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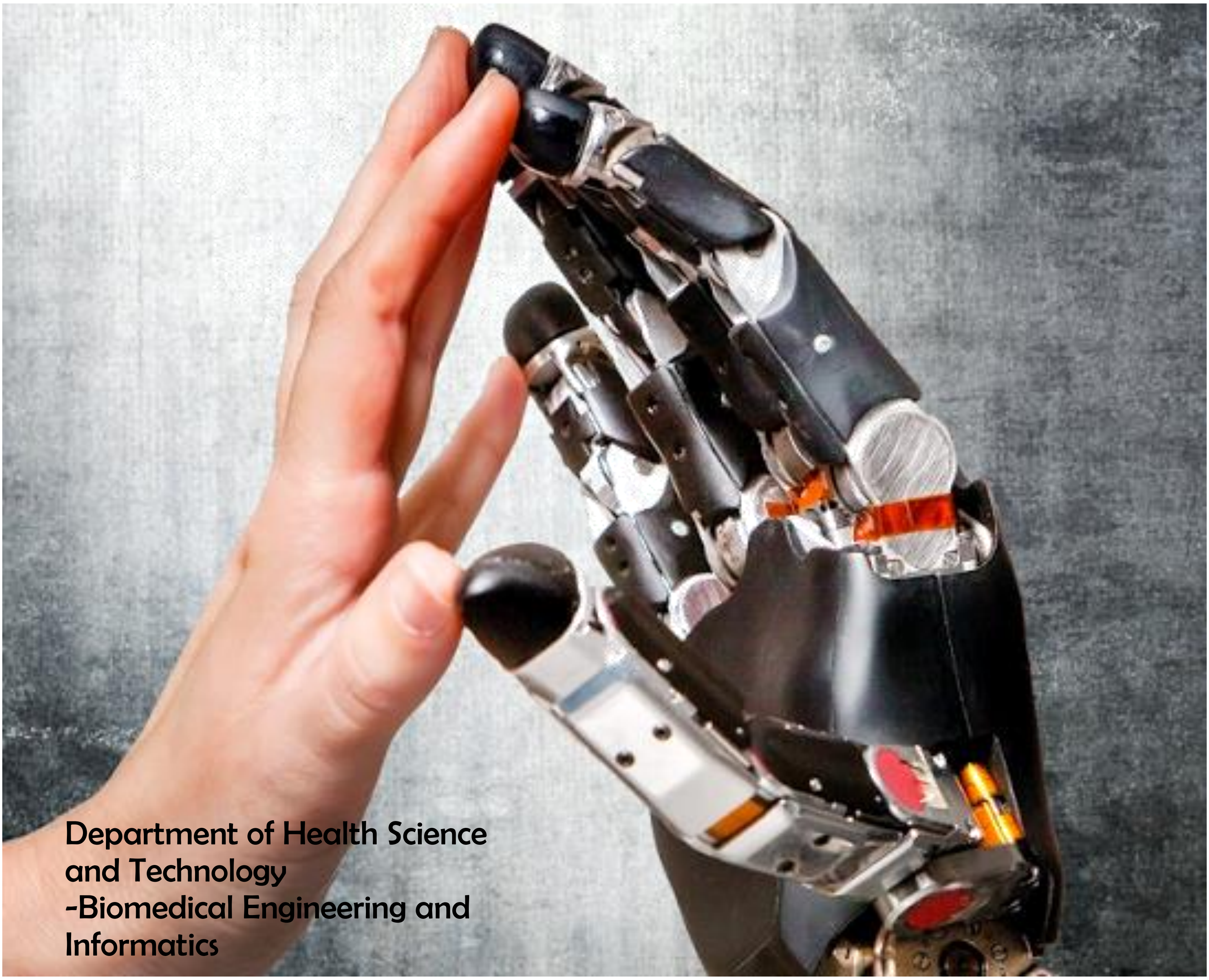
Investigation of the Effect and Robustness of Thresholding Time-domain Features on Hand Movement Classification



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Article

Investigation of the Effect and Robustness of Thresholding Time-domain Features on Hand Movement Classification

Rosa Hugosdottir and Julie Gade

Abstract— Time-domain (TD) features have been widely used in pattern recognition-based control systems. The TD features, zero crossing (ZC), slope sign change (SC), and Willison amplitude (WAMP) make use of thresholds to attenuate background noise. Inconsistent thresholds have been reported in the literature and relatively little work has been done to investigate the effect and robustness of thresholding. Therefore, the aim of this study was to develop a novel method for investigation of thresholding TD features based on classification performance. Experiments including multi-channel surface electromyography recordings during hand movements were carried out for three separate days. The effect and robustness of thresholding TD features were assessed by scatter matrix separability criterion (SMSC), support vector machine (SVM) classification, and statistical tests. Results obtained for identical thresholds for ZC, SC, and WAMP ranged between 0.67 µV and 1.76 µV for all channels and days. An interval recommended for future threshold investigation of a factor *r,* ranging between 0 and 0.52, was identified. Furthermore, results revealed that thresholds were not robust over a period of six days. This indicates that investigation of thresholding TD features should be performed for each specific application. The recommendation is to use the method, introduced in this study, for investigation of thresholding TD features in future applications.

I. INTRODUCTION

For individuals with upper-limb amputation, myoelectric signals used for pattern recognition play a key role in advanced control of multifunctional prostheses [1][2]. The success of pattern recognition-based control systems highly depends on classification accuracy, which is affected by the choice of features and classifiers [1][2][3]. In fact, it has been shown that classification accuracy is more affected by the choice of feature set than by the choice of classifier [4][5]. Three types of features are dominant in the literature: time-domain (TD), frequency-domain, and time-frequency-domain features [3][6]. TD features have been widely used in myoelectric classification due to their computational simplicity and they are easy to implement. TD features are based on signal amplitude extracted directly from raw electromyography (EMG) signals without any transformation [2][3][6]. Hudgins' TD feature set was introduced in 1993 [7] and has been applied in several studies [1][6][8][9]. These TD features include mean absolute value (MAV), waveform length (WL), zero crossing (ZC), and slope sign change (SC), and have shown to be an effective signal representation used for classification of EMG signals [7]. In previous work, it was reported that combining Hudgins' TD features with the TD feature, Willison Amplitude (WAMP), improved classification performance [9][10]. From now on, the feature set composed of Hudgins' TD features and WAMP is simply referred to as *TD features*.

Common to calculation of ZC, SC, and WAMP is the inclusion of a threshold to attenuate background noise [11][12]. Inconsistent thresholds have been reported in the literature, and often the threshold is neglected or ignored [6][11][13][14].

Few studies have investigated the effect of thresholding: in [5], surface EMG (sEMG) signals were recorded during hand open and wrist extension movements from two pairs of electrodes placed on muscle (m.) extensor carpi radialis. Thresholds from 0.5 to 5 μV for WAMP were investigated by the percentage error (PE) for varying signal-to-noise ratio (SNR). A threshold of 0.5 μV resulted in the lowest PE. This investigation was expanded in [15] to include ZC and SC. Hand close and wrist flexion movements, recorded from m. flexor carpi radialis, were added. Thresholds from 1 to 5 μV were investigated resulting in best thresholds of 3 μV for SC and 1 μV for ZC and WAMP. They further noted that the thresholds are gain and instrument dependent. In [12], sEMG signals were recorded during handgrip forces of 0 to 25 N from two electrode pairs placed on m. extensor carpi radialis with unspecified amplification. The sEMG signals were normalized by the maximum value and varying SNR for thresholds from 10^{-4} to 0.9 were investigated using the coefficient of determination (R^2). Optimal thresholds of 10^{-4} to 10^{-3} were identified for ZC and WAMP.

In other studies, thresholds have been used without investigating the effect of thresholding: in [7], a threshold of 2 μV for ZC and SC was used. Another

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study used a threshold of 50-100 mV for WAMP and no threshold for ZC for sEMG signals amplified with a non-specified gain [13]. In [11], thresholds of 1 μV for ZC and SC and 3 μV for WAMP were used. In [6], the thresholds were set to 16 mV for SC and 10 mV for ZC and WAMP, without mentioning amplification.

Novelty of the Present Study

In [15], it was stated that thresholds are gain and instrument dependent indicating that thresholds should be investigated for each specific application. To our knowledge, a generic method for threshold investigation has not been presented in the literature.

As mentioned, former studies have investigated thresholding effect for single features using classifier independent methods [5][12][15]. In relation to practical use of pattern recognition-based control systems, to our knowledge it has not been investigated how thresholding affects classification performance. Hence, classification errors may be a suitable measure of thresholding effects.

The thresholding effect for feature set combined of multiple features has, to our knowledge, not been investigated. When using TD features for classification, identical thresholds may apply to all features, contributing to simple investigation of thresholding.

To our knowledge, robustness of thresholding has not been investigated, since recordings from single day experiments were used [5][12][15]. Robustness of applied thresholds is essential for practical use of pattern recognition-based control systems.

Aim

The aim of this study was to develop a novel method for investigation of thresholding TD features based on classification performance.

Experiments including sEMG recordings during hand movements were carried out for three separate days. The effect and robustness of thresholding TD features were assessed by pattern recognition methods and statistical tests.

II. METHODS

The method is divided into a description of the conducted experiments and necessary data processing steps. A thorough description of the experiments is found in attached worksheets (chapter 5) as well as additional data processing steps performed to support the data processing described below (chapter 7).

A. *Experiment*

sEMG signals were recorded during hand movements for three separate days with two and four days in between.

1. Subjects

Eight healthy subjects participated in the experiments (five males and three females, age: 25±1 years). The experiments were approved by the Danish local ethical committee and carried out in accordance with the Declaration of Helsinki.

2. Data Recording

Signal Acquisition: sEMG signals were recorded from five channels (EMG-USB2, OT Bioelettronica) using Ag/AgCl surface electrodes (Ambu Neuroline 720) placed on the m. pronator teres, m. flexor digitorum superficialis, m. flexor carpi radialis, m. extensor digitorum, and m. extensor carpi radialis longus. The electrode placements of one subject are illustrated in Fig. 1. sEMG signals were amplified 2000 times, analog filtered between 10 and 500 Hz, and sampled at 2000 Hz.

Movement Sessions: Seven hand movements were selected based on frequent use in activities of daily living: hand open, hand close, wrist flexion, wrist extension, wrist supination, wrist pronation, and pinch grip. Furthermore, recordings of no movement (NM) were performed. Each day, four recordings were collected for each movement. Each movement was recorded for three seconds and sEMG signals were only recorded after the subjects had reached a steady-state contraction. The subjects were instructed to make medium, constant contraction force to the best of their ability.

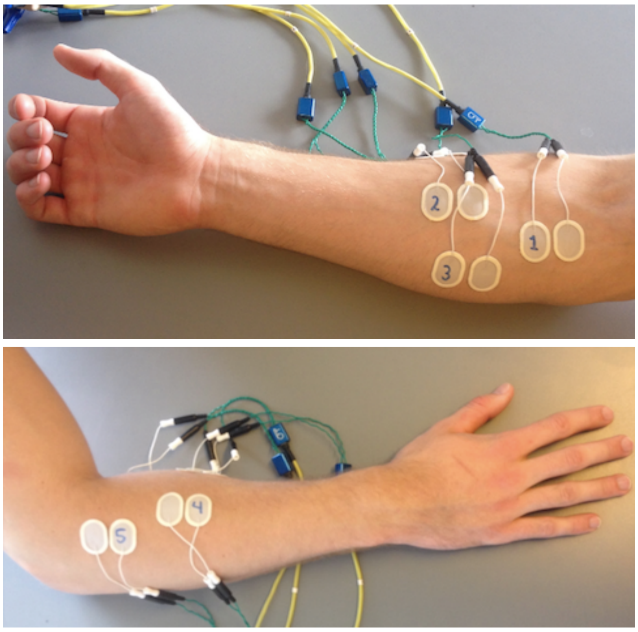

Figure 1. The electrode pairs are numbered from 1-5 according to the channels. Top) Electrode pairs placed at the anterior part of the forearm. Channel (ch) 1: m. pronator teres, ch2: m. flexor digitorum superficialis, and ch3: m. flexor carpi radialis. Bottom) Electrode pairs placed at the posterior part of the forearm. Ch4: m. extensor digitorum, ch5: m. extensor carpi radialis longus

B. Data Processing

The data processing steps described in the following sections contributed to achieving the aim of the study. A novel method for investigation of thresholding TD features is introduced. This method includes 1) preprocessing of sEMG signals, 2) threshold calculation for multiple channels based on noise estimation, 3) feature extraction, 4) a classifier independent method, scatter matrix separability criterion (SMSC), as a measure of class separability, and 5) support vector machine (SVM) classification as a measure of classification performance. Statistical tests were carried out to determine if:

- Individual thresholds should be set for the TD features or identical threshold applied
- Best thresholds and threshold intervals could be identified for the TD features
- Thresholding of TD features could be investigated using a classifier independent method
- Thresholding of TD features was robust over a period of time

1. Preprocessing

A 4th order butterworth bandpass filter (20-400 Hz) was used to filter the digital signal followed by a narrow notch bandstop filter to reduce power line interferences.

2. Threshold Calculation

In order to match any signal amplitude and to be independent of applied amplification, the threshold calculation was based on recordings of NM, assumed to represent the background noise of the signal. The root mean square (RMS) of NM recordings was calculated for all five EMG channels by Eq. 1.

$$RMS\_NM = \sqrt{\frac{1}{N}\sum_{j=1}^{N} x_j^2} \qquad (1)$$

where N is the number of samples and x represents each signal sample.

The minimum value of NM signals (*min_NM*) was subtracted from RMS, since no signal was represented below this value. The thresholds were calculated using Eq. 2.

$$T(r)_i = (RMS\_NM - \min\_NM)r \qquad (2)$$

where i is the number of channels and r is a constant of $\{r \in \mathbb{R} \mid r = 0{:}0.01{:}3.5\}$. In this way, thresholds from zero to above the assumed noise level were investigated.

3. Feature Extraction

Feature extraction was performed for thresholds calculated for all r. The features were extracted from signal segments of 200 ms with 175 ms overlap. The features extracted are described in the following.

MAV is the average of the absolute value of EMG signal amplitude and represents the intensity of a muscle contraction. MAV is given by Eq. 3 [11].

$$MAV = \frac{1}{N}\sum_{n=1}^{N} |(x_n)| \qquad (3)$$

WL is the cumulative length of the waveform and gives information about the amplitude and frequency variation of the signal. WL is given by Eq. 4 [11].

$$WL = \sum_{n=1}^{N-1} |(x_{n+1} - x_n)| \qquad (4)$$

ZC is represented by the number of times the EMG signal crosses zero, thus providing information about frequency. A threshold (ϵ) can be included to attenuate background noise. ZC is given by Eq. 5 [11][12].

$$ZC = \sum_{n=2}^{N} f[(x_n - \epsilon)(x_{n-1} - \epsilon)] \qquad (5)$$

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

SC measures the number of times the sign changes between the positive and negative slope of the signal. A threshold can be included to attenuate background noise. SC is defined as given in Eq. 6 [11][12].

$$SC = \sum_{n=2}^{N-1} f[(x_n - x_{n-1})(x_n - x_{n+1})] \qquad (6)$$

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

WAMP measures the number of times the signal's change in amplitude exceeds a threshold included to attenuate background noise. This feature is associated with the firing of motor unit action potentials and muscle contraction level. WAMP is given by Eq. 7 [11][12].

$$WAMP = \sum_{n=1}^{N-1} f\big(|(x_n - x_{n+1})|\big) \qquad (7)$$

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

4. Scatter Matrix Separability Criterion

The SMSC is a frequently used measure of class separability [16][17]. The scatter matrices include the within-class scatter matrix $\boldsymbol{S}_W$, the between-class scatter matrix $\boldsymbol{S}_\mathrm{B}$, and the total scatter matrix $\boldsymbol{S}_\mathrm{T}$. A small within-class scattering and large between-class scattering means large class separability. A combination of two of the scatter matrices can be used as a class separability criterion, *SMSC*, defined in Eq. 8

$$SMSC = \frac{tr(\mathbf{S}_\mathrm{B})}{tr(\mathbf{S}_\mathrm{T})} \tag{8}$$

where $tr(\boldsymbol{S}_B)$ and $tr(\boldsymbol{S}_T)$ represent the trace of the matrices, which is the sum of their diagonal [16][18][19].

a) Identification of Best Thresholds

SMSC was used to measure the class separability of the TD features using identical thresholds for all r. High SMSC represented good class separability. Therefore, the value of r, which corresponded to the highest SMSC, represented the best threshold for SMSC (T_{SMSC}). SMSC was measured for the three days.

5. Classification

SVM, which is a simple and frequently used classifier [3][20][21], was used for multiple purposes:

a) Four-fold Cross Validation

(1) Identification of Best Thresholds

Classification errors from four-fold cross validation were obtained for all r. For the three days, classification errors were obtained for 1) TD features using identical threshold, 2) single feature ZC (SF_{ZC}), 3) single feature SC (SF_{SC}), and 4) single feature WAMP (SF_{WAMP}). Low classification error represented good classification performance. Therefore, the value of r, which corresponded to the lowest error, represented the best threshold for SVM (T_{SVM}).

(2) Identification of Classification Errors

For the three days, classification errors from four-fold cross validation were obtained for TD features using identical thresholds of T_{SMSC} identified for each day.

Furthermore, for the three days, classification errors from four-fold cross validation were obtained for TD features using separate thresholds of T_{SVM} for SF_{ZC}, SF_{SC}, and SF_{WAMP}.

b) Cross Day Classification

With a fixed identical threshold for the TD features, identified for day one (D1), cross day classification errors were obtained for day 2 (D2) and -3 (D3): in each classification, three recordings from D1 acted as traning data and one recording from D2 and D3 acted as test data. The cross day classification errors were obtained for D2 and D3 by the average errors from the four classifications. Cross day classification errors were obtained for both T_{SMSC} and T_{SVM}.

