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MULTI-DAY ANALYSIS OF SURFACE AND INTRAMUSCULAR EMG FOR PROSTHETIC CONTROL

BY
MUHAMMAD ASIM WARIS

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AALBORG UNIVERSITY
DENMARK

MULTI-DAY ANALYSIS OF SURFACE AND INTRAMUSCULAR EMG FOR PROSTHETIC CONTROL

Ph.D. Thesis

by

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AALBORG UNIVERSITY
DENMARK

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CV

Muhammad Asim Waris received his Bachelor in Mechatronics engineering from National University of Sciences and Technology (NUST), Pakistan in 2011. He received Master degree in Biomedical Engineering from NUST, Pakistan in 2013. He also worked as a Research Assistant at NUST under the supervision of Dr Mohsin Jamil from 2012-2013. In 2015, He was enrolled as a PhD student at the Center for Sensory Motor Interaction at Aalborg University under the supervision of Dr Ernest Nlandu Kamavuako and Professor Winnie Jensen. His research interests include EMG signal processing, invasive recording of EMG signals, pattern recognition, rehabilitation, and myoelectric prosthetic control.

PREFACE

The current PhD thesis was conducted at the Center for Sensory-Motor Interaction (SMI), Aalborg University, Denmark, from 2015 to 2018. This work is based on four studies that are detailed in the following chapters.

Paper I:

Title: “Effect of Threshold Values on the Combination of EMG Time Domain Features: Surface versus Intramuscular EMG.

Authors: Asim Waris, Ernest Nlandu Kamavuako

Journal: *Journal of Biomedical Signal Processing and Control, vol. 45, pp. 267-273, 2018*

Paper II:

Title: The effect of time on EMG classification of hand motions in able-bodied and transradial amputees

Authors: Asim Waris, Imran Khan Niazi, Mohsin Jamil, Omer Gilani, Kevin Englehart, Winnie Jensen, Muhammad Shafique, Ernest Nlandu Kamavuako

Journal: *Journal of Electromyography and Kinesiology, vol.8, pp.15-20, 2018*

Paper III:

Title: Multiday Evaluation of Techniques for EMG Based Classification of Hand Motions

Authors: Asim Waris, Imran Khan Niazi, Mohsin Jamil, Kevin Englehart, Winnie Jensen, Ernest Nlandu Kamavuako

Journal: *IEEE Journal of Biomedical and Health Informatics,*

Paper IV:

Title: On the robustness of real-time myoelectric control investigations: A multiday Fitts’ law approach

Authors: Asim Waris, Irene Mendez, Kevin Englehart, Winnie Jensen, Ernest Nlandu Kamavuako

Journal: *Journal of Neural Engineering.*

Paper V:

Title: On the robustness of intramuscular real-time myoelectric control: A multiday Fitts' law approach

Authors: Asim Waris, Muhammad Zia-ur-Rehman, Imran Khan Niazi, Mads Jochumsen, Kevin Englehart, Winnie Jensen, Ernest Nlandu Kamavuako

Journal: *Medical Engineering and Physics (Submitted)"*.

English summary

Myoelectric control of upper limb prostheses has been an active area of research for many years. To date, surface electromyography (sEMG) is the main control signal employed in commercial systems. However, it has been suggested that signals obtained from implantable electrodes, such as intramuscular EMG, may be a better source to provide independent sources for control. From the control schemes point of view, pattern recognition (PR) has been extensively researched as means to enable a more robust, intuitive, effective and simultaneous control of a large number of degrees-of-freedom (DoF) as offered by current advanced prosthetic limbs. However, how to achieve robustness over time with different PR schemes has received less attention in the literature. In the current thesis, the essential objective was therefore to investigate the behaviour of EMG based PR myoelectric control over time. Three specific research questions (SRQ) were formulated to address this aim: 1) To what extent threshold values affect the time domain features and their combinations in surface and intramuscular recordings? This question was addressed in study I, where the threshold values of each feature were compared for the range of different values. This range was (R = 0:0.02:6) times the average root mean square of the baseline. For each threshold value, classification error was quantified using two classifiers first for each individual feature and then combined. Results have demonstrated that using appropriate threshold value is very important to assure acceptable performance. 2) What is the correlation between the performance of PR based myoelectric control schemes and time? This question was addressed in study II and III using surface and intramuscular EMG concurrently recorded from 10 able-bodied subjects and six trans-radial amputees for seven consecutive days. A standard linear regression analysis was carried out in study II on each EMG type for the identification of time effect (days) on classification accuracies. Study II showed that performance is significantly dependent on the time elapsed between training and test. In study III, Artificial neural network outperformed all other tested classifiers in terms of mitigating the effect of time on classification. 3) How do PR training strategies influence real-time performance over time? This question was addressed in Study IV, an experimental protocol was designed to determine the effect of training strategies on real-time PR control over time using a Fitts' law approach. The outcome of the studies indicate that increasing the amount of training set over time (by concatenation) can be useful to assure robust output of the system over time. Moreover, classification error can be mitigated as the time lag between training and testing increase.

