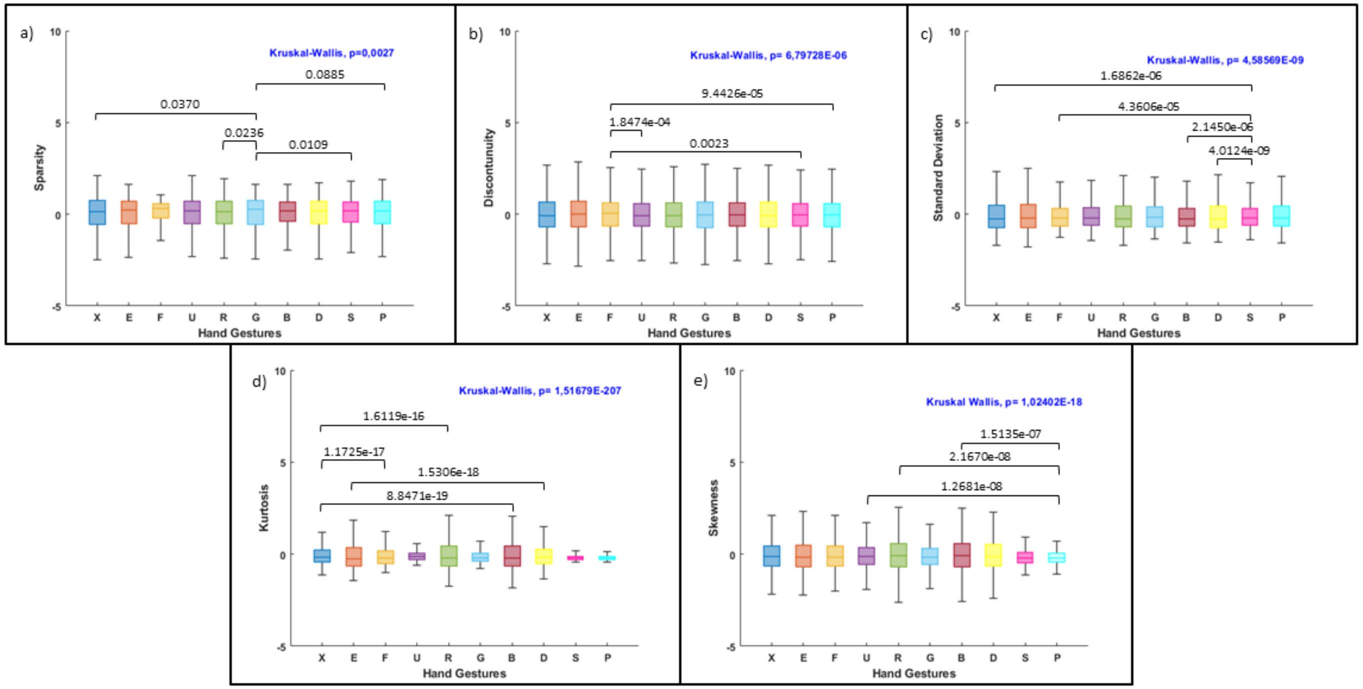

Figure 3.3: The box plots and p values of each base vector for all subjects a)Sparsity, b) Discontinuity, c) Standard Deviation, d) Kurtosis, and e) Skewness, respectively (X: Rest, E: Extension, F: Flexion, U: Ulnar Deviation, R: Radial Deviation, G: Grip, B: fingers abduction, D: fingers adduction, S: supination, and P: pronation).