6) Statistical Tests

A significance level of 0.05 was considered significant for all statistical tests. All the statistical tests were performed in SPSS except the paired-sample t-tests with Bonferroni Holm post hoc corrections, which were performed in MATLAB. The following statistical tests were performed:

a) Identical or Separate Thresholds for the TD Features?

A two-way repeated measures analysis of variance (RM ANOVA) with day and threshold (TD features using identical threshold of T_{SVM} and TD features using separate thresholds of T_{SVM} for SF_{ZC}, SF_{SC}, and SF_{WAMP}) as factors was performed. This to test if there was a difference in classification errors from four-fold cross validation.

b) Identification of Best Thresholds and Intervals

For both identical T_{SMSC} and T_{SVM} for the TD features, two-way RM ANOVAs with day and channel as factors were performed. This to test if there was a difference in thresholds between days and channels.

For the three days, paired-sample t-tests with Bonferroni-Holm post hoc corrections were performed for the global means (average of all subjects) of classification errors from four-fold cross validation obtained for identical T_{SVM} for the TD features. This to determine a threshold interval represented by r, based on classification errors not different from the lowest classification error.

c) Classifier Independent Method?

For identical T_{SMSC} and T_{SVM} for the TD features, a two-way RM ANOVA with day and threshold measure (T_{SMSC} and T_{SVM}) as factors was performed. This to test if there was a difference in classification errors from four-fold cross validation.

d) Threshold Robustness

Paired-sample t-tests were performed to test if there was a difference between cross day classification errors and classification errors from four-fold cross validation obtained for the TD features using identical thresholds. This test was performed for classification errors based on both T_{SVM} and T_{SMSC}.

A two-way RM ANOVA with day (D2 and D3) and threshold measure (T_{SMSC} and T_{SVM}) as factors was performed. This to test if there was a difference in cross day classification errors obtained for TD features using identical T_{SMSC} and T_{SVM}, fixed for D1.

III. RESULTS

Results of statistical tests including identification of best thresholds are described in the following.

A. Identical or Separate Thresholds for the TD Features?

The results of classification errors from four-fold cross validation obtained for TD features using identical T_{SVM} and separate T_{SVM} for SF_{ZC}, SF_{SC}, and SF_{WAMP} are displayed for the three days in Tab. I.

TABLE I. IDENTICAL AND SEPARATE T_{SVM}

Threshold / Day	Day 1	Day 2	Day 3
Identical T_{SVM}	0.14 ± 0.12	0.12 ± 0.10	0.12 ± 0.10
Separate T_{SVM}	0.13 ± 0.12	0.12 ± 0.09	0.11 ± 0.10

The global mean and standard deviation (STD) of classification errors obtained for TD features using identical T_{SVM} and separate T_{SVM} for SF_{ZC}, SF_{SC}, and SF_{WAMP}.

Classification errors were neither dependent on day (RM ANOVA, $p = 0.809$) nor threshold (RM ANOVA, $p = 0.472$). There was not a significant interaction between day and threshold (RM ANOVA, $p = 0.358$). Since a significant difference in classification errors was not found, identical threshold for the TD features applied.

B. Identification of Best Thresholds and Intervals

The results of identical T_{SMSC} for the TD features for five channels and three days are illustrated in Fig. 2.

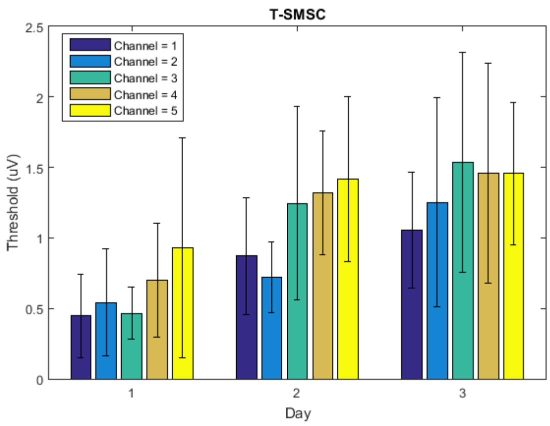

Figure 2. The global mean and STD of identical T_{SMSC} for the TD features for all channels and days.

T_{SMSC} were not dependent on day (RM ANOVA, $p = 0.058$). However, T_{SMSC} were dependent on channel (RM ANOVA, $p = 0.022$). The post hoc test showed no significant difference between channels (Bonferroni, $p > 0.05$). There was not a significant interaction between day and channel (RM ANOVA, $p = 0.429$). Since a significant difference in T_{SMSC} was not found, thresholds were considered consistent between days.

The results of identical T_{SVM} for the TD features for five channels and three days are illustrated in Fig. 3.

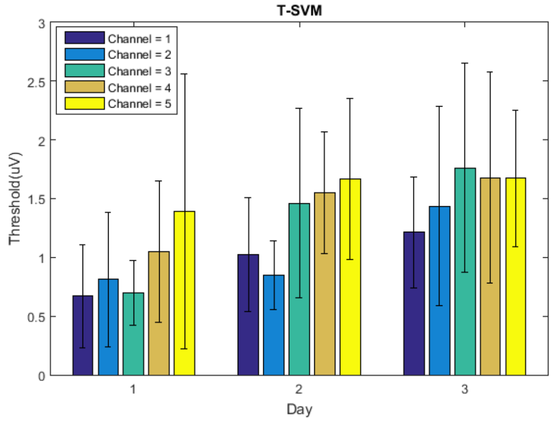

Figure 3. The global mean and STD of identical T_{SVM} for the TD features for all channels and days.

T_{SVM} were neither dependent on day (RM ANOVA, $p = 0.165$) nor channel (RM ANOVA, $p = 0.106$). There was not a significant interaction between day and channel (RM ANOVA, $p = 0.485$). Since a significant difference in T_{SVM} was not found, thresholds were considered consistent between days and channels.

In Fig. 4, the global mean of classification errors from four-fold cross validation obtained for TD features using identical thresholds is plotted against r for all three days.

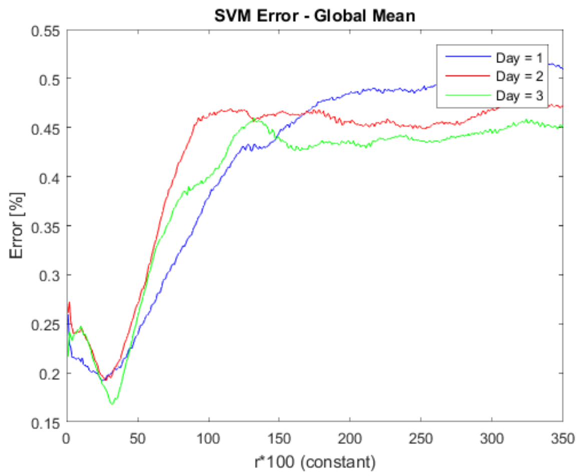

Figure 4. The global mean of classification errors obtained for TD features using identical thresholds plotted against the constant *r*100*.

The best r, representing the lowest classification error, and threshold intervals are displayed in Tab. II.

TABLE II. BEST *R* AND INTERVALS

Day / *r*-values	Best *r*	Interval
D1	25	$\{r \in \mathbb{R} \mid 0 < r < 1.03\}$
D2	28	$\{r \in \mathbb{R} \mid 0 < r < 0.74\}$
D3	32	$\{r \in \mathbb{R} \mid 0 < r < 0.74\}$

Best *r* and intervals

An *r*-value selected from these intervals to calculate the threshold does not significantly affect classification errors.

C. Classifier Independent Method?

The results of classification errors from four-fold cross validation obtained for TD features using identical T_{SMSC} and T_{SVM} are displayed for the three days in Tab. III.

TABLE III. CLASSIFICATION ERRORS FROM FOUR-FOLD CROSS VALIDATION

Threshold measure / Day	D1	D2	D3
T_{SMSC}	0.15 ± 0.11	0.14 ± 0.15	0.13 ± 0.11
T_{SVM}	0.14 ± 0.12	0.12 ± 0.10	0.12 ± 0.10

The global mean and STD of classification errors obtained for TD features using identical T_{SMSC} and T_{SVM}.

The classification errors were neither dependent on threshold measure (RM ANOVA, p = 0.223) nor day (RM ANOVA, p = 0.0635). There was not a significant interaction between threshold measure and day (RM ANOVA, p = 0.920). Since a significant difference in classification errors was not found, T_{SMSC} could be applied without affecting classification performance.

D. Threshold Robustness

The results of cross day classification errors for D2 and D3 obtained for TD features using identical fixed T_{SMSC} and T_{SVM}, identified for D1, are displayed in Tab. IV.

TABLE IV. CROSS DAY CLASSIFICATION ERRORS

Threshold/Day	D2	D3
T_{SMSC}	0.16 ± 0.12	0.35 ± 0.17
T_{SVM}	0.15 ± 0.12	0.34 ± 0.19

The global mean and STD of cross day classification errors obtained for TD features using identical fixed threshold, identified for D1.

Comparison of Classification Errors using T_{SMSC}:

For D2, there was not a significant difference in cross day classification errors (Tab. IV) and classification errors from four-fold cross validation (Tab. III) (paired sample t-test, p = 0.645). For D3, there was a significant difference in cross day classification errors and classification errors from four-fold cross validation (paired sample t-test, p < 0.0005). This indicated that thresholds were robust over two days while thresholds were not robust over a period of six days.

Comparison of Classification Errors using T_{SVM}:

For D2, there was not a significant difference in cross day classification errors (Tab. IV) and classification errors from four-fold cross validation (Tab. III) (paired sample t-test, p = 0.410). For D3, there was a significant difference in cross day classification errors and classification errors from four-fold cross validation (paired sample t-test, p = 0.002). This indicated that thresholds were robust over two days while thresholds were not robust over a period of six days.

Comparison between T_{SMSC} and T_{SVM}

The cross day classification errors were dependent on day (RM ANOVA, p = 0.003). However, classification errors were not dependent on threshold measure (RM ANOVA, p = 0.677). There was not a significant interaction between day and threshold measure (RM ANOVA, p = 0.802). Since a significant difference in classification was not found, T_{SMSC} could be used for cross day classification.

IV. DISCUSSION

A novel method for investigation of thresholding TD features based on classification performance was introduced. The effect and robustness of thresholding TD features were assessed by pattern recognition methods and statistical tests.

A. Identical or Separate Thresholds for the TD features?

In other studies [5][12][15], investigation of thresholding effect was based on single features. In contrast, in this study the investigation of thresholding effect was primarily based on identical thresholds for the TD features. When comparing classification errors from four-fold cross validation for identical and separate thresholds for the TD features, results showed that there was not a significant difference in classification errors, displayed in Tab. I. This indicated that identical thresholds could be used for the TD features without significantly affecting classification performance. Since identical thresholds can be applied, this may contribute to more simple investigation of thresholding TD features in future research.

B. Identification of Thresholds and Intervals

The identical best thresholds identified for the TD features are illustrated in Fig. 2 and 3 for each day and channel. Summarized, T_{SMSC} ranged between 0.45 μV and 1.54 μV and T_{SVM} ranged between 0.67 μV and 1.76 μV. In comparison, best threshold of 0.5 μV was identified for WAMP in [5], and best thresholds of 1 μV for WAMP and ZC and 3 μV for SC were identified by [15]. The thresholds identified in [5] and [15] were not specified for single channels. Compared to this study, T_{SMSC} was dependent on channel. This indicated that thresholds should be identified for single channels.

The best *r* for D1, D2, and D3 were found to be 25, 28, and 32 respectively. The intervals for TD features using identical thresholds, for which classification errors did not change significantly, resulted in the following intervals of r: D1: $\{r \in \mathbb{R} \mid 0 < r < 1.03\}$, D2: $\{r \in \mathbb{R} \mid 0 < r < 0.74\}$, D3: $\{r \in \mathbb{R} \mid 0 < r < 0.74\}$. Based on these intervals, one could choose a threshold calculated in this range without significantly affecting the classification performance. However, the classification errors in these intervals ranged between 0.17 % and 0.39 %. This is considered a great difference with regard to classification performance, and not acceptable for real-time applications. We consider a tolerance level of 10 % from the lowest errors to be acceptable, corresponding to an interval of $\{r \in \mathbb{R} \mid 0 < r < 0.52\}$ found from Fig. 4. For threshold investigation of TD features, an investigation of the best threshold in this interval is recommended.

C. *Classifier Independent Method?*

Results showed that there was not a significant difference in classification errors from four-fold cross validation obtained for TD features using identical T_{SVM} and T_{SMSC}, displayed in Tab. III. This indicated that a classifier independent method, SMSC, could be applied to investigate and identify thresholds for SVM classification. A comparison to other classifier independent methods, e.g. PE as used in [15] or R^2 used in [12] should be performed. Furthermore, other classifiers e.g. linear discriminant analysis and k-nearest neighbor [3], should be included for the method to be generalized.

D. *Threshold Robustness*

Robustness of the applied features is essential for practical use of pattern recognition-based control systems. Even though thresholds were not significant different between days as seen in Fig. 2 and 3, cross day classification was necessary to investigate the robustness of thresholding TD features using identical thresholds over days. For both T_{SMSC} and T_{SVM}, comparison of cross day classification errors (Tab. IV) and classification errors from four-fold cross validation (Tab. III) did not show a significant difference for D2. However, a significant difference was found in classification errors for D3. This indicated that thresholds were robust over two days while thresholds were not robust over a period of six days. Whether time is a critical factor affecting threshold robustness or the difference in classification errors within a six-day period was a coincidence is unknown and should be further investigated.

For research purposes using TD features with identical thresholds, classification performance should not be affected by the fact that thresholding is not robust over days: in offline mode, one can identify the best threshold and thereby optimize the classification performance for a specific application. The method for investigation of thresholding TD features introduced in this study is recommended for offline analysis.

For real-time applications using TD features with identical thresholds, it is problematic that thresholding is not robust with time. Through threshold investigation, the best threshold can be identified offline and applied during control of prosthesis. However, varying noise levels between days can affect the performance. Based on results from cross day classification, our recommendation is to investigate thresholding in a real-time application on a daily basis using the method introduced in this study. For the interval of r-values based on a tolerance level of 10 % in classification performance, the computation time is estimated around two minutes. This amount of time is considered to be worth improved real-time performance of prosthesis.

The cross day classification was based on three recordings from D1 acting as training data and one recording from D2 and D3 acting as test data. Alternatively, training and test data could have been arranged differently: all recordings from D1 could act as training data and two recordings from D2 and D3 could act as test data. Furthermore, thresholds identified for D2 could have been fixed and used to test D3 to provide additional information about threshold robustness.

Comparison of cross day classification errors obtained for TD features using identical T_{SMSC} and T_{SVM} showed that there was not a significant difference between cross day classification errors. This indicated that T_{SMSC} could be applied for cross day classification. This is in comparison to results obtained from the test of a classifier independent method.

E. *Experimental Procedure*

The experiments involved sEMG signals recorded during hand movements. When comparing sEMG signals between days, consistent characteristics of signal amplitude is important. The subjects were instructed to make medium, constant contraction force to the best of their ability. The contraction force is however subjective and it may be difficult to produce consistent contraction force for all days. Had subjects e.g. been provided with feedback on contraction force, more consistent contraction forces may have been obtained. The subjects' arm was positioned on an armrest to ensure consistent signal patterns during the movements between days. A fixation of the arm may have resulted in more consistent signal patterns.

Due to availability of experimental subjects, only healthy subjects participated in the experiments. To investigate the effect and robustness of thresholding TD features in pattern recognition-based control for upper-limb prosthesis, similar investigation should be performed for subjects with different levels of upper-limb amputation.

V. Conclusion

To improve pattern recognition-based control systems, a novel method for investigation of thresholding TD features based on classification performance was introduced in this study. Results obtained for identical thresholds for ZC, SC, and WAMP ranged between 0.67 μV and 1.76 μV for all channels and days. An interval recommended for future threshold investigation of a factor *r,* ranging between 0 and 0.52, was identified. Furthermore, results revealed that thresholds were not robust over a period of six days. This indicated that investigation of thresholding TD features should be performed for each specific application. The recommendation is to use the method for threshold investigation introduced in this study in future applications.

Acknowledgment

The authors would like to thank the subjects participating in this study for their motivation and commitment.

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Worksheets

Preface

The worksheets are made by group 15gr1071 at the 4th semester M.Sc. in Biomedical Engineering and Informatics at Aalborg University at the Department of Health Science and Technology. The project period lasted from the 1st of February 2015 to the 3rd of June 2015.

Reading Guide

Literature used in the worksheets is structured by the Harvard method and is referenced by [Last name, year] in the report. All literature information is assembled in a bibliography at the end of the worhsheets. Book sources are specified by author, title, year and publishing company. Figures and tables represented continuously during the worksheets are enumerated according to the section they are placed in. Abbreviations used through the worksheets are assembled in a list in the beginning of the worksheets.

Contents

Abbreviations

Activities of daily living	ADL
Best threshold for KNN	T_{KNN}
Best threshold for SMSC	T_{SMSC}
Best threshold for SVM	T_{SVM}
Electromyography	EMG
Hand close	HC
Hand open	HO
k-nearest neighbour	KNN
No movement	NM
Pinch grip	PG
Root mean square	RMS
Scatter matrix separability criterion	SMSC
Signal-to-noise ratio	SNR
Single feature SC	SF_{SC}
Single feature ZC	SF_{ZC}
Single feature WAMP	SF_{WAMP}
Slope sign change	SC
Standard deviation	STD
Support vector machine	SVM
Surface EMG	sEMG
Time domain	TD
Waveform length	WL
Willison amplitude	WAMP
Wrist extension	WE
Wrist flexion	WF
Wrist pronation	WP
Wrist supination	WS
Zero crossing	ZC

PART

I

Background

CHAPTER 1

Amputation and Prosthetic Use

Every year an estimated 185,000 persons undergo an amputation of the upper- or lower limb in the United States. In 2008, approximately 1.9 million persons were living with an amputation in the United States. Minor upper-limb amputations (fingers and hands) account for 500,000 cases whereas major upper-limb amputations (transradial- or higher-level) account for 41,000 cases. The main cause of amputation is trauma accounting for 90 % of all upper-limb amputations. The remaining causes of amputation is primarily dysvascular diseases and cancer [Braddom, 2010]. In Denmark, the incidence rate of major upper-limb amputation is approximately 0.6 per 100.000 per year [sundhed.dk, 2014].