Dansk resume

Myoelektrisk kontrol af overekstremproteser har været et aktivt forskningsområde i mange år. Hidtil er overfladeelektromyografi (sEMG) det primære styresignal, der anvendes i kommercielle systemer. Det er imidlertid blevet foreslået, at signaler opnået fra implanterbare elektroder, såsom intramuskulær EMG, kan være bedre til at tilvejebringe uafhængige måder til kontrol. Mønstergenkendelse (PR) er blevet undersøgt som middel til at muliggøre en mere robust, intuitiv og effektiv styring af frihedsgrader (DoF) i forhold til nuværende avancerede proteser. Opnåelsen af robusthed over tid med forskellige PR-ordninger har dog fået mindre opmærksomhed i litteraturen. I den nuværende afhandling var hovedformålet derfor at undersøge EMG-baseret PR myoelektrisk kontrol over tid. Tre specifikke spørgsmål (SRQ) blev derfor formuleret: 1) I hvilket omfang påvirker tærskelværdier tidsdomænefunktionerne og deres overflade- og intramuskulære kombinationer? Dette spørgsmål blev behandlet i undersøgelse I, hvor tærsklen for hver funktion blev beregnet som en faktor (R = 0: 0,02: 6) gange gennemsnittet af middelværdien af basislinjen. For hver tærskelværdi blev klassifikationsfejl kvantificeret ved anvendelse af to faktorer - først for hver enkelt funktion og derefter kombineret. Resultaterne har vist, at brug af passende tærskelværdi er meget vigtig for at sikre acceptabel ydeevne. 2) Hvad er sammenhængen mellem PR-baserede myoelektriske kontrolordninger og tid? Dette spørgsmål blev behandlet i undersøgelser II og III ved anvendelse af overflade- og intramuskulær EMG, der samtidig blev registreret fra 10 raske personer og seks transradiale amputerede i 7 på hinanden følgende dage. I studie II blev en standard lineær regressionsanalyse udført på hver EMG-type til identifikation af tidseffekt (dage) på klassifikationsnøjagtigheder. Studie II viste, at ydeevnen er væsentligt afhængig af tiden mellem træning og test. I studie III overgik det kunstige neurale netværk alle andre testede faktorer med hensyn til at mildne effekten af tid på klassificering. 3) Hvordan påvirker PR-træningsstrategier realtidspræstationer over tid? Dette spørgsmål blev behandlet i studie IV, hvor en eksperimentel protokol blev designet til at bestemme effekten af træningsstrategier på realtids PR-kontrol over tid ved hjælp af Fitts Lov. Resultater tyder på, at en forøgelse af træning over tid (ved sammenkobling) kan være gavnlig for at sikre en robust systemydelse over tid. Desuden bliver fejl formindsket, da tiden mellem træning og test formindskes.

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First of all, I would like to thank my supervisor Dr Ernest Nlandu Kamavuako for his support and guidance during my time as a PhD student. He always remained helpful and forgiving over my mistakes. His critique acted as the catalyst to refine and improve the quality of my research. I would also like to thank Professor Winnie Jensen for her relevant and useful input on this project. She was always available to help and guide me in the project. In addition, I appreciate the input from Professor Kevin Englehart on all my studies.

I would also like to thank the Aalborg University in general and Departement of Health and Technology in particular for giving this opportunity to complete my PhD project. I would also like to thank the Higher Education Commission of Pakistan and the National University of Sciences and Technology for giving me financial support during my stay in Denmark.