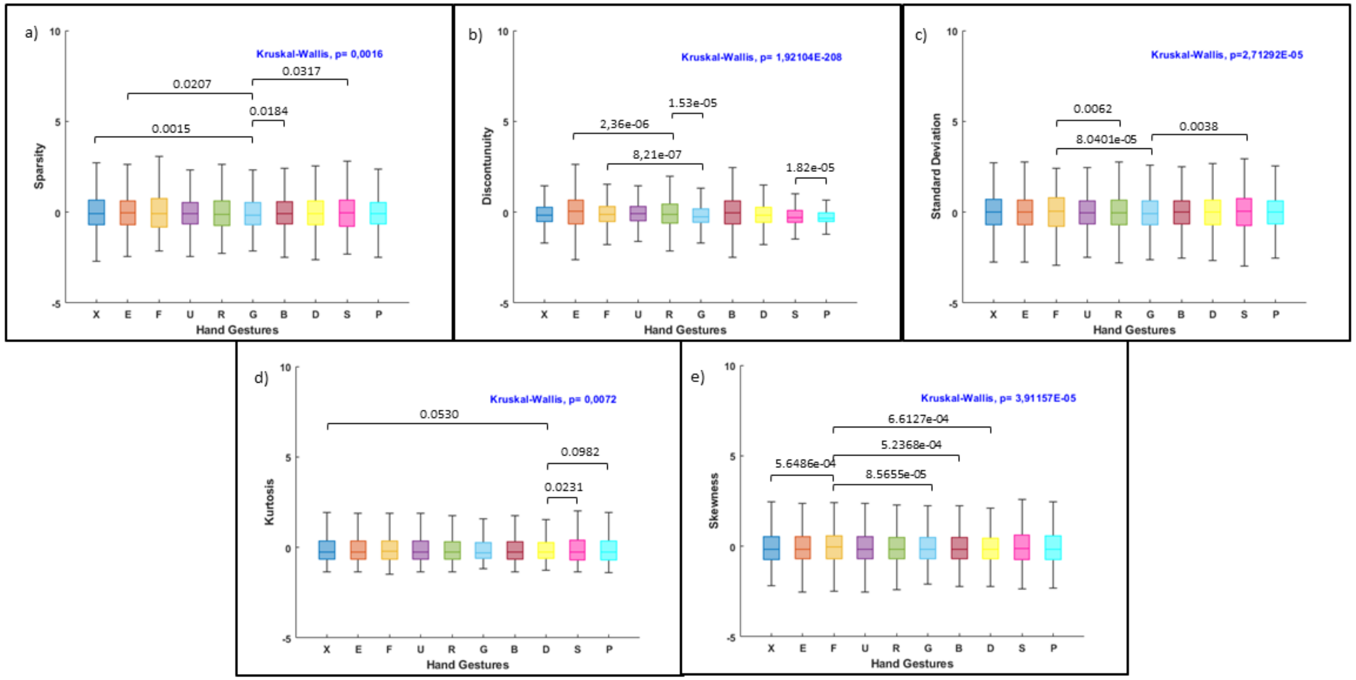

Figure 3.4: The box plots and p values of each coefficient vector for all subjects a)Sparsity, b) Discontinuity, c) Standard Deviation, d) Kurtosis, and e) Skewness, respectively (X: Rest, E: Extension, F: Flexion, U: Ulnar Deviation, R: Radial Deviation, G: Grip, B: fingers abduction, D: fingers adduction, S: supination, and P: pronation).

The intra-subject scenario‘s statistical analysis results are shown in Figure 3.6. The intra-subject scenario was applied to determine the data and subjects' number effect on the p-value. To evaluate this, the statistical of the ten features for each of the 40 participants were examined separately. The results show that the obtained p-value of all features is bigger than 0.001 for the studied ten gestures. The average p values of the sparsity, discontinuity, standard deviation, kurtosis, and skewness were found at 0.2884, 9,87e+02, 0,6111, 0.4999, and 0,4013, respectively. The same analyses were carried out with a combination of 5-subject, 10-subject, 20-subject, 30-subject, and 40-subject data, and the same statistical inference was obtained. The statistical significance of sparsity, discontinuity, and kurtosis begins when the data of 5 subjects were analyzed and they have the best p values in the analysis of 40 subjects. Their p values decreased to 0,2884, 9,87e+02, and 0.4999 in 40 subject analyses, respectively as seen in Figure 3.6. While, skewness and standard deviation did not achieve the same success.