Normal human arm functions use complex coordinated and simultaneous movements of the hand, wrist, and elbow to interact with the surrounding environment. These movements are particularly prevalent in many activities of daily living (ADL) such as eating and dressing [Clement et al., 2011; Pulliam et al., 2011]. Thus, amputation of the upper-limb can cause significant functional impairments for patients [Pulliam et al., 2011].

For most amputees, restoration of movement can be obtained through the use of prosthetic devices. The use of prosthetic devices has shown positive effect on the quality of life for amputees. Several prosthetic devices are available: cosmetic-, body-powered-, hybrid-, and electrically-powered prostheses [Lake & Dodson, 2006; O'Keeffe, 2011]. Within the electrically-powered prostheses, it is well known that electromyography (EMG) signals generated by the contractions of residual muscles recorded with electrodes are used to control prosthetic devices [Mathiesen et al., n.d.; Pulliam et al., 2011]. Only surface EMG (sEMG) signals are considered in this study. Control systems based on sEMG signals are usually known as myoelectric control systems. Particularly pattern recognition-based control systems play a key role in advanced control of multifunctional prosthesis [Y. Huang et al., 2005; G. Li, 2011].

CHAPTER 2

Pattern Recognition-based Control Systems

For amputees requiring the control of multiple prosthetic movements, pattern recognition-based control can be applied. The idea is to control a prosthesis using a set of repeatable and distinguishable sEMG patterns that exist when movements are performed with the residual limb [G. Li, 2011]. An observation of the sEMG signal consists of several features representing the characteristics of the signal. These are assigned to a class from a predefined set of classes, representing the intended prosthetic movements. In order to link observations to classes, a learning procedure training the classifier in distinguishing observations is used. The performance of the classification is represented by the classification accuracy or error [O. Duda et al., 2001]. The classification accuracy is defined as:

$$\frac{\text{Correctly classified samples}}{\text{Total number of samples tested}} \cdot 100\% \tag{2.1}$$

The classification error is defined as: (1- classification accuracy) [G. Li, 2011].

Basically, pattern recognition-based control systems consist of four steps: data acquisition, preprocessing, feature extraction, and classification, seen in figure 2.1, and explained in the following sections. The processing steps affect the performance of the classifier [Farrell & Weir, 2008; G. Li, 2011; O. Duda et al., 2001]. An addition to the pattern-recognition based control system is measurement of class separability, which is also described in the following [G. Wang et al., 2006].

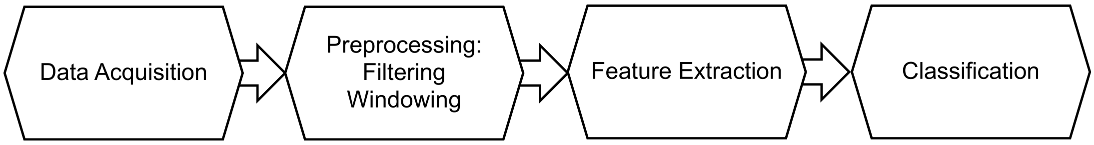


Figure 2.1: *Pattern recognition-based control systems usually consist of four steps: data acquisition, preprocessing, feature extraction, and classification. Modified from [G. Li, 2011].*

2.1 Data Acquisition

When controlling several movements, sEMG recordings from multiple channels containing sufficient signal pattern information are needed for accurate classification of intended movements. The number of EMG channels and configuration of electrode placements have to be considered for several reasons: 1) the data processing of a large number of electrodes is computationally expensive and thereby impractical for myoelectric control in real-time, 2) a classifier could over-fit the training data because of redundant - or irrelevant information [Geng et al., 2014; G. Li, 2011]. Another aspect to consider in acquisition of sEMG signals is the state of the signal. The sEMG signal comprises to states: steady state originating from a constantly maintained contraction in a muscle and transient state originating from a burst of fibers as a muscle goes from rest to a contraction [Englehart & Hudgins, 2003]. Research has obtained inconsistent results suggesting that pattern recognition should be based on classification of both signal types [Phinyomark et al., 2013]. However, in this study only steady state sEMG signals are considered.

2.2 Preprocessing

Filtering

sEMG signals are often contaminated with noise or unwanted components, e.g. motion artefacts. These unwanted components can be removed or attenuated using a filter [Farrell & Weir, 2008; G. Li, 2011]. A filter with bandpass frequencies between 10 and 500 Hz is often applied [Hargrove et al., 2009; G. Li, 2011; Zecca et al., 2002]. If the sEMG signal is highly contaminated with power line interferences, a notch filter is suggested [Hargrove et al., 2009; Ortiz-Catalan, 2014; Zecca et al., 2002].

Windowing

sEMG signals from all channels are segmented into a series of windows. The segment is selected by multiplying the signal with a window of a certain length, usually 100-256 ms [G. Li, 2011; Phinyomark et al., 2010; Phinyomark, Hu, et al., 2012]. The window length has to be adequately long since the stability of the features is determined by the length of the window. With regard to available computing capacity, windows with time overlap are often applied to represent a continuous data stream. Due to operational delay in real-time control, the duration of the overlapping is shorter than the length of the window [Asghari Oskoei & Hu, 2007; G. Li, 2011; Phinyomark, Hu, et al., 2012].

2.3 Feature Extraction

The purpose of feature extraction is to find representative characteristics from sEMG signals. Using a raw sEMG signal directly in a classifier is impractical due to the large number of inputs and the non-stationary characteristic of the raw sEMG signal. Therefore, features extracted from the sEMG signal can be used to map the signal into smaller dimension vectors, called feature vectors. In the literature, a wide spectrum of features has been introduced for myoelectric classification. Three types of features are dominant in the literature: time domain (TD), frequency domain, and time-frequency domain features [Asghari Oskoei & Hu, 2007; G. Li, 2011; Phinyomark et al., 2013; Shin et al., 2014].

2.4 Measurement of Class Separability

From the literature, it is commonly known that the discriminability between classes in a feature space can be measured by the class separability [G. Wang et al., 2006]. A high quality feature space is characterized by clusters having maximum class separability and minimum overlap [Zardoshti-Kermani et al., 1995]. Therefore, the more separable these classes are a less complex and computationally expensive classifier can be applied [Mthembu & Marwala, 2008]. The literature has proposed a variety of class separability measures, listed below:

- Bayes risk [Etemad & Chellappa, 1998]
- Scatter matrix separability criterion (SMSC) [Boostani & Moradi, 2003; Etemad & Chellappa, 1998; Scott, 1999; L. Wang, 2008; L. Wang & Chan, 2002; Zhou et al., 2010]
- Divergence [Etemad & Chellappa, 1998; Scott, 1999]
- Separability index [Mthembu & Marwala, 2008]
- Hypothesis margin [Gilad-Bachrach et al., 2004; Mthembu & Marwala, 2008]
- Davies-Bouldin index [Boostani & Moradi, 2003; G. Wang et al., 2006; Zardoshti-Kermani et al., 1995]
- Fishers linear discriminate index [Oskoei & Hu, 2006]
- Fuzzy-entropy-based index [H.-P. Huang et al., 2003]
- Euclidean distance [Englehart et al., 1999; Lee & Bretschneider, 2012; Phinyomark et al., 2010]
- Bhattacharyya distance [Lee & Bretschneider, 2012; Park & Lee, 1998; Scott, 1999]
- Mahalanobis distance [Mao & Tang, 2011]

- Hellinger distance [Lee & Bretschneider, 2012]
- Roy's largest eigenvalue [Lee & Bretschneider, 2012]
- Standard deviation [Phinyomark et al., 2010]

2.5 Classification

A classifier separates movement patterns from the features space into different classes [O. Duda et al., 2001]. When choosing an appropriate classifier, these conditions should be met: the computational load should be low in order to control a prosthesis in real-time and the classifier must separate patterns to appropriate classes accurately [Asghari Oskoei & Hu, 2007]. A wide variety of classifiers have been proposed in the literature, e.g. linear discriminant analysis, artificial neural network, support vector machine (SVM), k-nearest neighbour (KNN), neuro-fuzzy network etc. [Asghari Oskoei & Hu, 2007; Englehart & Hudgins, 2003; Englehart et al., 1999; Oskoei & Hu, 2008; Phinyomark et al., 2013; Shin et al., 2014].

CHAPTER 3

Elaboration on Features

Investigators have proposed a variety of feature sets in order to increase the information extracted from myoelectric signals and to obtain high classification accuracy [Englehart et al., 2001, 1999; Oskoei & Hu, 2006; Phinyomark, Phukpattaranont, & Limsakul, 2012; Phinyomark et al., 2013; Zardoshti-Kermani et al., 1995]. There seems to be no obvious tendency of which features are used. The choice of features and feature sets may depend on preferences, classifier, and purpose of a study. Using a single feature for classification may result in low accuracy. Multiple feature sets have been employed and gained success in the classification of multiple EMG signals [Asghari Oskoei & Hu, 2007].

3.1 Time-domain Features

TD features are based on signal amplitude extracted directly from raw sEMG signals without any transformation. TD features have been widely used in myoelectric classification due to their computational simplicity. Furthermore, TD features are easy to implement [Asghari Oskoei & Hu, 2007; G. Li, 2011; Phinyomark et al., 2013; Shin et al., 2014]. Hudgins' TD feature set was introduced in 1993 [Hudgins et al., 1993] and has been applied in several studies [Englehart & Hudgins, 2003; Y. Huang et al., 2005; Phinyomark et al., 2013; Scheme & Englehart, 2014]. These TD features include mean absolute value (MAV), waveform length (WL), slope sign change (SC), and zero crossing (ZC) and have shown to be an effective signal representation for classification of myoelectric signals [Hudgins et al., 1993]. In previous work, it was reported that combining Hudgins TD features with the TD feature, Willison Amplitude (WAMP), improved classification performance [Kamavuako et al., 2012; Scheme & Englehart, 2014]. From now on, the combination of Hudgin's TD features and WAMP is simply referred to as *TD features*. The TD features are defined below:

Mean Absolute Value

MAV is the average of the absolute value of EMG signal amplitude and represents the intensity of a muscle contraction. The feature is given by [Phinyomark et al., 2010]:

$$MAV = \frac{1}{N}\sum_{n=1}^{N}|x_n| \tag{3.1}$$

Waveform Length

WL is the cumulative length of the waveform and gives information about the amplitude and frequency variation of the signal. The feature is given by [Phinyomark et al., 2010]:

$$WL = \sum_{n=1}^{N-1}|x_{n+1} - x_n| \tag{3.2}$$

Zero Crossing

ZC is represented by the number of times the sEMG signal crosses zero, thus providing information about frequency. A threshold (ϵ) can be included to attenuate background noise. ZC is given by [Kamavuako et al., 2013; Phinyomark et al., 2010]:

$$ZC = \sum_{n=2}^{N} f\left[(x_n - \epsilon)(x_{n-1} - \epsilon)\right] \tag{3.3}$$

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

Slope Sign Change

SC measures the number of times the sign changes between the positive and negative slope of the sEMG signal. A threshold can be included to attenuate background noise. SC is given by [Kamavuako et al., 2013; Phinyomark et al., 2010]:

$$SC = \sum_{n=2}^{N-1} f\left[(x_n - x_{n-1})(x_n - x_{n+1})\right] \tag{3.4}$$

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

Willison Amplitude

WAMP measures the number of times the signal's change in amplitude exceeds a predefined threshold included to attenuate background noise. This feature is associated with the firing of motor unit action potentials and muscle contraction level. WAMP is given by [Kamavuako et al., 2013; Phinyomark et al., 2010]:

$$WAMP = \sum_{n=1}^{N-1} f(|x_n - x_{n+1}|) \tag{3.5}$$

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

CHAPTER 4

State-of-the-art for Threshold Investigation

The features ZC, SC, and WAMP include a threshold in order to attenuate background noise. There seems to be no obvious tendency of applied thresholds for the features.

In some studies, the thresholds are investigated:

- In a study by [Phinyomark et al., 2008] WAMP were investigated for varying signal-to-noise (SNR) ratio. sEMG signals were recorded from two pairs of electrodes placed on the extensor carpi radialis longus muscle of a healthy subject. The signals were sampled with 1000 Hz and amplified 1000 times. The threshold for ZC was included without investigation and set to 20 mV (2 μV without amplification). A threshold from 5 to 50 mV (0.5 to 5 μV without amplification) was investigated for WAMP by the percentage error (PE):

$$PE = \frac{feature_{clean} - feature_{noise}}{feature_{clean}} \cdot 100\% \tag{4.1}$$

  The performance of WAMP improved with smaller thresholds and a 5 mV (0.5 μV without amplification) threshold resulted in the best performance. This study was further expanded in [Phinyomark et al., 2009] to include ZC and SC. sEMG signals were recorded from two pairs of electrodes placed on the extensor carpi radialis longus and flexor carpi radialis muscles of a healthy subject. The signals were sampled with 1000 Hz and an amplified 1000 times. The thresholds for ZC, SC, and WAMP were investigated by the PE. Thresholds varied from 10 to 50 mV (1-5 μV without amplification) with a step size of 10 mV (1 μV without amplification). It was found that the best threshold corresponding to the lowest PE was 30 mV (3 μV without amplification) for SC, whereas the best thresholds were 10 mV (1 μV without amplification) for ZC and WAMP. However, they further conclude that the threshold is gain and instrument dependent.

- In our previous work [Gade & Hugosdottir, 2015] the thresholds for ZC, SC, and WAMP were investigated. sEMG signals were recorded from 12 electrode pairs placed on the stump and surrounding areas of a proximal transhumeral amputee. The signals were sampled with 2048 Hz and amplified 5.000 times. The thresholds were investigated by LDA classificaion. The best threshold for all features was found to be 1.456 mV (0.2912 μV without amplification) corresponding to the lowest LDA classification error.

- In a study by [Kamavuako et al., 2013] thresholds for ZC, SC, and WAMP were investigated for varying SNR ratio. sEMG signals were recorded from the extensor carpi radialis muscle by two pairs of electrodes of ten healthy subjects. The signals were sampled with 10,000 Hz and normalized by the maximum value before analysis. They did not mention amplification. The thresholds investigated ranged from 10^{-4} to 0.9. Best thresholds of 10^{-4} to 10^{-3} were identified for ZC and WAMP.

In other studies, the thresholds are predefined but not investigated:

- In [Hudgins et al., 1993] ZC and SC were extracted from sEMG signals. sEMG signals were recorded from one pair of electrodes placed on the biceps brachii and triceps brachii muscle of four healthy subjects and one above-elbow amputee. They assumed a noise of 4 μV peak-to-peak prior to amplification of the sEMG. The signals were sampled with 1000 Hz and amplified 5000 times. Therefore a threshold of +-10 mV (2 μV without amplification) was set for ZC and SC. Several other studies have used Hudgins calculation of ZC and SC [Englehart & Hudgins, 2003; Farrell & Weir, 2008; Hargrove et al., 2007; Shin et al., 2014; Zecca et al., 2002].

- In a study by [Zardoshti-Kermani et al., 1995] ZC and WAMP were extracted from sEMG signals. sEMG signals were recorded from two pairs of electrodes placed on biceps and triceps muscles of an above-elbow amputee. The signals were sampled with 1000 Hz and amplified with a non-specified gain. A threshold of 50 to 100 mV was used for WAMP. No threshold was used for ZC.

- In [Phinyomark et al., 2010] ZC, SC, and WAMP were extracted from sEMG signals. sEMG signals were recorded from the extensor carpi radialis longus and flexor carpi radialis by two pairs of electrodes of a healthy subject. The signals were sampled with 1000 Hz and an amplified 1000 times. They state that the best threshold for SC and ZC is 10 mV (1 μV without amplification) and about 30 mV (3 μV without amplification) for WAMP.

- In a study by [Phinyomark et al., 2013] ZC, SC, and WAMP were extracted from sEMG signals. sEMG signals were recorded during 21 days four pairs of electrodes placed on the forearm of a healthy subject. The signals were sampled with 2048 Hz. The threshold for SC were set to 16 mV and 10 mV for ZC and WAMP. They did not mention amplification.

In table 4.1, an overview of the above-mentioned studies including either predefined or investigated thresholds for ZC, SC, and WAMP is displayed. As seen, inconsistent thresholds have been reported in the literature and often the threshold is neglected or ignored. One important aspect has been highlighted by [Phinyomark et al., 2009]; the threshold is gain and instrument dependent. To our knowledge, the effect of thresholding ZC, SSC, and WAMP and the robustness of these thresholds have not been investigated with regard to classification performance. An optimal threshold may improve the pattern recognition-based control system and thereby the overall performance of prosthesis. Given that relatively little work has been done to investigate the effect and robustness of thresholding ZC, SSC, and WAMP, the aim of this study was to develop a novel method for investigation of thresholding TD features based on classification performance.