Lastly, I would like to thank my family, wife, friends, and colleagues at the Institute for making it some memorable years.

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LIST OF ABBREVIATIONS

EMG	……………………..	Electromyography
sEMG	……………….…….	Surface Electromyography
iEMG	………………………	Intramuscular Electromyography
PR	………………………	Pattern Recognition
SRQ	………………………	Specific research questions
ADL	………………………	Activities of daily life
DOF	……………………..	Degrees of freedom
RMS	……………….…….	Root Mean Square
TD	………………………	Time domain
ZC	………………………	Zero Crossings
WAMP	………………………	Willison Amplitude
MYOP	……………………..	Myopulse
CARD	……………….…….	Cardinality
LDA	………………………	Linear Discriminant Analysis
TMR	………………………	Targeted Muscle Reinnervation
NMF	………………………	Negative matrix factorization
KNN	……………………..	K- Nearest Neighbor
NM	……………….…….	No Motion
ANOVA	………………………	Analysis of Variance
CE	………………………	Classification Error
MAV	………………………	Mean Absolute Value
WCE	……………………..	Within-day Classification Error
cEMG	……………….…….	Combined Electromyography
BCE	………………………	Between-day Classification Error
PCA	………………………	Principal Component Analysis
ANN	………………………	Artificial Neural Networks
TREE	……………………..	Decision Tree

NB	…………………….….	Naïve Bayes
ID	………………………	Index of Difficulty
TP	………………………	Throughput
PE	………………………	Path Efficiency
OS	……………………..	Overshoot
CR	…………………….….	Completion Rate
CCE	………………………	Intramuscular Electromyography
BDT	………………………	Between Day Testing
CDT	………………………	Combined Day Testing

THESIS AT A GLANCE

	OBJECTIVES	METHODOLOGY	FINDINGS
I	Identify the optimum threshold values for features in sEMG and iEMG. recordings.	9 healthy participants. 4 surface channels and 02 intramuscular, EMG channels, 8 hand motions.	Optimum threshold values for features were identified. It was found that threshold values affect the time domain features and their combination in surface and intramuscular EMG recordings as some features need to incorporate threshold value so to add in class separability.
II	Quantify the effect of time on PR based myoelectric control for sEMG and iEMG recording	10 healthy and 6 Amputees, 6 surfaces and 6 intramuscular EMG channels, 7 hand motion timed to the visual cue.	a. It was found that the within-day performance of myoelectric control can be improved over time, but the performance of the system regularly reduces as the time difference between training and testing day increases. Performance improved with daily training but not significantly, though seven days of experiment might not be long enough to capture a meaningful outcome.
	Compare most widely used classifiers in PR based myoelectric control	10 healthy and 6 Amputees, 6 surfaces and 6 intramuscular EMG channels, 7 hand	It was found that the performance of classifiers varies within-day and between days. For within day classification error

III	over days for sEMG and iEMG recordings.	motion timed to the visual cue.	(WCE), Artificial neural network (ANN) performed significantly (P<0.05) better than all other tested classifiers.
IV	Quantify the effect of multiple train-test strategies on sEMG and iEMG over days with real-time testing’s	10 healthy participants for sEMG and 5 healthy subjects for iEMG for real-time testing. 08 surface and 03 intramuscular channels.	a. Different train-test strategies affected the real-time performance for surface EMG. b. Different train-test strategies affected the real-time performance for intramuscular EMG.

CHAPTER 1: INTRODUCTION

Being an essential part of the body, the human hand performs complex and delicate motions. Muscle groups activate in a coordinated manner to accomplish fine tasks. Muscles, which are acting as actuators in the human body are activated by the electric signals transmitted through peripheral nerves from the brain. Each muscle in the upper limb activates in an appropriate and regulated manner to contribute to an adept movement.

Amputation is the surgical removal of a limb due to trauma or a medical ailment. Trans-radial or trans-humeral amputation severely limit an individual to perform activities of daily life (ADL). The accurate number of amputees across the world is hard to calculate since most countries do not keep track of people with major amputation. In addition to this, the reasons for amputation also differ between countries. In developing countries, the eminent reason for an amputation is trauma whereas, in developed countries, vascular complications of diabetes is the leading cause (Esquenazi, 2004). In countries like the USA, Japan, and Denmark, 68% of amputations per annum are caused by disease (Esquenazi, 2004).