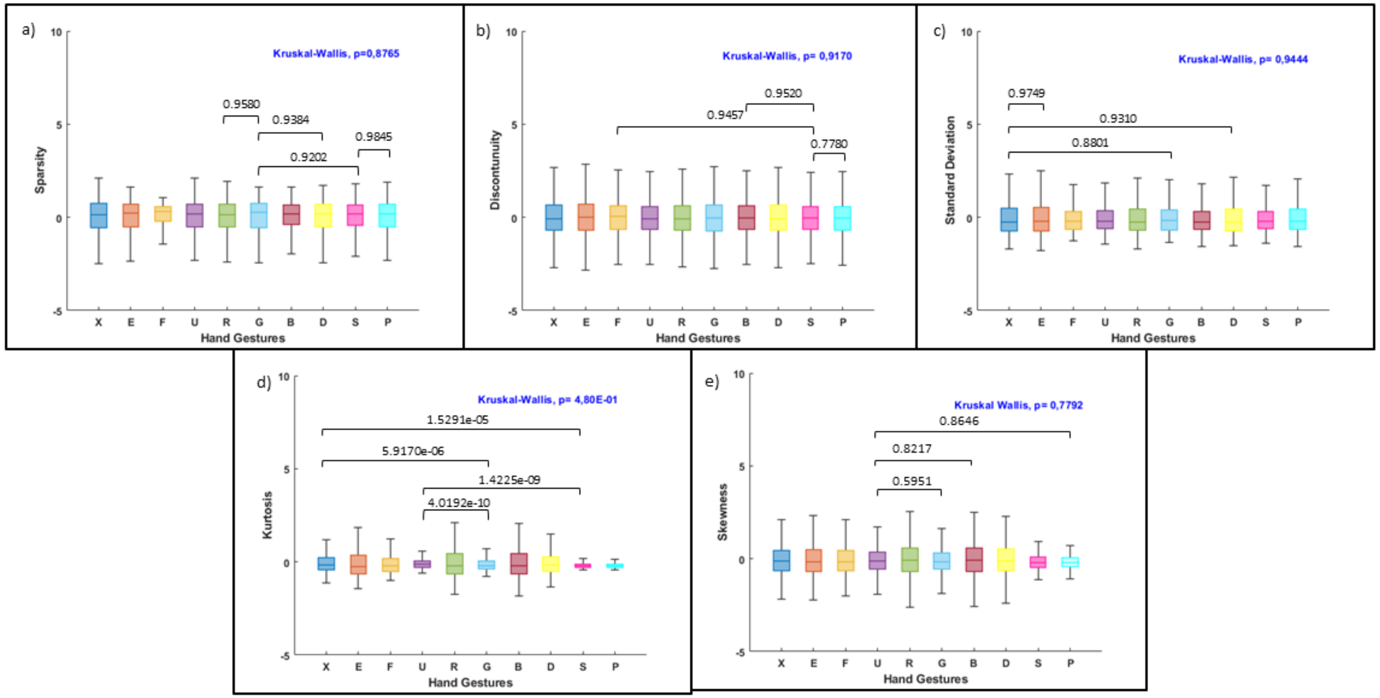

Figure 3.5: The box plots and p values of each base vector for 5 subjects: a)Sparsity, b) Discontinuity, c) Standard Deviation, d) Kurtosis, and e) Skewness, respectively (X: Rest, E: Extension, F: Flexion, U: Ulnar Deviation, R: Radial Deviation, G: Grip, B: fingers abduction, D: fingers adduction, S: supination, and P: pronation)