Summary Table								
Parameters/ Study	*[Hudgins et al., 1993]*	*[Zardoshti-Kermani et al., 1995]*	*[Phinyomark et al., 2010]*	*[Phinyomark et al., 2013]*	*[Phinyomark et al., 2008]*	*[Phinyomark et al., 2009]*	*[Gade & Hugosdottir, 2015]*	*[Kamavuako et al., 2013]*
No. of subjects	5	1	1	1	1	1	1	10
State of health	4 healthy, 1 above-elbow amputation	Above-elbow amputation	Healthy	Healthy	Healthy	Healthy	Transhumeral amputation	Healthy
No. of electrode pairs	1	2	2	4	2	2	12	2
Sample rate (Hz)	1000	1000	1000	2048	1000	1000	2048	1000
Gain	5000	x	1000	X	1000	1000	5000	x
Predefined threshold (mV)	ZC=10 SSC=10	ZC=0 WAMP=50-100	ZC=10 SSC=10 WAMP=30	ZC=10 SSC=16 WAMP=10	ZC=20	x	x	x
Threshold identified by investigation (mV)	x	x	x	x	WAMP=5	ZC=10 SSC=30 WAMP=10	ZC=1.456 SSC=1.456 WAMP = 1.456	ZC=10^{-4}-10^{-3}, WAMP=10^{-4}-10^{-3} (no unit)

Table 4.1: *Overview of studies including either predefined or investigated thresholds for ZC, SC, and WAMP.*

PART II

Methods

CHAPTER 5

Experiments

The purpose of the experiments were to collect sEMG signals during hand movements. sEMG signals were recorded during three separate days in preparation for the investigation of the effect and robustness of thresholding TD features.

5.1 Experimental Setup

The required equipment in the experiment was divided into hardware/software and is listed below.

Hardware

- A computer
- A 12-channel EMG amplifier (EMG-USB, OT Bioelettronica)
  - Gain: 2,000
  - Filter setting: 10-500 Hz
- A DAC cable
- One six-channel bipolar adapter Jack Connectors (AD8x2JD, OT Bioelettronica, Italy)
- Ten self-adhesive solid gel surface electrodes (Ambu Neuroline 720)
- A wrist-band used as a common reference electrode
- Abrasive paste for skin preparation

Software

- Mr Kick: a data acquisition software for the acquisition of EMG signals
  - Sample rate: 2,000 Hz

The experimental setup was as follows: the 12-channel EMG amplifier was connected to the computer, installed with Mr. Kick software, by a DAQ cable. The six-channel bipolar adapter Jack Connectors was connected to the EMG amplifier and attached with ten electrodes to provide five EMG channels.

5.2 Experimental Protocol

5.2.1 Subjects

Eight healthy subjects participated in the experiments (three females and five males, 25 ± 1 years old). The experiments were approved by the Danish local ethical committee and carried out in accordance with the Declaration of Helsinki.

5.2.2 Electrode Placements

Movements

Each subject performed the following movements with the right (dominant) arm:

- Wrist flexion (WF)
- Wrist extension (WE)
- Wrist supination (WS)
- Wrist pronation (WP)
- Hand opening (HO)
- Hand closing (HC)
- Pinch grip (PG)
- No movement (NM)

The selected movements were chosen based on frequent use in ADL and inspiration from studies using these movements in myoelectric control of a prosthesis [Phinyomark et al., 2010, 2013; Shin et al., 2014].

Anatomy of the Forearm

The movements and the muscles in the forearm involved in these movements are listed in table 5.1.

Muscles involved in movements of the forearm	
Movement	**Muscles**
WF	Flexor carpi radialis, flexor carpi ulnaris, palmaris longus, (flexor digitorum superficialis, flexor digitorum profundus, flexor pollicis longus)
WE	Extensor carpi ulnaris, extensor carpi radialis longus and brevis, (extensor digitorum, extensor indicis, extensor digiti minimi, extensor pollicis longus and brevis)
WS	Supinator (deep muscle)
WP	Pronator teres
HO	Extensor digitorum, extensor indicis, extensor digiti minimi, extensor pollicis longus and brevis
HC	Flexor digitorum superficialis, flexor digitorum profundus
Pinch grip	Flexor digitorum superficialis (intrinsic hand muscles)

Table 5.1: *Overview of muscles involved in selected hand movements and associated functions of the forearm muscles. The muscles listed in parentheses assist in performing the movements [H. Martini & L. Nath, 2009].*

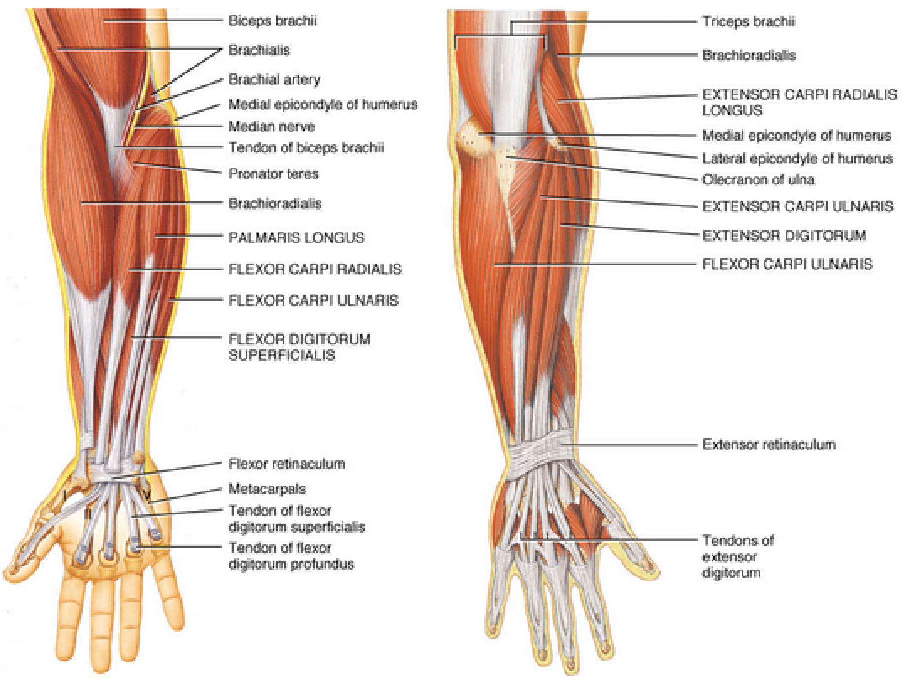
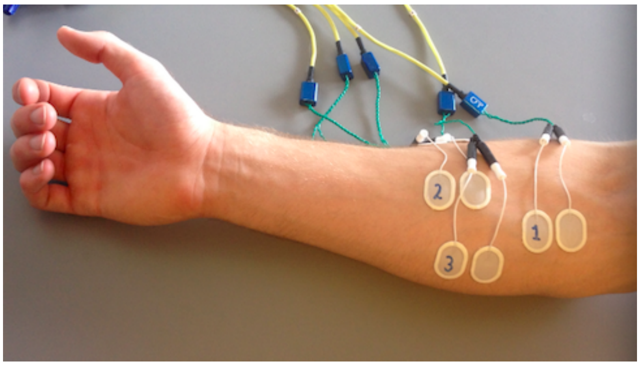
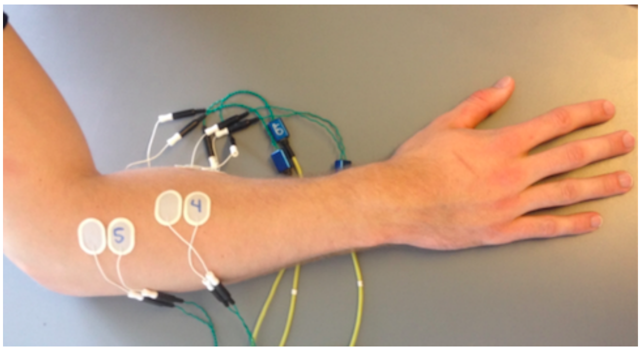


Figure 5.1: *The muscles of the hand and forearm. Left: anterior view. Right: Posterior view. [Standring, 2008].*

To find appropriate placements for the sEMG electrodes, the muscles were palpated during performance of the different movements. The electrode pairs were placed transversely, meaning the electrodes were placed perpendicular to the long axis [Day, 2002]. A permanent marker was used to ensure identical electrode placements for individual subjects between days. In figure 5.2, the placements of the electrodes and associated channel numbers are shown.



(a)



(b)

Figure 5.2: *The electrode pairs are numbered from 1-5 according to the channels. a) Electrodes pairs placed at the anterior part of the forearm. Channel 1: pronator teres muscle, channel 2: flexor digitorum superficialis muscle, and channel 3: flexor carpi radialis muscle. b) Electrode pairs placed at the posterior part of the forearm. Channel 4: extensor digitorum muscle, and channel 5: extensor carpi radialis muscle.*

The following steps were performed when placing the electrodes:

- The skin was cleaned and moistured with electrode gel to ensure optimal sEMG signals
- One electrode pair placed on the pronator teres muscle (channel 1)
- One electrode pair placed on flexor digitorum superficialis muscle (channel 2)
- One electrode pair placed on the flexor carpi radialis muscle (channel 3)

- One electrode pair placed on the extensor digitorum muscle (channel 4)
- One electrode pair placed on the extensor carpi radialis muscle (channel 5)

5.2.3 Movement Sessions

sEMG signals were collected over three separate days with two and four days in between. Every day, each subject performed four movement sessions. One movement session consisted of each of the movements performed for three seconds with 10-20 seconds rest in between. After each movement session, three seconds recordings of no movement (NM) were performed. The subjects were given a three minutes break between the movement sessions. sEMG signals were only collected after the subjects had reached a steady-state contraction of the required movement. The subjects were instructed to make medium, constant contraction force to the best of their ability during the movement sessions.

CHAPTER 6

Theory of Applied Methods

In this chapter, theory of the class separability measure, SMSC, and classifiers, SVM and KNN, are described.

6.1 Scatter Matrix Separability Criterion

SMSC is a commonly used measure of class separability [L. Wang, 2008; L. Wang & Chan, 2002]. The scatter matrices include the within-class scatter matrix $\mathbf{S}_W$, the between-class scatter matrix $\mathbf{S}_B$, and the total scatter matrix $\mathbf{S}_T$. With $(\mathbf{x}, y) \in (\mathbb{R}^d \times \gamma)$ being a sample, $\mathbb{R}^d$ the d-dimensional feature space, γ the set of class labels, and the number of classes is the size of γ, the scatter matrices are defined as

$$\mathbf{S}_W = \sum_{i=1}^{c} \left[\sum_{j=1}^{n_i} (\mathbf{x}_{ij} - \mathbf{m}_i)(\mathbf{x}_{ij} - \mathbf{m}_i)^T \right] \tag{6.1}$$

$$\mathbf{S}_B = \sum_{i=1}^{n_i} n_i (\mathbf{m}_i - \mathbf{m})(\mathbf{m}_i - \mathbf{m})^T \tag{6.2}$$

$$\mathbf{S}_T = \sum_{i=1}^{c} \left[\sum_{j=1}^{n_i} (\mathbf{x}_{ij} - \mathbf{m})(\mathbf{x}_{ij} - \mathbf{m})^T \right] \tag{6.3}$$

where $\mathbf{S}_T = \mathbf{S}_W + \mathbf{S}_B$. The number of samples in the ith class is denoted as n_i, $\mathbf{m}_i$ is the mean vector for the ith class and $\mathbf{m}$ is the mean vector for all classes. A small within-class scattering and large between-class scattering means a large class separability. A combination of two of the scatter matrices can be used as a class separability criterion, $SMSC$, defined as

$$SMSC = \frac{tr(\mathbf{S}_T)}{tr(\mathbf{S}_W)} \tag{6.4}$$

where $tr(\mathbf{S}_T)$ and $tr(\mathbf{S}_W)$ represent the trace of the matrices, which is the sum of their diagonal. A large SMSC value represents high class separability [Han & Liu, 2013; L. Wang, 2008; Zhou et al., 2010].

6.2 Classification

KNN and SVM were chosen for this study since these classifiers are simple and have been frequently applied in the literature [Kim et al., 2011; Oskoei & Hu, 2008; Shin et al., 2014; Zardoshti-Kermani et al., 1995]. KNN and SVM are described in the following sections.

6.2.1 K-nearest Neighbour

KNN is a simple and non-parametric method, why it does not make any assumptions on the underlying data distribution. The method classifies a new observation based on the k nearest observations in the training data. A new observation is classified by a majority vote of its neighbours, with the new observation being assigned to the class most common among its k-nearest neighbours often measured by a distance function e.g. euclidean distance [O. Duda et al., 2001]. A k-value of an odd number is often preferable in order to avoid ties. In case of ties, a new observation can randomly be assigned to a class. If k equals one, the new observation is assigned to the class of its nearest neighbour [O. Duda et al., 2001].

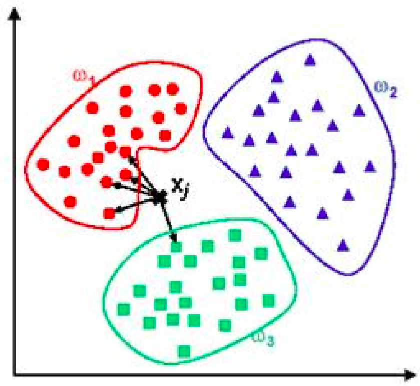


Figure 6.1: *KNN example using euclidean distance and k equal to 5 [*http://mathalytics.blogspot.dk*, n.d.].*

In the example in figure 6.1, three classes w_i are represented and the goal is to assign the new observation x_j to a class w_i. In this case, k = 5 and euclidean distance is used. As indicated by the arrows from x_j, of the five closest neighbours, one belong to class w_3 and four belong to class w_1. Therefore, x_j is assigned to class w_3, which is the dominant class [O. Duda et al., 2001].

6.2.2 Support Vector Machine

In its basic nature, SVM is a parametric binary classifier separating two classes using an optimal hyperplane. The aim of SVM is to find an optimal hyperplane that maximizes the distance between the points of the classes being closest to each other. The points of classes being closest to each other are termed support vectors, and the distance between them is referred to as the margin, see figure 6.2 [O. Duda et al., 2001].

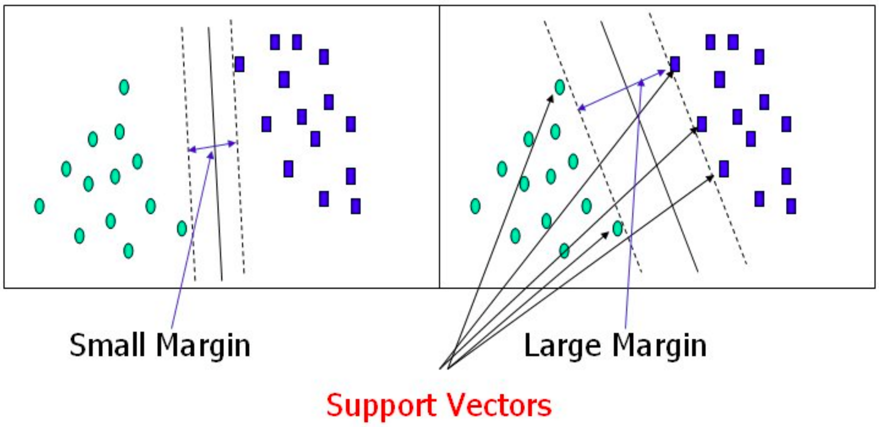


Figure 6.2: *SVM examples illustrating support vectors and corresponding margins [*https://www.dtreg.com/solution/view/20*, n.d.].*

Some assumptions are associated with SVM: the observations are a random sample, and the density for the data in each class follows a normal distribution [O. Duda et al., 2001]. Furthermore, the data points have to be linearly separable, where a line on graphs of x_1, x_2 can discriminate between two classes and a hyperplane on graphs of $x_1, x_2, ..., x_c$ can separate more than two classes (c > 2) [Fletcher, 2009].

For the multi-class problem of SVM there are two approaches [T. Li et al., 2006; O. Duda et al., 2001]:

1. One-against-one approach: $c(c-1)/2$ discriminant functions are used to separate every pair of classes.
2. One-against-rest approach: this can be viewed as a c discriminant function case, where each class is trained to separate one class from the rest.

In this study, the one-against-one approach was used for the SVM classification.

Classification Strategies

Two classification strategies exist: unsupervised- and supervised learning. Using the unsupervised learning strategy, there is no a priori knowledge of number of classes or patterns and the classifier finds patterns within the input data itself. For a supervised learning strategy, used in SVM and KNN classification, the classifier is first trained using data with known classes. Usually, the sEMG recordings from a movement are divided into training- and testing data. A classifier is built using the training data and the performance of the trained classifier is evaluated using the testing data to measure the classification accuracy [G. Li, 2011]. One way to train a classifier and test the performance of a classifier is to use k-fold cross validation, where the data set is divided into k-subsets. The $(k-1)$-subsets form the training set, and one of the k-subsets is used as the test set. The classifier is trained and tested k-times, each time with a different set representing the training- and test set. The error is computed as the average error across all k-trials [O. Duda et al., 2001].

6.3 Statistics

The statistics in this study was assessed by SPSS software [Lund & Lund, 2003]. The methods described in following sections were applied for statistical analysis and testing of assumptions.

6.3.1 Repeated Measures Analysis of Variance

In general, analysis of variance (ANOVA) is used to test for significant differences between groups on a dependent variable. Despite the name, ANOVA is trying to determine whether the *means* of the different levels of the factor(s) are different in the population. A repeated measures (RM) ANOVA is used when e.g. each condition of the experiment includes the same group of participants, which is the case in this study [Lund & Lund, 2003; Zar, 2010]. The one-way RM ANOVA is used to test if there are any significant differences between the population means of three or more levels of a factor. The two-way RM ANOVA compares the mean differences between groups that have been split into two factors. Interaction terms and main effects are examined. If an interaction between two factors exist this means that the effect of one factor is not independent of the presence of a particular level of the other factor [Zar, 2010]. A main effect is the effects of one of the factors on the dependent variable, ignoring the effects of the other factor. Moreover, post hoc tests of pairwise comparisons can reveal exactly where a significant difference between means are present [Lund & Lund, 2003]. The three-way RM ANOVA is used to test if there is an interaction effect between three factors on a dependent variable [Lund & Lund, 2003; Zar, 2010]. Interaction terms and main effects are examined.