In Denmark, arm amputations constitute 3% of all amputations (Kejlaa, 1992). According to the national centre of health statistics, nearly 2.1 million people in the United States suffer limb loss. (Amputee coalition, 2014, Ziegler-Graham et al., 2008). Almost 185,000 people suffer from amputation every year where 57% are trans-radial amputations (Amputee coalition, 2014, Ziegler-Graham et al, 2008; Esquenazi et al, 1996; Merrill et al, 2011).

In the year 2009, estimated costs related to amputations were totalled 8.3 billion USD (HCUP Nationwide Inpatient Sample (NIS), 2009). After complete recovery and healing, some of the lost functionalities and appearance of the amputated limb can be replaced by an artificial limb.

1.1. Upper limb prosthesis

Artificial device to replace a missing body part is called a prosthesis. In this thesis, ‘prosthesis’ refers to an upper limb prosthesis only.

Three types of prostheses are commercially available; 1) cosmetic, 2) body-powered and 3) electrically-powered. Cosmetic prostheses are used when the natural appearance is the priority for the amputee. A wide range of cosmetic prostheses is available with different designs, colour, and materials. Body-powered prostheses are most commonly used and are actuated by a harness fused with a cable (Huinink et al., 2016, Popov et al., 2008, Kuba et al 1992, Pfeiffer 1996, Lee and Shimoyama 1999, Schulz et al 2001, Beck et al 2003). It constitutes a triceps cuff, a socket, suspension, and a cable system with flexible or rigid hinges. This type of prosthesis utilizes the body’s motions to control the distal device (i.e. a hand or a hook). It is connected to the body via cables and a harness. This enables control of the hand or hooks to open. Because of the simple control and design, these prostheses are easy to use with high durability and may be used to accomplish potentially adverse tasks involving environmental factors like water or dust. The advantage of these prostheses is that they are proprioceptive which is why numerous patients report a boost in precision and control. Proprioception is the ability to sense the orientation, location, position, as well as movement of the limb relative to the rest of the body. Body-powered devices are low cost and durable but several other factors such as limited degrees of freedom (DOF), unattractive appearance, the control harness restriction, pain and discomfort during wearing have kept their rejection rate up to 58% (Biddiss et al., 2007, Biddiss et al., 2007, McFarland et al., 2010, Dudkiewicz et al., 2004).

Electrically-powered prosthetic devices typically controlled by superficial electromyography (EMG) signals from the muscles left in the amputated limb and provide natural restoration of some functions for trans-radial amputees. EMG signals are taken from physiologically suitable muscles to operate a prosthetic hand or wrist. Electrically-powered prosthetic devices can be divided into two types depending upon their control schemes; 1) conventional myoelectric control strategies, or 2) pattern recognition (PR) based myoelectric control (Li et al., 2010, Hargrove et al., 2011, Smith et al., 2011, Hargrove et al., 2007, Chu et al., 2006). Conventional control strategies employs a simpler approach. The EMG signals are measured at one or more sites. The amplitude of these signals is encoded to activate one or more functions of the prosthesis. (Sears et al. l991, Fougner et al., 2012, Hoover et al., 2013, Jiang et al., 2014, Ferris et al., 2009, Tang et al., 2014, Pistohl et al., 2013, Parker et al., 2006). Pattern recognition (PR) based myoelectric control (Li et al., 2010, Hargrove et al., 2011, Smith et al., 2011, Hargrove et al., 2007, Chu et al., 2006) has found widespread commercial application. When a restricted number of muscles are accessible in the residual limb, single-site controlled myoelectric control scheme is used. This system uses one electrode to control motions of paired prosthetic activity. In clinics, however, dual-site controlled myoelectric devices are used for trans-radial amputees. Such devices utilize two separate electrodes for paired activity from antagonistic muscles (i.e. wrist flexor and wrist extensor). In case of more than two degrees of freedom, mode and sequential switches are used to monitor a second DOF via the same pair of electrodes. Since multiple DOFs are to be controlled by the same electrodes, it affects their functionality since switching requires a nonintuitive impulse such as muscle co-contraction (Alley et al., 2004).