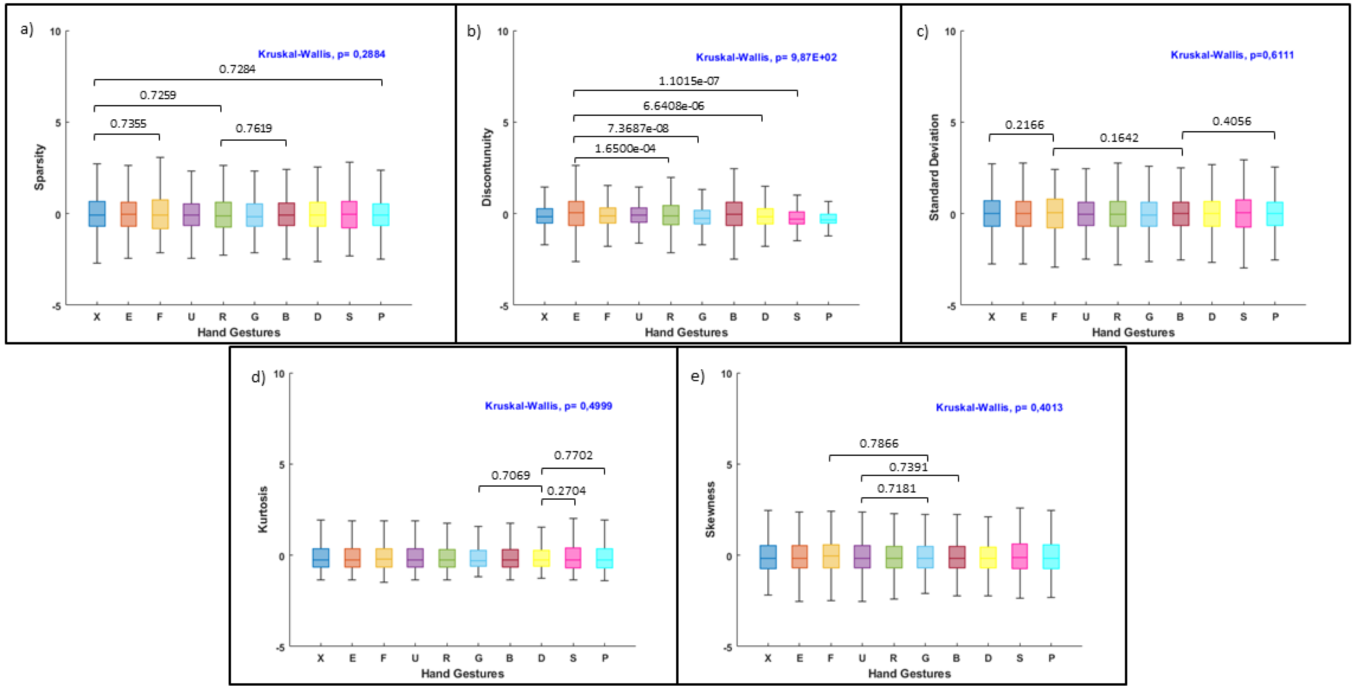

Figure 3.6: The box plots and p values of each coefficient vector for 5 subjects: a)Sparsity, b) Discontinuity, c) Standard Deviation, d) Kurtosis, and e) Skewness, respectively (X: Rest, E: Extension, F: Flexion, U: Ulnar Deviation, R: Radial Deviation, G: Grip, B: fingers abduction, D: fingers adduction, S: supination, and P: pronation)

3.2 Classification Results

The results showed that each of the extracted features is an informative candidate for the classification step. In the next step, the classification was applied to measure the success of the studied features in the classification of hand gestures are presented. The 5 fold- CV was performed to avoid overfitting.

In order to determine the effect of 10 NMF features, whose effects on hand gesture classification were investigated, on classification performance, a single classification was made with 10 features. As shown in Table 3.2, increase was obtained according to the accuracy values obtained in TF moments. Although the numbers of both feature groups are different, higher classification was obtained in NMF method. Neural network-based models, which are frequently preferred among machine learning models, offered more successful results. In fact, deep learning-based models which are neural network advanced versions, have been developed and more advanced results can be obtained. Therefore, when the feature set is developed and other feature combinations are tried, it is predicted that models such as machine learning and deep learning can yield good results with NMF based data. Because, as can be seen, the positive effect of NMF on classification is greater than TF moments. More successful results can be achieved with an accurate and meaningful feature group and an optimum number of features. However, another popular method, SVM, produced the second highest accuracy, but the majority is still in neural network models.

The highest classification obtained from the features extracted from TF moments was obtained with coarse KNN as 39.5%. It is mathematically seen that the features extracted from NMF increase the classification success.

Table 3.1: TF-based classification results of the highest five model

Model	ACC (%)
Coarse KNN	39.5
Medium KNN	36.7
Cubic KNN	36.6
Weighted KNN	35.1
Kernel Naïve Bayes	33.5

Table 3.2: NMF-based classification results of the highest five model

Model	ACC (%)
Wide Neural Network	47.4
Quadratic SVM	46.5
Medium Neural Network	46.4
Trilayered Neural Network	45.7
Bilayered Neural Network	45.5

Chapter 4

Conclusion

In this study, MSST-based features are used for the first time to analyze and classify them for hand movement classification. sEMG signals of 40 subjects were used to apply MSST. There were two types of feature groups and they were extracted from MSST matrices. Their statistical significance cases were investigated. The first feature group consists of four TF moments and the second group consists of ten NMF-based features.

In each group, most of the features were found as statistically significant by providing the significance condition. Only some of them could not meet the statistically significant condition. Especially NMF-based features achieved more successful results. The features whose statistical significance was investigated were then subjected to the classification process.

Looking at the classification results, NMF-based features achieved higher classification accuracy than TF moments. However, the obtained classification performance still needs improvement. For this reason, it is seen that different features obtained from MSST matrices, whose effects on EMG-based hand gesture classification are investigated in this thesis, can be developed by using different feature combinations or models. With further research to be carried out in line with these results, it is suggested that TF moments and NMF-based features extracted from MSST of sEMG signals may not be an alternative approach for hand gesture classification.

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Appendix

Publications from the Thesis

Conference Papers

1. Saripinar, L., Kisa, D. H., Ozdemir, M. A., & Guren, O. (2022, September). Statistical Analysis of Time-Frequency Features Based on Multivariate Synchrosqueezing Transform for Hand Gesture Classification. arXiv preprint arXiv:2209.13350.

Curriculum Vitae

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Education :

2015–2020	İzmir Kâtip Çelebi University, Dept. of Biomedical Eng. (BSc)
2020–2023	İzmir Kâtip Çelebi University, Dept. of Biomedical Eng. (MSc)

Work Experience:

I graduated from İzmir Katip Çelebi University, Department of Biomedical Engineering in 2020 and I started my graduate education in my own department at my own school. I started to work as a Quality Management Representative in the Dikili Çiflik A.Ş. The company I have been working with for about two years serves two different sectors, namely food and plant tissue culture. As the Quality Officer, I am responsible for maintaining the ISO 9001 Quality Management Systems and ISO 22000 Food Safety Management System operating in the food department. At the same time, I take an active role in the execution of the integrated quality system studies being established in the plant tissue culture laboratory.