Common for the one-, two- and three-way RM ANOVA are the following assumptions [Lund & Lund, 2003; Zar, 2010]:

- Outliers: there should be no significant outliers in any level of the factor(s)
- Normality: the dependent variable should be approximately normally distributed for each level of the factor(s)
- Sphericity: the variances of the differences between all combinations of levels of the factor(s) must be equal

Boxplot Test of Outliers

There are several methods available to detect outliers, and boxplots are one of the most straightforward and simple methods. The boxplot determines whether there are outliers in any of the levels of the independent variable(s). SPSS divides outliers into data points located more than 1.5 and 3.0 box-lengths from the edge of their box, labelled *outlier* and *extreme outlier* respectively, see figure 6.3 [Lund & Lund, 2003].

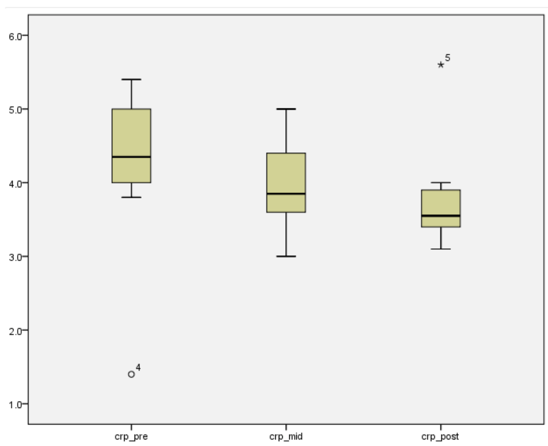


Figure 6.3: *Boxplot example from SPSS. An outlier is represented by a circle and an extreme outlier is represented by an asterisk [Lund & Lund, 2003].*

Outliers are generally not considered as troublesome as extreme outliers. Outliers may be ignored, but in case of extreme outliers several things can be considered: use non-parametric tests, modify or transform the outliers, or simply use the RM ANOVA regardless [Lund & Lund, 2003].

Shapiro-Wilk Test of Normality

One of the most common normality tests is the Shapiro-Wilk test, which is recommended for small sample sizes (< 50 samples) [Lund & Lund, 2003; Razali & Wah, 2011]. If the Shapiro-Wilk test is significant (i.e. has a p-value less than or equal to 0.05), significant departures from normality are found in the data. If the Shapiro-Wilk test is not significant, the data follows a normal distribution [Lund & Lund, 2003].

If data is not normally distributed, several things can be considered: use non-parametric tests, transform the data, or simply use the RM ANOVA regardless. RM ANOVA is rather robust to departures from normality, especially if the sample sizes are equal [Lund & Lund, 2003].

Mauchly's Test of Sphericity

The assumption of sphericity is that the differences between the levels of the independent variable(s) have equal variances. If the Mauchly's Test is significant (i.e. has a p-value less than or equal to 0.05), data does not have equal variances and sphericity is therefore not met. If the Mauchly's test is not significant, the variances are equal. The effect of violating sphericity is a loss of power, and an adjustment needs to be made to the degrees of freedom so that the test still returns a correct p-value. There are three different estimates of sphericity used to correct the degrees of freedom: Greenhouse and Geisser's, Huynh and Feldt's, and The Lower Bound estimate. In practice, only Greenhouse-Geisser and Huynh-Feldt are used, and they produce very similar corrections [Lund & Lund, 2003].

6.3.2 Paired-sample t-test

A paired-sample t-test is used to test for significant differences between paired observations, e.g. the participants are the same individuals tested at two time points, on a dependent variable. The following assumptions apply for the paired-sample t-test [Lund & Lund, 2003]:

- Outliers: there should be no significant outliers in the differences between the groups
- Normality: the differences between the groups should be approximately normally distributed

If data is not normally distributed, several things can be considered: use non-parametric tests, transform the data, or simply use the paired-sample t-test regardless. However, the paired-sample t-test is rather robust to departures from normality [Lund & Lund, 2003].

CHAPTER 7

Data Processing

The data processing steps described in the following sections contributed to achieving the aim of the study. A novel method for investigation of thresholding TD features is introduced. This method includes 1) preprocessing of sEMG signals, 2) threshold calculation for multiple channels based on noise estimation, 3) feature extraction, 4) a classifier independent method, SMSC, as a measure of class separability, and 5) SVM and KNN classification as a measure of classification performance. Statistical tests were carried out to compare thresholds and classification errors.

7.1 Data Acquisition

Information about data acquisition is described in chapter 5.

7.2 Preprocessing

Filtering

To remove noise and unwanted components and maintain signal components containing information about the myoelectric activity, frequencies below 20 and above 400 were discarded using a fourth order butterworth bandpass filter. To remove power line interferences (50 Hz), a narrow notch bandstop filter was applied.

Windowing

Before extracting features, the signals were segmented into series of windows. In this study the window length was set to 200 ms with an overlap of 175 ms.

7.3 sEMG Signal Analysis

The root mean square (RMS) of the sEMG signals was calculated for all days, movements, and channels to obtain information about sEMG signal amplitudes.

7.4 Threshold Calculation

The noise of the signal was of most interest, since a threshold condition can be included to avoid background noise. In order to match any signal amplitude and to be independent of applied amplification, the threshold calculation was based on recordings of NM, assumed to represent the background noise level of the signal. The RMS of NM recordings for all five EMG channels was calculated by Eq. 7.1.

$$RMS_{NM} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \tag{7.1}$$

where N is the number of samples and x represent each signal sample.

The minimum value of NM signals (min_{NM}) was found and subtracted from RMS, since no signal is represented below this value. The threshold values were calculated using Eq. 7.2

$$T(r)_i = (RMS_{NM} - min_{NM})r \tag{7.2}$$

where i is the number of channels and r is a constant $\{r \in \mathbb{R} \mid r = 0:0.01:3.5\}$. The threshold was increased sufficiently high to examine the space above RMS. In this way, the threshold was calculated from zero to above the assumed noise level.

7.5 Feature Extraction

Features described in section 3.1 were extracted. Feature extraction was performed for the TD features and single features of ZC (SF_{ZC}), SC (SF_{SC}), and WAMP (SF_{WAMP}) for all r.

7.6 Scatter Matrix Separability Criterion

SMSC, described in section 6.1, was used to measure the class separability for all r. For all three days, SMSC was obtained for 1) TD features using identical threshold, 2) SF_{ZC}, 3) SF_{SC}, and 4) SF_{WAMP}.

7.6.1 Identification of Best Thresholds

High SMSC represented good class separability. Therefore, the value of r, which corresponded to the highest SMSC, represented the best threshold for SMSC (T_{SMSC}). T_{SMSC} was found for the three days.

7.7 Classification

SVM and KNN classification, described in section 6.2, was used for multiple purposes:

7.7.1 Four-fold Cross Validation

7.7.1.1 Identification of Best Thresholds

Classification errors from four-fold cross validation were obtained for all r. For the three days, classification errors were obtained for 1) TD features using identical threshold, 2) SF_{ZC}, 3) SF_{SC}, and 4) SF_{WAMP}. Low classification error represented good classification performance. Therefore, the value of r, which corresponded to the lowest error, represented the best threshold for SVM (T_{SVM}) and KNN (T_{KNN}).

7.7.1.2 Identification of Classification Errors

For all three days, four-fold cross validation was performed to obtain classification errors for SVM and KNN for the TD features using identical thresholds of T_{SMSC}. Furthermore, SVM classification errors were obtained for the TD features using separate thresholds of T_{SMSC} for SF_{ZC}, SF_{SC}, and SF_{WAMP}. In addition, SVM classification errors were obtained for the TD features using thresholds identified for single features by [Phinyomark et al., 2009].

7.7.2 Cross Day Classification

With a fixed identical threshold for the TD features identified for day one (D1), SVM cross day classification errors were obtained for day 2 (D2) and -3 (D3): in each classification, three recordings from D1 acted as traning data and one recording from D2 and D3 acted as test data. The SVM cross day classification errors were obtained for D2 and D3 by the average errors from the four classifications. SVM cross day classification errors were obtained for both T_{SMSC} and T_{SVM}.

7.8 Statistical Tests

The following statistical tests and their purposes are described in this section:

- sEMG signal analysis
- Identification of threshold intervals
- Comparison of best thresholds
- Comparison of classification errors
- Cross day classification

A significance level of 0.05 was considered significant for all statistical tests. All the statistical tests were performed in SPSS, except the paired-sample t-tests with Bonferroni Holm post hoc corrections, which were performed in MATLAB.

For each test, associated assumptions were tested. For two- and three-way RM ANOVA, main effects and interaction terms were examined. In case of significant main effects and interaction terms, pairwise comparisons obtained by post hoc test using a Bonferroni correction were examined.

7.8.1 sEMG Signal Analysis

A three-way RM ANOVA was carried out to determine if main effects, two-way interactions, and a three-way interaction between *day*, *movement*, and *channel* on *RMS* values existed. The three factors and the dependent variable were set up as follows:

- Factor 1: *Day* (D1, D2, D3)
- Factor 2: *Movement* (WF, WE, WS, WP, HO, HC, PG)
- Factor 3: *Channel* (C1, C2, C3, C4, C5)
- Dependent variable: *RMS*

7.8.2 Identification of Threshold Intervals

For the three days, paired-sample t-tests with Bonferroni-Holm post hoc corrections were performed for the global means (average of all subjects) of SMSC, SVM-, and KNN classification errors from four-fold cross validation obtained for identical T_{SMSC}, T_{SVM}, and T_{KNN} for the TD features respectively. This to determine a threshold interval represented by *r*, based on SMSC or classification errors not different from the highest SMSC or lowest classification error.

7.8.3 Comparisons of Best Thresholds

7.8.3.1 Comparison of Best Thresholds for each Threshold Measure

The following test was performed for identical 1) T_{SMSC}, 2) T_{SVM}, and 3) T_{KNN} for the TD features.

A two-way RM ANOVA was carried out to determine if main effects and two-way interactions between *day* and *channel* on *thresholds* existed. The setup of the factors: 1) *day* and 2) *channel* is illustrated in table 7.1.

D1	D2	D3
C1 - C5	C1 - C5	C1 - C5

Table 7.1: *Setup of the two factors day (D1, D2, D3) and channel (C1, C2, C3, C4, C5) with threshold (T_{SMSC}, T_{SVM} or T_{KNN}) as a dependent variable.*

7.8.3.2 Comparisons of Best Thresholds Between the Threshold Measures

Using identical threshold for the TD features, a three-way RM ANOVA was carried out to determine if main effects, two-way interactions and a three-way interaction between *threshold measure*, *day*, and *channel* on *threshold* (T_{SMSC}, T_{SVM} and T_{KNN}) existed. The setup of the three factors: 1) *threshold measure*, 2) *day*, and 3) *channel* is illustrated in table 7.2.

SMSC			SVM			KNN		
D1	D2	D3	D1	D2	D3	D1	D2	D3
C1 - C5	C1 - C5	C1 - C5	C1 - C5	C1 - C5	C1 - C5	C1 - C5	C1 - C5	C1 - C5

Table 7.2: *Setup of the three factors threshold measure (SMSC, SVM, KNN), day (D1, D2, D3), and channel (C1, C2, C3, C4, C5) with threshold as a dependent variable.*

7.8.3.3 Comparison of Best Threshold for TD Features and Best Threshold for SF_{ZC}, SF_{SC}, and SF_{WAMP}

The following test was performed for 1) T_{SMSC} and 2) T_{SVM}.

A three-way repeated measures ANOVA was carried out to determine if main effects, two-way interactions, and three-way interactions between *day*, *features* (TD features, SF_{ZC}, SF_{SC}, and SF_{WAMP}), and *channel* on *threshold* (T_{SMSC} or T_{SVM}) existed. The setup of the factors: 1) *day*, 2) *features*, and 3) *channel* is illustrated in table 7.3.

D1				D2				D3			
TD features	SF_{ZC}	SF_{SC}	SF_{WAMP}	TD features	SF_{ZC}	SF_{SC}	SF_{WAMP}	TD features	SF_{ZC}	SF_{SC}	SF_{WAMP}
C1 - C5	C1 - C5	C1 - C5	C1 - C5	C1 - C5	C1 - C5	C1 - C5	C1 - C5	C1 - C5	C1 - C5	C1 - C5	C1 - C5

Table 7.3: *Setup of the three factors day (D1, D2, D3), feature (TD features , SF_{ZC}, SF_{SC}, SF_{WAMP}) and channel (C1, C2, C3, C4, C5) with threshold (T_{SMSC} or T_{SVM}) as a dependent variable.*

7.8.4 Comparison of Classification Errors

7.8.4.1 Comparison of SVM Classification Errors based on Identical T_{SMSC} and T_{SVM} for the TD Features

A two-way RM ANOVA was carried out to determine if main effects and an interaction between *threshold measure* (SMSC and SVM) and *day* on *SVM classification errors* existed. The setup of the two factors: 1) *threshold measure* and 2) *day* is illustrated in table 7.4.

SMSC			SVM		
D1	D2	D3	D1	D2	D3

Table 7.4: *Setup of the two factors threshold measure (SMSC, SVM) and day (D1, D2, D3) with SVM classification errors from four-fold cross validation using identical thresholds for the TD features as a dependent variable.*

7.8.4.2 Comparison of KNN Classification Errors based on Identical T_{SMSC} and T_{KNN} for the TD Features

A two-way RM ANOVA was carried out to determine if main effects an interaction between *threshold measure* (SMSC and KNN) and *day* on *KNN classification errors* existed. The setup of the two factors: 1) *threshold measure* and 2) *day* is illustrated in table 7.5.

SMSC			KNN		
D1	D2	D3	D1	D2	D3

Table 7.5: *Setup of the two factors threshold measure (SMSC, KNN) and day (D1, D2, D3) with KNN classification errors from four-fold cross validation using identical thresholds for the TD features as a dependent variable.*

7.8.4.3 Comparison of No Threshold and Identical Thresholds for the TD Features

Threshold: T_{SVM}

A two-way RM ANOVA was carried out to determine if main effects and interaction effect between *day* and *threshold* (no threshold (T_0) and T_{SVM}) on *SVM classification errors* existed. The setup of the two factors: 1) *day* (D1, D2, D3) and 2) *threshold* (T_0 and T_{SVM}) is illustrated in table 7.6.

D1		D2		D3	
T_0	T_{SVM}	T_0	T_{SVM}	T_0	T_{SVM}

Table 7.6: *Setup of the two factors day (D1, D2, D3) and threshold (T_0, T_{SVM}) with SVM classification errors from four-fold cross validation using identical thresholds for the TD features as a dependent variable.*

Threshold: T_{SMSC}

A two-way RM ANOVA was carried out to determine if main effects and an interaction effect between *day* and *threshold* (no threshold (T_0) and T_{SMSC}) on *SVM classification errors* existed. The setup of the two factors: 1) *day* (D1, D2, D3) and 2) *threshold* (T_0 and T_{SMSC}) is illustrated in table 7.7.

D1		D2		D3	
T_0	T_{SMSC}	T_0	T_{SMSC}	T_0	T_{SMSC}

Table 7.7: *Setup of the two factors day (D1, D2, D3) and threshold (T_0, T_{SMSC}) with SVM classification errors from four-fold cross validation using identical thresholds for the TD features as a dependent variable.*

7.8.4.4 Comparison of Identical and Separate Thresholds for the TD Features

Threshold: T_{SVM}

A two-way RM ANOVA was carried out to determine if main effects and an interaction effect between *threshold* (TD features using identical T_{SVM} and TD features using separate thresholds of T_{SVM} for SF_{ZC}, SF_{SC}, and SF_{WAMP}) and *day* on *SVM classification errors* existed. The setup of the two factors: 1) *threshold* and 2) *day* is illustrated in table 7.8.

Identical T_{SVM}			Separate T_{SVM}		
D1	D2	D3	D1	D2	D3

Table 7.8: *Setup of the two factors threshold (identical T_{SVM}, separate of T_{SVM}) and day (D1, D2, D3) with SVM classification errors from four-fold cross validation as a dependent variable.*

Threshold: T_{SMSC}

A two-way RM ANOVA was carried out to determine if main effects and an interaction effect between *threshold* (TD features using identical T_{SMSC} and TD features using separate thresholds of T_{SMSC} for SF_{ZC}, SF_{SC}, and SF_{WAMP}) and *day* on *SVM classification errors* existed. The setup of the two factors: 1) *threshold* and 2) *day* is illustrated in table 7.9.

Identical T_{SMSC}			Separate T_{SMSC}		
D1	D2	D3	D1	D2	D3

Table 7.9: *Setup of the two factors threshold (identical T_{SMSC}, separate of T_{SMSC}) and day (D1, D2, D3) with SVM classification errors from four-fold cross validation as a dependent variable.*

7.8.4.5 Comparison of Thresholds Identified by other Study and Identical Thresholds for the TD Features

Threshold: T_{SVM}

A two-way RM ANOVA was carried out to determine if main effects and an interaction between *threshold* (TD features using identical threshold for T_{SVM} and TD features using separate thresholds identified for single features by [Phinyomark et al., 2009] (T_{PMARK}, see section 4) and *day* on *SVM classification errors* existed. The setup of the two factors: 1) *threshold* and 2) *day* is illustrated in table 7.10.

Identical T_{SVM}			T_{PMARK}		
D1	D2	D3	D1	D2	D3

Table 7.10: *Setup of the two factors threshold (TD features using identical threshold of T_{SVM}, TD features using separate thresholds of T_{PMARK}) and day (D1, D2, D3) with SVM classification errors from four-fold cross validation as a dependent variable.*

Threshold: T_{SMSC}

A two-way RM ANOVA was carried out to determine if main effects and an interaction between *threshold* (TD features using identical threshold for T_{SMSC} and TD features using separate thresholds of T_{PMARK}) and *day* on *SVM classification errors* existed. The setup of the two factors: 1) *threshold* and 2) *day* is illustrated in table 7.11.