In the past few decades, PR-based control strategies have been extensively studied. The assumption underlying these techniques is that a specific muscle generates a repeatable EMG signal. These repeatable patterns may be depicted by a set of features differing from one movement to another (Hargrove et al., 2008, Tkach et al., 2010). If, over a period of time, these patterns change, or the control accuracy of the prosthetic limb regresses then new calibration data must be provided to update the PR model.

Due to advancement in high-speed embedded controllers and signal processing techniques, significant improvement in these PR algorithms has been made since then. Not only are these systems more user-friendly, but they can also control multiple DOFs as well. This has improved the performance of the system while keeping the number of electrodes to a bare minimum. Even with these advancements in technology, PR-based myoelectric control strategies are challenged by many issues including user adaptation over time, inter-electrode distances, muscle fatigue, limb position, and electrode shift. Apart from these factors, conditions such as overall impedance changes, movement strategy, and psychological factors largely affect the performance of the system pertaining to controllability and classification. (Scheme et al., 2010, Hargrove et al., 2006, Young et al., 2011, Young et al., 2012, Tkach et al., 2010, Fougner et al., 2011). One of the main advantages of these systems is they do not require independent channels, which can be challenging to obtain if the residual stump is small.

It is important to understand how these changes overall impact the nervous system in general and neuromuscular system in particular. Despite the low number of studies investigating these adaptive neuromuscular changes in myoelectric control over time, it can be concluded that using surface EMG, day-to-day performance affected adaptation, but that the need of daily training to assure acceptable classification accuracy is an open question

1.2. Origin, nature and noise in the EMG signal

Electromyography (EMG) is the technique to detect and record the electric activity produced during neuromuscular activation. EMG is more often than not referred to as myoelectric activity. This myoelectric activity or EMG signal is based upon action potentials resulting from depolarization and repolarization at the surface at the muscle fibre membrane.

EMG signals are commonly recorded on the surface of the skin and are effective in specifying and expressing the intent of movement for external device control. In upper limb prosthesis, EMG signals are the main control sources in the field of neural rehabilitation.

The raw electromyogram (EMG) is a broadly Gaussian random signal that needs integrating/filtering/processing to extract the root mean square (RMS) value for use in amplitude-based EMG control (Childress et al., 2004, Parker et al., 1985). Therefore, analyzing and classifying EMG signals can be challenging due to the complicated EMG patterns impacted by the physiology and anatomy of the muscles.

Apart from the inherent EMG signal characteristics, noise from different sources and the environment can also influence the quality of the EMG signals. Such as noise originating from electronic equipment, that may generate frequency components ranging from 0 Hz to thousands of Hz (Riaz et al., 2006). This noise may significantly be reduced by carefully designing the circuit and using high-quality components. Power line interferences arising from 60 Hz or (50Hz) radiations of power sources affects EMG signal. Carefully grounding the devices can help in reducing this noise. Heart activity can also severely affect EMG signal especially recording from the upper trunk and shoulder muscles. Placing ground electrode at a different position and good skin preparations can reduce the level of this noise. Different denoising algorithms are being developed to remove these ECG bursts without disturbing the content of EMG signals. Local EMG signal can also be contaminated by the crosstalk which can cause an incorrect interpretation of signal (Chowdary et al., 2013). Targeted muscle recordings can reduce cross talk considerably.

1.3. Surface EMG

Many studies have proposed various techniques in detecting muscle activity using surface EMG. Surface EMG is still being used as a major neural control source for all commercially available powered upper limb prosthesis. This is mainly because surface EMG signals are non-invasive in nature and easy to record.

Surface EMG recordings have been extensively used by researchers to implement more advanced PR based myoelectric control. Long term consistency of surface EMG signals is important as it can influence the performance of PR based myoelectric control (Ortiz-Catalan et al., 2012). However, the EMG signal from the surface can be dramatically affected by environmental conditions due to precipitation, temperature etc. The exact placement of electrodes can be an issue since surface electrodes cannot be placed indefinitely. If the electrodes are misplaced, the retraining of the PR algorithm is required. If the electrodes are placed improperly, it could lead to muscle imbalance which would further result in patterns generated differently than earlier ones. Eventually, this will cause signals acquired from the larger muscles to mask those acquired from small muscles. Muscle imbalance may also lead to prosthesis socket instability (Lake et al., 2003).

The surface area required on an amputated limb should be wide enough to place a requisite number of surface electrode, which in some comes cases may be difficult because of a small stump size. Similarly, in some cases, only scar tissue is available for placing surface electrodes on the amputated limb. In that case, low to nil neural activity can be recorded from surface electrodes. Artifacts can be another issue for surface recordings due to limb movements and electrode liftoff. Since all these factors affect the long-term use of surface EMG in myoelectric control, more robust detection schemes are required to implement.

1.4. Intramuscular EMG recordings EMG

Implantable electrodes are the key to resolve the practical obstacles which are at present hindering the sustainable solution for an advanced prosthetic control based on surface EMG over a long period of time. With recent developments in the field, these electrodes are coming into age. The difference between sEMG and int iEMG detection is the volume conductor that separates the muscle fibres from detection electrodes. In Intramuscular EMG effect of the volume, the conductor is limited and the action potential of individual motor units can easily be identified from the interference signal as shown in Figure 1.1. In the case of surface electrodes, this effect is diminished owing to the severe low pass filtering and diffusion due to the presence of a volume conductor. This effect significantly reduces the upper-frequency limit of surface EMG to 500 Hz from 2.5 KHz of intramuscular EMG.

In contrast to sEMG, iEMG can detect signals from small as well as deep muscles thus providing localized information. Hence, it increases the information to control a prosthetic device (McDonnall et al., 2012, McDonnall et al., 2017). Furthermore, implanted intramuscular EMG electrodes may provide high inter-day repeatability, multiple and independent channels, a stable and robust signal source that has limited influence by factors such as electrode shifts, skin impedance and precipitation (Merrill et al., 2011, Basmjian et al., 1985). In our studies, iEMG signals recorded by not targeting any specific muscle.

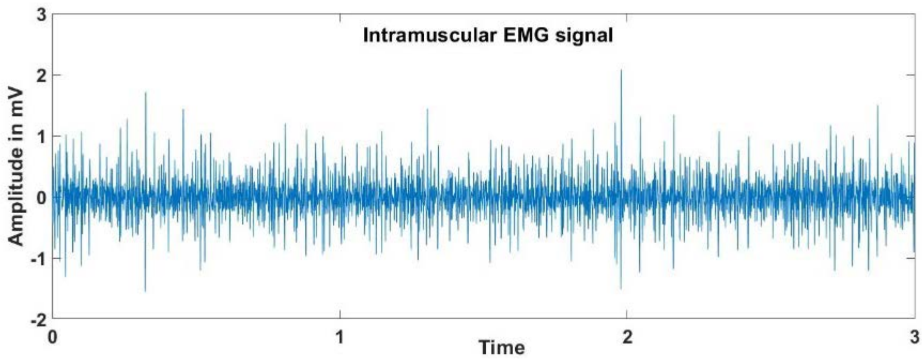


Figure 1.1 Untargeted intramuscular EMG signal acquisition from forearm flexor muscles.

CHAPTER 2: STATE-OF-THE-ART MYOELECTRIC CONTROL

In the passages below growth in the area of myoelectric control are explained in detail.

2.1 Direct control and its limitations

Three distinct generations in myoelectric control can be formed keeping in view the technological advancements over the years. The first generation comprised of ON/OFF control scheme with a constant speed or actuation rate. This technique is referred to as crisp control, bang-bang or binary control (Reiter, 1948). The second generation offered a threshold regulation on a large-scale, state machine, signal amplification, proportional control, and the adjustment of muscle contraction rate. This system takes out the control information from the entire EMG signal based on a calculated estimate of the amplitude (Dorcas et al., 1966) or the rate of change (Childress et al., 1970) of the EMG signals.

The current clinical standard for upper-limb EMG based prosthetic control is based upon amplitude-based dual site control. Dual-site control is commonly used for patients with trans-radial limb loss. In this system, separate electrodes are used for paired activity from antagonistic muscles (i.e. wrist flexor and wrist extensor). When more than two degrees of freedom (DOF) are involved, a mode switch is used. This switch allows the same electrode pair to be used to control numerous functions. Switching in mode is performed by a brief co-contraction of the muscle or by a switch to toggle between different functions of a prosthesis (Parket et al.,1985, Williams, 1990). Even though these control systems, based on thresholds or direct control, have been a clinically and commercially viable option for EMG prosthetic devices, they do not provide intuitive and reliable device control for multiple DOFs (Micera et al., 2010).