Identical T_{SMSC}			T_{PMARK}		
D1	D2	D3	D1	D2	D3

Table 7.11: *Setup of the two factors threshold (TD features using identical threshold of T_{SMSC}, TD features using separate thresholds of T_{PMARK}) and day (D1, D2, D3) with SVM classification errors from four-fold cross validation as a dependent variable.*

7.8.5 Cross Day Classification

Comparison of Classification Errors using Best Thresholds

The following test was performed for 1) T_{SMSC} and 2) T_{SVM}.

Paired-sample t-tests were performed to test if there was a difference between cross day classification errors and classification errors from four-fold cross validation obtained for the TD features using identical thresholds.

Comparison Between Threshold Measures

A two-way RM ANOVA was carried out to determine if main effects and an interaction between *threshold measure* (SMSC and SVM) and *day* (D2 and D3) on *cross day classification errors* existed. The setup of the two factors: 1) *threshold measure* and 2) *day* is illustrated in table 7.12.

SMSC		SVM	
D2	D3	D2	D3

Table 7.12: *Setup of the two factors threshold measure (SMSC and SVM) and day (D2, D3) with cross day classification errors as a dependent variable.*

Part III

Results

CHAPTER 8

sEMG Signal Analysis

The results of assumptions testing and the three-way RM ANOVA are shown in table 8.1 and 8.2.

Table of Assumptions		
Assumption	**Violated [yes/no]**	**p-value/ Greenhouse-Geisser (GG)**
Outliers	No	
Extreme Outliers	No	
Normality	Yes	$p<0.0005$
Sphericity		
Day	Yes	$p = 0.000$
Movement	Yes	$p = 0.000$
Channel	Yes	$p = 0.000$
*Day*Movement*	Yes	GG = 0.072
*Day*Channel*	Yes	GG = 0.125
*Movement*Channel*	Yes	GG = 0.036
*Day*Movement*Channel*	Yes	GG = 0.018

Table 8.1: *Table of assumptions for outliers, extreme outliers, normality, and sphericity.*

Three-way ANOVA: Interactions and Main Effects		
Interaction/factor	**Statistically significant [yes/no]**	**F statistic and p-value**
Three-way interaction		
*Day*Movement*Channel*	No	F(1.004, 7.028) = 0.905, p = 0.373
Two-way interaction		
*Day*Movement*	No	F(1.004, 7.029) = 0.902, p = 0.374
*Day*Channel*	No	F(1.004, 7.027) = 0.927, p = 0.368
*Movement*Channel*	No	F(1, 7.001) = 1.287, p = 0.294
Main effect		
Day	No	F(1.004, 7.028) = 0.923, p = 0.369
Movement	No	F(1, 7.001) = 1.364, p = 0.281
Channel	No	F(1, 7) = 1.354, p = 0.283

Table 8.2: *Table of results for interaction terms and main effects.*

From table 8.1 it is seen that the assumption of normality was violated and the assumption of no outliers was met. The assumption of sphericity was violated in all cases, why the Greenhauser-Geisser correction was used.

Table 8.2 shows that there was not a statistically significant three-way interaction between *days*, *movements*, and *channels*, F(1.004, 7.028) = 0.905, p = 0.373. Furthermore, no statistically significant two-way interactions was found. Neither did main effects reveal a statistically significant difference.

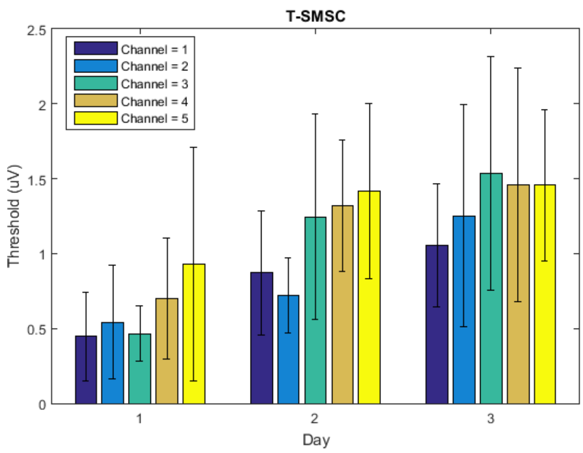
In conclusion, the *RMS* did not change between *days*, *movements*, and *channels*. Therefore, the amplitude of the sEMG signals were considered consistent and did not affect the results of further investigation.

CHAPTER 9

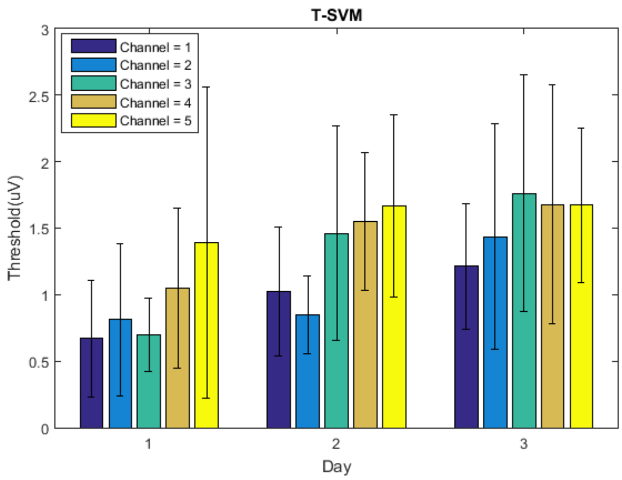
Identification of Best Thresholds and Intervals

9.1 Identical Thresholds for TD features

The global mean (average for all subjects) of T_{SMSC} and T_{SVM} and standard deviation (STD) are illustrated for all channels and days in figure 9.1. T_{KNN} is in most cases equal to zero and are therefore not displayed.



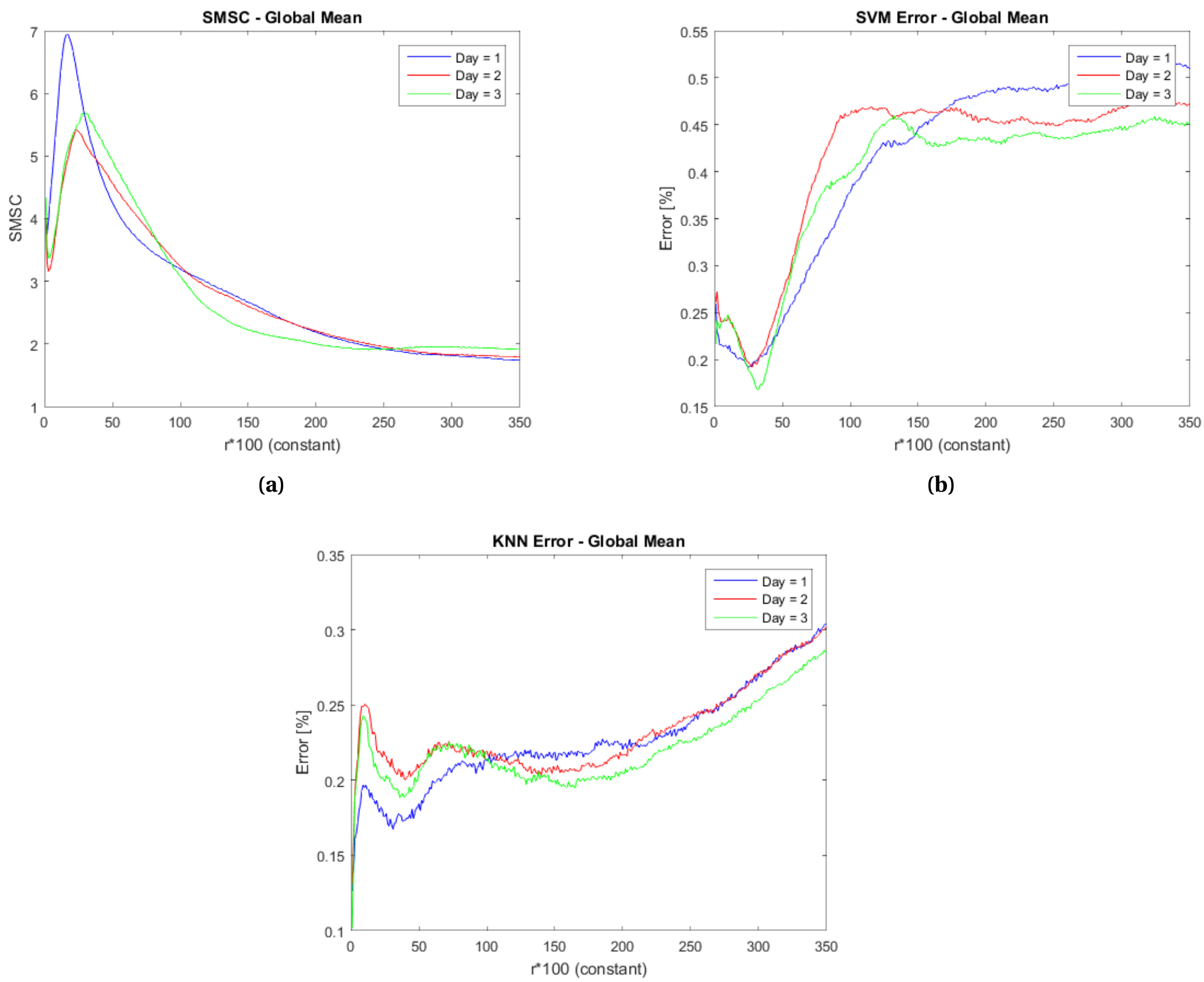
(a)



(b)

Figure 9.1: *Global mean and STD for all channels and days. a) T_{SMSC} and b) T_{SVM}*

In figure 9.2, the global mean of SMSC, SVM-, and KNN classification errors from four-fold cross validation obtained for TD features using identical thresholds is plotted against r for all three days.



(a) **(b)** **(c)**

Figure 9.2: *The global mean of classification errors obtained for TD features using identical thresholds plotted against the constant r*100 r. a) SMSC, b) SVM, and c) KNN.*

For SMSC, SVM-, and KNN classification, the best r and threshold intervals obtained by the paired-sample t-tests with Bonferroni-Holm post corrections for all days, are displayed in table 9.1

Best r and Threshold Intervals		
	Best r	**Interval**
SMSC		
D1	24	$r \in \{0.04 : 0.45\}$
D2	27	$r \in \{0\}$ and $\{0.06 : 0.93\}$
D3	31	$r \in \{0 : 93\}$
SVM		
D1	16	$r \in \{0 : 1.03\}$
D2	23	$r \in \{0 : 0.74\}$
D3	27	$r \in \{0 : 0.74\}$
KNN		
D1	0	$r \in \{0 : 0.76\}$
D2	0	$r \in \{0 : 0.04\}$ and $\{0.18 : 2.10\}$
D3	0	$r \in \{0, 1\}$

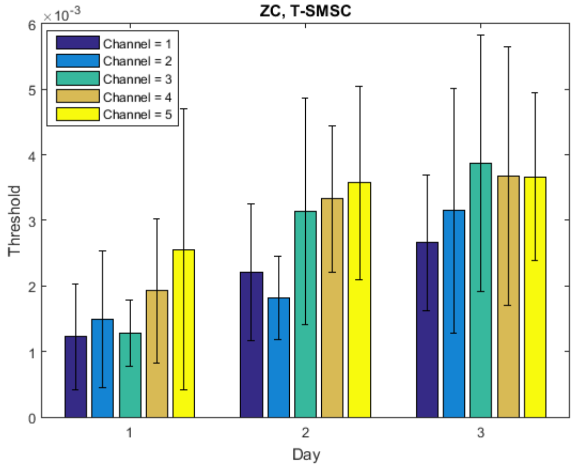
Table 9.1: *Best r and threshold intervals.*

Due to complexity of testing assumptions for each pair of r (a total of 30,537 for each day), the assumptions were not tested. However, it was assumed that the assumption of normality was violated.

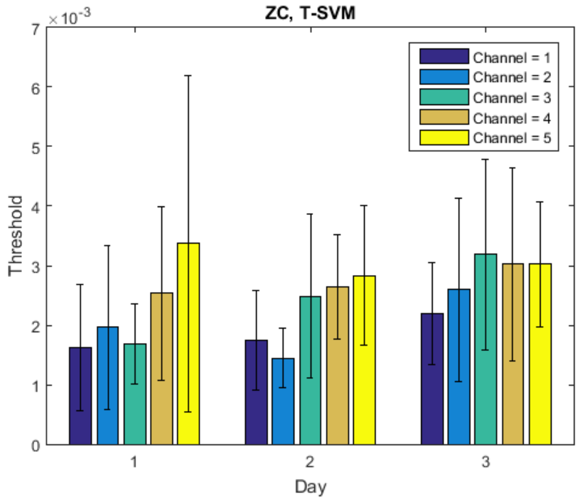
An r-value selected from these intervals to calculate the threshold does not significantly affect SMSC, SVM-, and KNN classification errors.

9.2 Single Feature: ZC

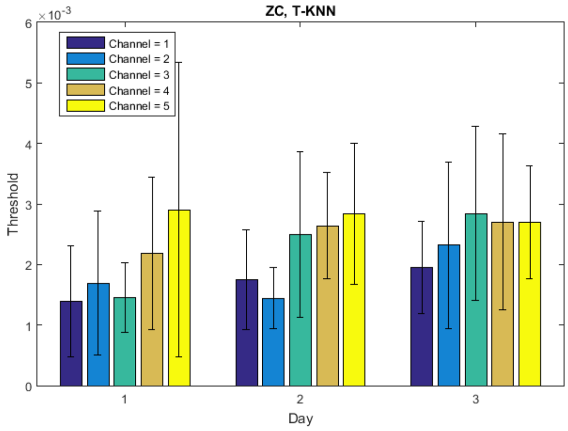
The global mean of T_{SMSC}, T_{SVM}, and T_{KNN} and STD are illustrated for all channels and days in figure 9.3.



(a)



(b)

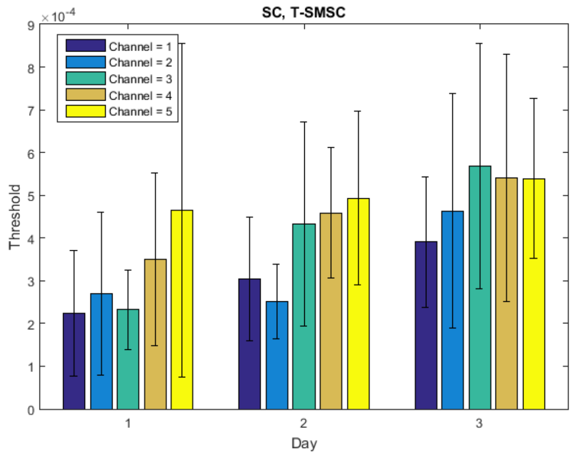


(c)

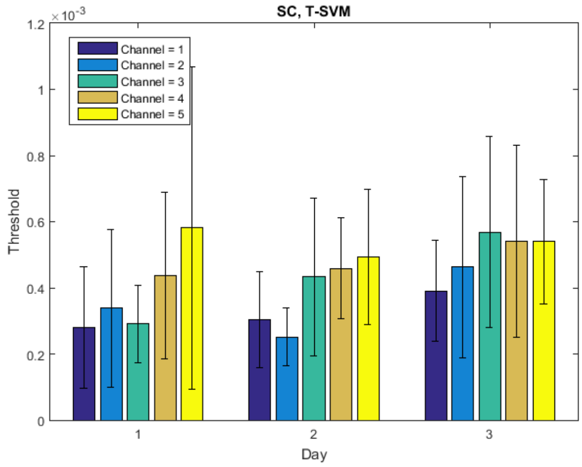
Figure 9.3: *Global mean and STD for all channels and days. a) T_{SMSC}, b) T_{SVM}, and c) T_{SMSC}.*

9.3 Single Feature: SC

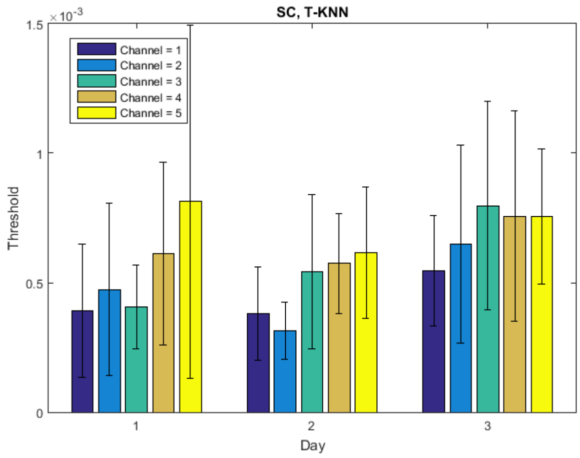
The global mean of T_{SMSC}, T_{SVM}, and T_{KNN} and STD are illustrated for all channels and days in figure 9.4.



(a)



(b)

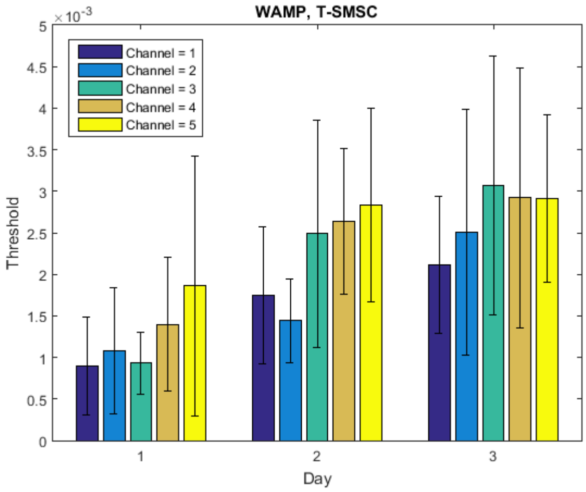


(c)

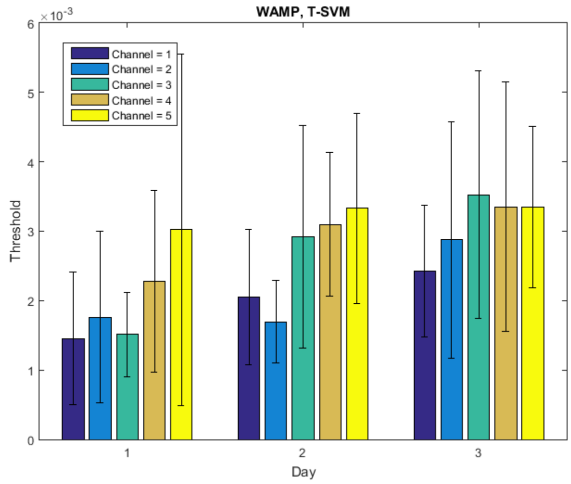
Figure 9.4: *Global mean and STD for all channels and days. a) T_{SMSC}, b) T_{SVM}, and c) T_{SMSC}.*

9.4 Single Feature: WAMP

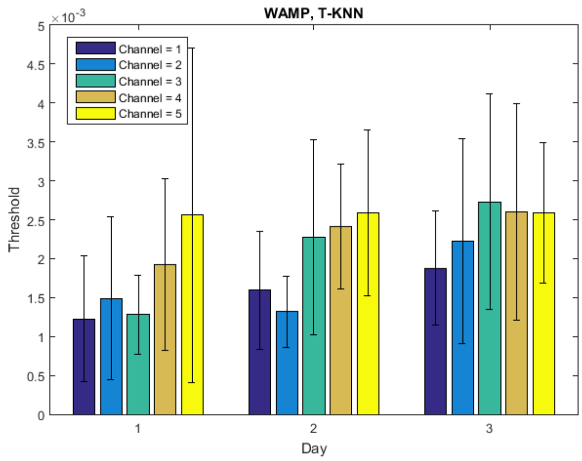
The global mean of T_{SMSC}, T_{SVM}, and T_{KNN} and STD are illustrated for all channels and days in figure 9.5.



(a)



(b)



(c)

Figure 9.5: *Global mean and STD for all channels and days. a) T_{SMSC}, b) T_{SVM}, and c) T_{SMSC}.*

CHAPTER 10

Comparison of Best Thresholds

10.1 Comparison of Best Thresholds for each Threshold Measure

Identical T_{SMSC} for TD features

The results of assumptions testing are illustrated in table 10.1. The results for two-way RM ANOVA are illustrated in table 10.2.

Table of Assumptions		
Assumption	**Violated [yes/no]**	**p-value/ Greenhouse-Geisser (GG)**
Outliers	No	
Extreme Outliers	No	
Normality	Yes	p<0.0005
Sphericity		
Day	No	p = 0.955
Channel	No	p = 0.290
*Day*Channel*	Yes	GG = 0.421

Table 10.1: *Table of assumptions for outliers, extreme outliers, normality, and sphericity.*

Two-way RM ANOVA: Interaction and Main Effects		
Interaction/factor	**Statistically significant [yes/no]**	**F statistic and p-value**
Two-way interaction *Day*Channel*	 No	 F(3.367, 23.566) = 0.976, p = 0.429
Main effect *Day* *Channel*	 No Yes	 F(2,14) = 3.509, p = 0.059 F(4,28) = 3.399, p = 0.022

Table 10.2: *Table of results for interaction and main effects.*

From table 10.1 it is seen that the assumption of normality was violated and the assumption of no outliers was met. The assumption of sphericity was violated in one case, why the Greenhauser-Geisser correction was used for that case.

Table 10.2 shows that there was not a statistically significant two-way interaction between *day* and *channel*, F(3.367, 23.566) = 0.976, p = 0.429. However, one main effect of *channel* revealed a statistically significant difference, F(4,28) = 3.399, p = 0.022. The post hoc test showed no statistically significant difference between any *channel* (p > 0.05).

Identical T_{SVM} for TD features

The results of assumptions testing are illustrated in table 10.3. The results for two-way RM ANOVA are illustrated in table 10.4.

Table of Assumptions		
Assumption	**Violated [yes/no]**	**p-value/ Greenhouse-Geisser (GG)**
Outliers	No	
Extreme Outliers	No	
Normality	Yes	p = 0.027
Sphericity *Day* *Channel* *Day*Channel*	 No No Yes	 p = 0.903 p = 0.423 GG = 0.436

Table 10.3: *Table of assumptions for outliers, extreme outliers, normality, and sphericity.*

Two-way RM ANOVA: Interaction and Main Effects		
Interaction/factor	**Statistically significant [yes/no]**	**F statistic and p-value**
Two-way interaction *Day*Channel*	No	F(3.490,24.431) = 0.869, p = 0.485
Main effect *Day* *Channel*	No No	F(2,14) = 2.059, p = 0.165 F(4,28) = 2.110, p = 0.106

Table 10.4: *Table of results for interaction and main effects.*

From table 10.3 it is seen that the assumption of normality was violated and the assumption of no outliers was met. The assumption of sphericity was violated in one case, why the Greenhauser-Geisser correction was used for that case.

Table 10.4 shows that there was not a statistically significant two-way interaction between *day* and *channel*, F(3.490,24.431) = 0.869, p = 0.485. Neither did main effects reveal a statistically significant difference.

Identical T_{KNN} for TD features

The results of assumptions testing are illustrated in table 10.5. The results for two-way RM ANOVA are illustrated in table 10.6.

Table of Assumptions		
Assumption	**Violated [yes/no]**	**p-value/ Greenhouse-Geisser (GG)**
Outliers	Yes (1)	
Extreme Outliers	Yes (6)	
Normality	Yes	p < 0.0005
Sphericity *Day* *Channel* *Day*Channel*	Yes Yes Yes	p < 0.0005 p < 0.0005 GG = 0.125

Table 10.5: *Table of assumptions for outliers, extreme outliers, normality, and sphericity.*

Two-way RM ANOVA: Interaction and Main Effects		
Interaction/factor	**Statistically significant [yes/no]**	**F statistic and p-value**
Two-way interaction		
*Day*Channel*	No	F(1.001,7.010) = 0.967, p = 0.358
Main effect		
Day	No	F(1.001,7.006) = 1.425, p = 0.271
Channel	No	F(1.000,7.003) = 1.074, p = 0.334

Table 10.6: *Table of results for interaction and main effects.*

From table 10.5 it is seen that the assumption of normality was violated and seven outliers were found. The assumption of sphericity was violated in all cases, why the Greenhauser-Geisser correction was used.

Table 10.6 shows that there was not a statistically significant two-way interaction between *day* and *channel*, F(1.001,7.010) = 0.967, p = 0.358. Neither did main effects reveal a statistically significant difference.

10.2 Comparisons of Best Thresholds Between the Threshold Measures

The results of assumptions testing are illustrated in table 10.7. The results for three-way RM ANOVA and pairwise comparisons are illustrated in table 10.8 and table 10.9.

Table of Assumptions		
Assumption	**Violated [yes/no]**	**p-value/ Greenhouse-Geisser (GG)**
Outliers	No	
Extreme Outliers	No	
Normality	Yes	p<0.0005
Sphericity		
Measure	Yes	p = 0.001
Day	No	p = 0.931
Channel	Yes	p = 0.006
*Measure*Day*	No	p = 0.169
*Measure*Channel*	Yes	GG = 0.189
*Day*Channel*	Yes	GG = 0.206
*Measure*Day*Channel*	Yes	GG = 0.101

Table 10.7: *Table of assumptions for outliers, extreme outliers, normality, and sphericity for the factors and interaction terms. Threshold measure is referred to as measure.*

Three-way RM ANOVA: Interactions and Main Effects		
Interaction/factor	**Statistically significant [yes/no]**	**F statistic and p-value**
Three-way interaction		
*Measure*Day*Channel*	No	F(1.609, 11.261) = 1.040, p = 0.369
Two-way interaction		
*Measure*Day*	No	F(4, 28) = 1.318, p = 0.288
*Measure*Channel*	No	F(1.509, 10.562) = 0.252, p = 0.721
*Day*Channel*	No	F(1.651, 11.560) = 0.898, p = 0.415
Main effect		
Measure	No	F(1.060, 7.421) = 0.148, p = 0.726
Day	Yes	F(2, 14) = 5.586, p = 0.016
Channel	No	F(1.557, 10.902) = 2.949, p = 0.103

Table 10.8: *Table of results for interaction terms and main effects. Threshold measure is referred to as measure.*

Pairwise Comparisons using Bonferroni Correction		
Factors	**Statistically significant [yes/no]**	**Among variables and p-value**
Day	Yes	D1,D2 (p = 0.049)

Table 10.9: *Table of results for pairwise comparisons using Bonferroni correction. Threshold measure is referred to as measure.*

From table 10.7 it is seen that the assumption of normality was violated and the assumption of no outliers was met. The assumption of sphericity was violated in five cases, why the Greenhauser-Geisser correction was used for these.

Table 10.8 shows that there was not a statistically significant three-way interaction between *days*, *movements*, and *channels*, F(1.609, 11.261) = 1.040, p = 0.369. Furthermore, no statistically significant two-way interactions were found. However, one main effect of *day* revealed a statistically significant difference. In table 10.9 it is seen, that the statistically significant difference is found between D1 and D2, p = 0.049.

10.3 Comparison of Best Threshold for TD Features and Best Threshold for SF_{ZC}, SF_{SC}, and SF_{WAMP}

Threshold: T_{SVM}

The results of assumptions testing are illustrated in table 10.10. The results for three-way RM ANOVA and pairwise comparisons are illustrated in table 10.11 and table 10.12.

Table of Assumptions		
Assumption	**Violated [yes/no]**	**p-value/ Greenhouse-Geisser (GG)**
Outliers	No	
Extreme Outliers	No	
Normality	Yes	p<0.0005
Sphericity		
Day	No	p = 0.484
Features	Yes	p = 0.002
Channel	no	p = 0.365
*Day*Features*	yes	p =0.004
*Day*Channel*	Yes	GG = 0.469
*Features*Channel*	Yes	GG = 0.247
*Day*Features*Channel*	Yes	GG = 0.149

Table 10.10: *Table of assumptions for outliers, extreme outliers, normality, and sphericity.*

Three-way RM ANOVA: Interactions and Main Effects		
Interaction/factor	**Statistically significant [yes/no]**	**F statistic and p-value**
Three-way interaction		
*Day*Features*Channel*	No	F(3.578,25.048) = 0.601, p = 0.648
Two-way interaction		
*Day*Features*	No	F(2.460,17.222) = 1.737, p = 0.202
*Day*Channel*	No	F(3.751,26.256) = 0.830, p = 0.512
*Features*Channel*	No	F(2.964,20.746) = 2.444, p = 0.093
Main effect		
Day	No	F(2,14) = 3.423, p = 0.062
Features	Yes	F(1.326,9.285) = 17.914, p = 0.001
Channel	Yes	F(4,28) = 2.996, p = 0.035

Table 10.11: *Table of results for interaction-terms and main effects.*

Pairwise Comparisons using Bonferroni Correction		
Factors	**Statistically significant [yes/no]**	**Among variables and p-value**
Features	Yes	F1,F3 ($p = 0.028$), F2,F3 ($p = 0.001$), F3,F4 ($p < 0.0005$)
Channel	No	

Table 10.12: *Table of results for pairwise comparisons using Bonferroni correction. For simplification, the features factor is represented by : F1, F2, F3, F4, corresponding to: TD features, SF_{ZC}, SF_{SC}, and SF_{WAMP}, respectively.*

From table 10.10 it is seen that the assumption of normality was violated and the assumption no outliers was met. The assumption of sphericity was violated in five cases, why the Greenhauser-Geisser correction was used for these.

Table 10.11 shows that there was not a statistically significant three-way interaction between *day*, *features*, and *channel*, $F(3.578,25.048) = 0.601$, $p = 0.648$. Furthermore, no statistically significant two-way interactions was found. However, main effect of *features* and *channel* revealed a statistically significant difference ($F(1.326,9.285) = 17.914$, $p = 0.001$ and $F(4,28) = 2.996$, $p = 0.035$ respectively). In table 10.12 it is seen, that the statistically significant difference is found between the following features: TD features and SF_{SC} ($p = 0.028$), SF_{ZC} and SF_{SC} ($p = 0.001$), and SF_{SC} and SF_{WAMP} ($p < 0.0005$).

Threshold: T_{SMSC}

The results of assumptions testing are illustrated in table 10.13. The results for three-way RM ANOVA and pairwise comparisons are illustrated in table 10.14 and table 10.15.

Table of Assumptions		
Assumption	**Violated [yes/no]**	**p-value/ Greenhouse-Geisser (GG)**
Outliers	No	
Extreme Outliers	No	
Normality	Yes	p<0.0005
Sphericity		
Day	No	p = 0.082
Features	Yes	p < 0.0005
Channel	no	p = 0.412
*Day*Features*	yes	p < 0.0005
*Day*Channel*	Yes	GG = 0.427
*Features*Channel*	Yes	GG = 0.207
*Day*Features*Channel*	Yes	GG = 0.105

Table 10.13: *Table of assumptions for outliers, extreme outliers, normality, and sphericity.*

Three-way RM ANOVA: Interactions and Main Effects		
Interaction/factor	**Statistically significant [yes/no]**	**F statistic and p-value**
Three-way interaction		
*Day*Features*Channel*	No	F(2.514,17.598) = 1.038, p = 0.389
Two-way interaction		
*Day*Features*	No	F(1.542,10.796) = 0.993, p = 0.380
*Day*Channel*	No	F(3.418,23.927) = 1.072, p = 0.385
*Features*Channel*	No	F(2.484,17.391) = 1.975, p = 0.162
Main effect		
Day	No	F(2,14) = 1.923, p = 0.183
Features	Yes	F(1.614,11.301) = 11.833, p < 0.002
Channel	no	F(4,28) = 2.699, p = 0.096

Table 10.14: *Table of results for interaction terms and main effects.*

Pairwise Comparisons using Bonferroni Correction		
Factor	**Statistically significant [yes/no]**	**Among variables and p-value**
Features	Yes	F1,F3 ($p = 0.015$), F2,F3 ($p = 0.034$), F3,F4 ($p = 0.015$)

Table 10.15: *Table of results for pairwise comparisons using Bonferroni correction. For simplification, the feature set factor is represented by : F1, F2, F3, F4, corresponding to: All TD features, SF_{ZC}, SF_{SC}, and SF_{WAMP}, respectively.*

From table 10.13 it is seen that the assumption of normality was violated and the assumption of no outliers were met. The assumption of sphericity was violated in five cases, why the Greenhauser-Geisser correction was used for these.

Table 10.14 shows that there was not a statistically significant three-way interaction between *day*, *features*, and *channel*, $F(2.514,17.598) = 1.038$, $p = 0.389$. Furthermore, no statistically significant two-way interactions was found. However, one main effect of *features* revealed a statistically significant difference $F(1.614,11.301) = 11.833$, $p < 0.002$. In table 10.15 it is seen, that the statistically significant difference is found between the following *features*: TD features and SF_{SC} ($p = 0.015$), SF_{ZC} and SF_{SC} ($p = 0.034$), and SF_{SC} and SF_{WAMP} ($p = 0.015$).

CHAPTER 11

Comparison of Classification Errors

11.1 Comparison of SVM Classification Errors based on Identical T_{SMSC} and T_{SVM} for the TD Features

Results of SVM classification errors from four-fold cross validation based on identical T_{SMSC} and T_{SVM} for the TD features for all days are displayed in table 11.1.

SVM Classification Errors of T_{SMSC} and T_{SVM}			
Threshold/Day	**D1**	**D2**	**D3**
T_{SMSC}	0.15 ± 0.11	0.14 ± 0.15	0.13 ± 0.11
T_{SVM}	0.14 ± 0.12	0.12 ± 0.10	0.12 ± 0.10

Table 11.1: *Global mean and STD of SVM classification errors based on identical T_{SMSC} and T_{SVM} for all days.*

The results of assumptions testing are illustrated in table 11.2. The results of the two-way RM ANOVA are illustrated in table 11.3.

Table of Assumptions		
Assumption	**Violated [yes/no]**	**p-value/ Greenhouse-Geisser (GG)**
Outliers	yes (8)	
Extreme Outliers	No	
Normality	Yes	p<0.0005
Sphericity		
Measure	No	GG = 1.000
Day	Yes	p = 0.016
*Measure*Day*	No	p = 0.164

Table 11.2: *Table of assumptions for outliers, extreme outliers, normality, and sphericity for the factors and interaction. Threshold measure is referred to as measure.*

Two-way RM ANOVA: Interaction and Main Effects		
Interaction/factor	**Statistically significant [yes/no]**	**F statistic and p-value**
Two-way interaction		
*Measure*Day*	No	F(2,14) = 0.084, p = 0.920
Main effect		
Measure	No	F(1,7) = 1.788, p = 0.223
Day	No	F(1.144,8.009) = 0.291, p = 0.635

Table 11.3: *Table of results for interaction and main effects. Threshold measure is referred to as measure.*

From table 11.2 it is seen that the assumption of normality was violated and eight outliers were found. The assumption of sphericity was violated in one case, why the Greenhauser-Geisser correction was used for that case.

Table 11.3 shows that there was not a statistically significant two-way interaction between *threshold measure* and *day*, F(2,14) = 0.084, p = 0.920. Neither did main effects reveal a statistically significant difference.

11.2 Comparison of KNN Classification Errors based on Identical T_{SMSC} and T_{KNN} for TD the Features

Results of KNN classification errors from four-fold cross validation based on identical T_{SMSC} and T_{KNN} for the TD features for all days are displayed in table 11.4.

KNN Classification Errors of T_{TSMSC} and T_{KNN}			
Threshold/Day	**D1**	**D2**	**D3**
T_{SMSC}	0.12 ± 0.12	0.11 ± 0.11	0.13 ± 0.10
T_{KNN}	0.13 ± 0.15	0.13 ± 0.12	0.12 ± 0.10

Table 11.4: *Global mean and STD of KNN classification errors based on identical T_{SMSC} and T_{KNN} for all days.*

The results of assumptions testing are illustrated in table 11.5. The results of the two-way RM ANOVA are illustrated in table 11.6.

Table of Assumptions		
Assumption	**Violated [yes/no]**	**p-value/ Greenhouse-Geisser (GG)**
Outliers	Yes (8)	
Extreme Outliers	No	
Normality	Yes	p<0.0005
Sphericity		
Measure	No	GG = 1.000
Day	No	p = 0.123
*Measure*Day*	Yes	p = 0.03

Table 11.5: *Table of assumptions for outliers, extreme outliers, normality, and sphericity for the factors and interaction. Threshold measure is referred to as measure.*

Two-way RM ANOVA: Interaction and Main Effects		
Interaction/factor	**Statistically significant [yes/no]**	**F statistic and p-value**
Two-way interaction		
*Measure*Day*	No	F(1.185,8.293) = 3.898, p = 0.078
Main effect		
Measure	No	F(1,7) = 0.454, p = 0.522
Day	No	F(2,14) = 0.055, p = 0.947

Table 11.6: *Table of results for interaction and main effects. Threshold measure is referred to as measure.*

From table 11.5 it is seen that the assumption of normality was violated and eight outliers were found. The assumption of sphericity was violated in one case, why the Greenhauser-Geisser correction was used for that case.

Table 11.6 shows that there was not a statistically significant two-way interaction between *threshold measure* and *day*, F(1.185,8.293) = 3.898. Neither did main effects reveal a statistically significant difference.

11.3 Comparison of No Threshold and Identical Thresholds for the TD Features

Threshold: T_{SVM}

Results of SVM classification errors from four-fold cross validation for T_0 and identical T_{SVM} for the TD features for all days are displayed in table 11.7.

Classification Errors of T_0 and T_{SVM}			
Threshold/Day	**D1**	**D2**	**D3**
T_0	0.26 ± 0.15	0.15 ± 0.11	0.26 ± 0.16
T_{SVM}	0.14 ± 0.12	0.12 ± 0.10	0.12 ± 0.10

Table 11.7: *Global mean and STD of SVM classification errors for T_0 and identical T_{SVM} for the TD features for all days.*

The results of assumptions testing are illustrated in table 11.8. The results of the two-way RM ANOVA and pairwise comparisons are illustrated in table 11.9 and table 11.10.

Table of Assumptions		
Assumption	**Violated [yes/no]**	**p-value/ Greenhouse-Geisser (GG)**
Outliers	yes (3)	
Extreme Outliers	No	
Normality	Yes	p = 0.002
Sphericity		
Day	No	p = 0.062
Threshold	No	GG = 1.000
*Day*Threshold*	No	p = 0.873

Table 11.8: *Table of assumptions for outliers, extreme outliers, normality, and sphericity for the factors and interaction.*

Two-way RM ANOVA: Interaction and Main Effects		
Interaction/factor	**Statistically significant [yes/no]**	**F statistic and p-value**
Two-way interaction		
*Day*Threshold*	Yes	F(2,14) = 3.954, p = 0.044
Main effect		
Day	Yes	F(2,14) = 4.331, p = 0.034
Threshold	Yes	F(1,7) = 24.798, p = 0.002

Table 11.9: *Table of results for interaction and main effects.*

Pairwise Comparisons using Bonferroni Correction		
Factors	**Statistically significant [yes/no]**	**Among variables and p-value**
Day*Threshold	Yes	T_0:D1,D2 (p = 0.003)
Threshold*Day	Yes	D1: T_0, T_{SVM} (p = 0.001), D3: T_0, T_{SVM} (p = 0.003),
Threshold	Yes	T_0, T_{SVM} (p = 0.002)
Day	Yes	D1,D2 (p = 0.031)

Table 11.10: *Table of results for pairwise comparisons using Bonferroni correction.*

From table 11.8 it is seen that the assumption of normality was violated and three outliers were found. The assumption of sphericity was met in all cases.

Table 11.9 shows that there was a statistically significant two-way interaction between *day* and *threshold*, F(2,14) = 3.954, p = 0.044. In table 11.10, it is seen that the statistically significant difference for T_0 is found between D1,D2, p = 0.003. Furthermore, a statistically significant difference for D1 and D3 between T_0, T_{SVM} was found, p = 0.001 and p = 0.003 respectively. Main effect of *threshold* revealed a statistically significant difference. Main effect of *day* did also reveal a statistically significant difference. In table 11.10, it is seen that the statistically significant difference is found between D1 and D2, p = 0.003.

Threshold: T_{SMSC}

Results of SVM classification errors from four-fold cross validation for T_0 and identical T_{SVM} for the TD features for all days are displayed in table 11.11.

Classification Errors of T_0 and T_{SMSC}			
Threshold/Day	**D1**	**D2**	**D3**
T_0	0.26 ± 0.15	0.15 ± 0.11	0.26 ± 0.16
T_{SMSC}	0.14 ± 0.15	0.22 ± 0.14	0.13 ± 0.11

Table 11.11: *Global mean and STD of SVM classification errors for T_0 and identical T_{SMSC} for the TD features for all days.*

The results of assumptions testing are illustrated in table 11.12. The results of the two-way RM ANOVA are illustrated in table 11.13.

Table of Assumptions		
Assumption	**Violated [yes/no]**	**p-value/ Greenhouse-Geisser (GG)**
Outliers	yes (3)	
Extreme Outliers	No	
Normality	Yes	p = 0.001
Sphericity		
Day	No	p = 0.523
Threshold	No	GG = 1.000
*Day*Threshold*	No	p = 0.335

Table 11.12: *Table of assumptions for outliers, extreme outliers, normality, and sphericity for the factors and interaction.*

Two-way RM ANOVA: Interaction and Main Effects		
Interaction/factor	**Statistically significant [yes/no]**	**F statistic and p-value**
Two-way interaction		
*Day*Threshold*	No	F(2,14) = 0.623, p = 0.551
Main effect		
Day	No	F(2,14) = 0.521, p = 0.605
Threshold	Yes	F(1,7) = 34.464, p = 0.001

Table 11.13: *Table of results for interaction and main effects.*

From table 11.12 it is seen that the assumption of normality was violated and three outliers were found. The assumption of sphericity was met in all cases.

Table 11.13 shows that there was not a statistically significant two-way interaction between *day* and *threshold*, F(2,14) = 0.623, p = 0.551. However, one main effect of *threshold* revealed a statistically significant difference, F(1,7) = 34.464, p = 0.001.

11.4 Comparison of Identical and Separate Thresholds for the TD Features

Threshold: T_{SVM}

Results of SVM classification errors from four-fold cross validation for identical T_{SVM} for the TD features and separate T_{SVM} for SF_{ZC}, SF_{SC}, and SF_{WAMP} are illustrated for all days in table 11.14.

Classification Errors of Identical- and Separate T_{SVM}			
Threshold/Day	**D1**	**D2**	**D3**
Identical T_{SVM}	0.14 ± 0.12	0.12 ± 0.10	0.12 ± 0.10
Separate T_{SVM}	0.13 ± 0.12	0.12 ± 0.09	0.11 ± 0.10

Table 11.14: *Global mean and STD of SVM classification errors for identical T_{SVM} for the TD features and separate T_{SVM} for SF_{ZC}, SF_{SC}, and SF_{WAMP} for all days.*

The results of assumptions testing are illustrated in table 11.15. The results of the two-way RM ANOVA are illustrated in table 11.16.

Table of Assumptions		
Assumption	**Violated [yes/no]**	**p-value/ Greenhouse-Geisser (GG)**
Outliers	Yes (6)	
Extreme Outliers	No	
Normality	Yes	p<0.0005
Sphericity		
Threshold	No	GG = 1.0
Day	Yes	p = 0.003
*Threshold*Day*	Yes	p = 0.016

Table 11.15: *Table of assumptions for outliers, extreme outliers, normality, and sphericity for the factors and interaction.*

Two-way RM ANOVA: Interaction and Main Effects		
Interaction/factor	**Statistically significant [yes/no]**	**F statistic p-value**
Two-way interaction		
*Threshold*Day*	No	F(1.145,8.016) = 0.376, p = 0.585
Main effect		
Threshold	No	F(1,7) = 4.557, p = 0.07
Day	No	F(1.075,7.562) = 0.337, p = 0.594

Table 11.16: *Table of results for interaction and main effects.*

From table 11.15 it is seen that the assumption of normality was violated and six outliers were found. The assumption of sphericity was violated in two cases, why the Greenhauser-Geisser correction was used in these cases.

Table 11.16 shows that there was not a statistically significant two-way interaction between *threshold* and *day*, F(1.145,8.016) = 0.376, p = 0.585. Neither did main effects reveal a statistically significant difference.

Threshold: T_{SMSC}

Results of SVM classification errors from four-fold cross validation for identical T_{SMSC} for the TD features and separate T_{SMSC} for SF_{ZC}, SF_{SC}, and SF_{WAMP} are illustrated for all days in table 11.17.

Classification Errors of Identical- and Separate T_{SMSC}			
Threshold/Day	**D1**	**D2**	**D3**
Identical T_{SMSC}	0.15 ± 0.11	0.14 ± 0.15	0.13 ± 0.11
Separate T_{SMSC}	0.14 ± 0.11	0.14 ± 0.15	0.13 ± 0.11

Table 11.17: *Global mean and STD of SVM classification errors for identical T_{SMSC} for the TD features and separate T_{SMSC} for SF_{ZC}, SF_{SC}, and SF_{WAMP} for all days.*

The results of assumptions testing are illustrated in table 11.15. The results of the two-way RM ANOVA are illustrated in table 11.19.

Table of Assumptions		
Assumption	**Violated [yes/no]**	**p-value/ Greenhouse-Geisser (GG)**
Outliers	Yes (6)	
Extreme Outliers	No	
Normality	Yes	p<0.0005
Sphericity		
Threshold	No	GG = 1.0
Day	No	p = 0.054
*Threshold*Day*	Yes	p < 0.0005

Table 11.18: *Table of assumptions for outliers, extreme outliers, normality, and sphericity for the factors and interaction.*

Two-way RM ANOVA: Interaction and Main Effects		
Interaction/factor	**Statistically significant [yes/no]**	**F statistic p-value**
Two-way interaction		
*Threshold*Day*	No	F(1.012,7.081) = 0.969, p = 0.358
Main effect		
Threshold	No	F(1,7) = 0.577, p = 0.472
Day	No	F(2,14) = 0.101, p = 0.904

Table 11.19: *Table of results for interaction and main effects.*

From table 11.15 it is seen that the assumption of normality was violated and six outliers were found. The assumption of sphericity was violated in one case, why the Greenhauser-Geisser correction was used for that case.

Table 11.19 shows that there was not a statistically significant two-way interaction between *threshold* and *day*, F(1.012,7.081) = 0.969, p = 0.358. Neither did main effects reveal a statistically significant difference.

11.5 Comparison of Thresholds Identified by other Study and Identical Thresholds for the TD Features

Threshold: T_{SVM}

Results of SVM classification errors from four-fold cross validation for identical T_{SVM} for the TD features and thresholds identified by [Phinyomark et al., 2009] (T_{PMARK}) are illustrated for all days in figure 11.20.

Classification Errors of T_{SVM} and T_{PMARK}			
Threshold/Day	**D1**	**D2**	**D3**
T_{SVM}	0.14 ± 0.12	0.12 ± 0.10	0.12 ± 0.10
T_{PMARK}	0.14 ± 0.11	0.14 ± 0.10	0.14 ± 0.09

Table 11.20: *Global mean and STD of SVM classification errors for identical T_{SVM} for the TD features and T_{PMARK} for all days.*

The results of assumptions testing are illustrated in table 11.21. The results of the two-way RM ANOVA are illustrated in table 11.22.

Table of Assumptions		
Assumption	**Violated [yes/no]**	**p-value/ Greenhouse-Geisser (GG)**
Outliers	Yes (3)	
Extreme Outliers	No	
Normality	Yes	p<0.0005
Sphericity		
Threshold	No	GG = 1.0
Day	No	p = 0.073
*Threshold*Day*	No	p = 0.877

Table 11.21: *Table of assumptions for outliers, extreme outliers, normality, and sphericity for the factors and interaction.*

Two-way RM ANOVA: Interaction and Main Effects		
Interaction/factor	**Statistically significant [yes/no]**	**F statistic p-value**
Two-way interaction		
*Threshold*Day*	No	F(2,14) = 0.516, p = 0.608
Main effect		
Threshold	No	F(1,7) = 1.707, p = 0.233
Day	No	F(2,14) = 0.149, p = 0.766

Table 11.22: *Table of results for interaction and main effects.*

From table 11.21 it is seen that the assumption of normality was violated and three outliers were found. The assumption of sphericity was met in all cases.

Table 11.22 shows that there was not a statistically significant two-way interaction between *threshold* and *day*, F(2,14) = 0.516, p = 0.608. Neither did main effects reveal a statistically significant difference.

Threshold: T_{SMSC}

Results of SVM classification errors from four-fold cross validation for identical T_{SMSC} for the TD features and thresholds identified by [Phinyomark et al., 2009] (T_{PMARK}) are illustrated for all days in figure 11.23.

Classification Errors of T_{SMSC} and T_{PMARK}			
Threshold/Day	**D1**	**D2**	**D3**
T_{SMSC}	0.15 ± 0.11	0.14 ± 0.15	0.13 ± 0.11
T_{PMARK}	0.14 ± 0.11	0.14 ± 0.10	0.14 ± 0.09

Table 11.23: *Global mean and STD of SVM classification errors for identical T_{SMSC} for the TD features and T_{PMARK} for all days.*

The results of assumptions testing are illustrated in table 11.24. The results of the two-way RM ANOVA are illustrated in table 11.25.

Table of Assumptions		
Assumption	**Violated [yes/no]**	**p-value/ Greenhouse-Geisser (GG)**
Outliers	Yes (4)	
Extreme Outliers	No	
Normality	Yes	p<0.0005
Sphericity		
Threshold	No	GG = 1.0
Day	No	p = 0.204
*Threshold*Day*	No	p = 0.361

Table 11.24: *Table of assumptions for outliers, extreme outliers, normality, and sphericity for the factors and interaction.*

Two-way RM ANOVA: Interaction and Main Effects		
Interaction/factor	**Statistically significant [yes/no]**	**F statistic p-value**
Two-way interaction		
*Threshold*Day*	No	F(2,14) = 0.224, p = 0.802
Main effect		
Threshold	No	F(1,7) = 0.000, p = 0.990
Day	No	F(2,14) = 0.081, p = 0.923

Table 11.25: *Table of results for interaction and main effects.*

From table 11.24 it is seen that the assumption of normality was violated and four outliers were found. The assumption of sphericity was met in all cases.

Table 11.25 shows that there was not a statistically significant two-way interaction between *threshold* and *day*, F(2,14) = 0.224, p = 0.802. Neither did main effects reveal a statistically significant difference.

11.6 Cross Day Classification

Global mean and STD for D2 and D3 of SVM cross day classification errors obtained for TD features using identical fixed T_{SMSC} and T_{SVM} identified for D1 are displayed in table 11.26

Cross Day Classification Errors		
Threshold/Day	**D2**	**D3**
T_{SMSC}	0.16 ± 0.12	0.35 ± 0.17
T_{SVM}	0.15 ± 0.12	0.34 ± 0.19

Table 11.26: *Global mean and STD of cross day classification errors for D2 and D3 using fixed T_{SMSC} and T_{SVM} identified for D1*

Comparison of Classification errors using Best Thresholds

Threshold: T_{SVM}

For D2, there was not a significant difference in cross day classification errors 11.26 and classification errors from four-fold cross validation 11.1 (paired sample t-test, p = 0.410). For D3, there was a significant difference in cross day classification errors and classification errors from four-fold cross validation (paired sample t-test, p = 0.002). This indicated that thresholds were robust over two days while thresholds were not robust over a period of six days.

Threshold: T_{SMSC}

For D2, there was not a significant difference in cross day classification errors 11.26 and classification errors from four-fold cross validation 11.1 (paired sample t-test, p = 0.645). For D3, there was a significant difference in cross day classification errors and classification errors from four-fold cross validation (paired sample t-test, p < 0.0005). This indicated that thresholds were robust over two days while thresholds were not robust over a period of six days.

Comparison between Threshold Measures

The results of assumptions are illustrated in table 11.27. The results of the two-way RM ANOVA are illustrated in table 11.28.

Table of Assumptions		
Assumption	**Violated [yes/no]**	**p-value/ Greenhouse-Geisser (GG)**
Outliers	No	
Extreme Outliers	No	
Normality	Yes	p = 0.039
Sphericity		
Threshold measure	No	GG = 1.000
Day	No	GG = 1.000
*Threshold measure*day*	No	GG = 1.000

Table 11.27: *Table of assumptions for outliers, extreme outliers, normality, and sphericity for the factors and interaction terms.*

Two-way ANOVA: Interaction and Main Effects		
Interaction/factor	**Statistically significant [yes/no]**	**F statistic and p-value**
Two-way interaction		
*Threshold measure*Day*	No	F(1,7) = 0.068, p = 0.802
Main effect		
Threshold measure	No	F(1,7) = 0.188, p = 0.677
Day	Yes	F(1,7) = 20.970, p = 0.003

Table 11.28: *Table of results for interaction and main effects.*

From table 11.27 it is seen that the assumption of normality was violated and assumption of no outliers was met. The assumption of sphericity was met in all cases.

Table 11.28 shows that there was not a statistically significant two-way interaction between *threshold measure* and *day*, F(1,7) = 0.068, p = 0.802. However, one main effect of *day* revealed a statistically significant difference, F(1,7) = 20.970, p = 0.003.

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