More natural control of a prosthetic device is required. Ideally, taking independent EMG signals from several sites should resolve this issue but it does not. Taking independent EMG signals is hard because of phenomena such as EMG crosstalk and the difficulty in activating an individual muscle by the user. Due to these drawbacks, computational models are required to extract sufficient discriminative information between tasks.

To the author's best knowledge, all leading industrial developers of myoelectric hands Ottobock (Germany), Shanghai Kesheng (China), LTI (USA), Motion Control (USA), RSL-Steeper (U.K.), and Touch Bionics (USA) use proportional control as an option although this is not confirmed through scientific literature. However, surveys on the use of these prostheses uncover that 30%–50% (Atkins et al., 1996, Biddiss et al., 2007) of amputees do not use their prosthetic limb regularly, due to its low functionality, poor cosmetic appearance, lack of sensory feedback, and low controllability.

2.2 Pattern recognition

The third generation includes programmable microprocessors granting an infinite range of adjustable myoelectric parameters (Oskoei et al., 2007). Microprocessor based applications in myoelectric control are growing rapidly which not only benefits functionality but is cost-effective as well. It also employs advanced techniques of signal processing hence allowing complex signal filtering. This results in increased responsiveness. More importantly, it accommodates PR-based control schemes thereby increasing the variety of control functions and improve robustness. These techniques assume that a specific muscle generates repeatable EMG signals. Following are the steps involve in any PR technique shown in Figure 2-1.

2.2.1 Pre-Processing

Pre-processing of EMG signals is the first step in a PR in which signals are filtered after being recorded from the selected muscles. The power spectrum of signals can be utilized to set the band limits. As it is generally admitted that, spectra of surface and intramuscular EMG signals are scattered within a range of 20–500 Hz and 100 -1500 Hz respectively (Merletti, 1999, Phinyomark et al., 2012, Boostani et al., 2003). Different filter types (Butterworth, Chebyshev etc) with low and high pass cut off frequencies are generally used in this step.

2.2.2 Segmentation

Segmentation of the EMG signal is the second step after filtering of the raw signals with analogue and digital filters. EMG signals are segmented into a set of overlapping windows. It is an important step as signal stationarity varies depending upon the window size and contraction type (static or dynamic) (Thongpanja1 et al., 2013). If the assumption is of having 80% stationary signal, then the window size of 250 ms or lesser is considered suitable for static contractions. A window size of 250ms or lesser is considered suitable for static contractions (Thongpanja1 et al., 2013).

2.2.3 Feature extraction

In this part, information about signals is extracted from the overlapping windows. Generally, numerous sets of features are extracted in time, frequency, and time-frequency domains to scrutinize the information of the myoelectric signals. Time domain (TD) features are the most commonly used in EMG control due to their simplicity of computation and because they are relatively easy to implement and do not require signal transformations. Combining a relatively stable and robust time domain parameters may significantly improve the classification performance without raising computational complexity (Zardoshti-Kermani et al., 1995). Features such as Zero Crossings (ZC), Slope Sign Change (SSC), Willison Amplitude (WAMP) and Myopulse (MYOP) and Cardinality (CARD) are commonly computed via a threshold value to reduce the impact of background noise. Selection propriety in representative features has been investigated in several studies. However, only a few have examined the impact of optimum threshold on classification accuracies. It was seen in most studies that threshold values for features were ignored or fixed values were used. Kamavuako et al., 2015 in a study evaluated threshold effect of ZC and SSC on feature space and classification accuracies for surface recording and it was found that performance of a PR based system can be improved by using optimum threshold values for each feature. Some researchers may include feature reduction or feature selection step between extraction and classification, depending on the number of features extracted.

2.2.4 Classification

In the classification step, a set of features that are extracted in the feature extraction step are used for characterization of multiple classes (Hargrove et al. 2008). Variety of PR techniques have been used in a variety of industrial research applications. However, despite the long tradition of PR techniques, there is no consensus on a technique which is most suitable for all scenarios. In the field of myoelectric prosthesis control, LDA is the most widely used classifier as its application with both offline and online control has been demonstrated by numerous studies (Bellingegni et al., 2017, Simon et al., 2011, Young et al., 2014).

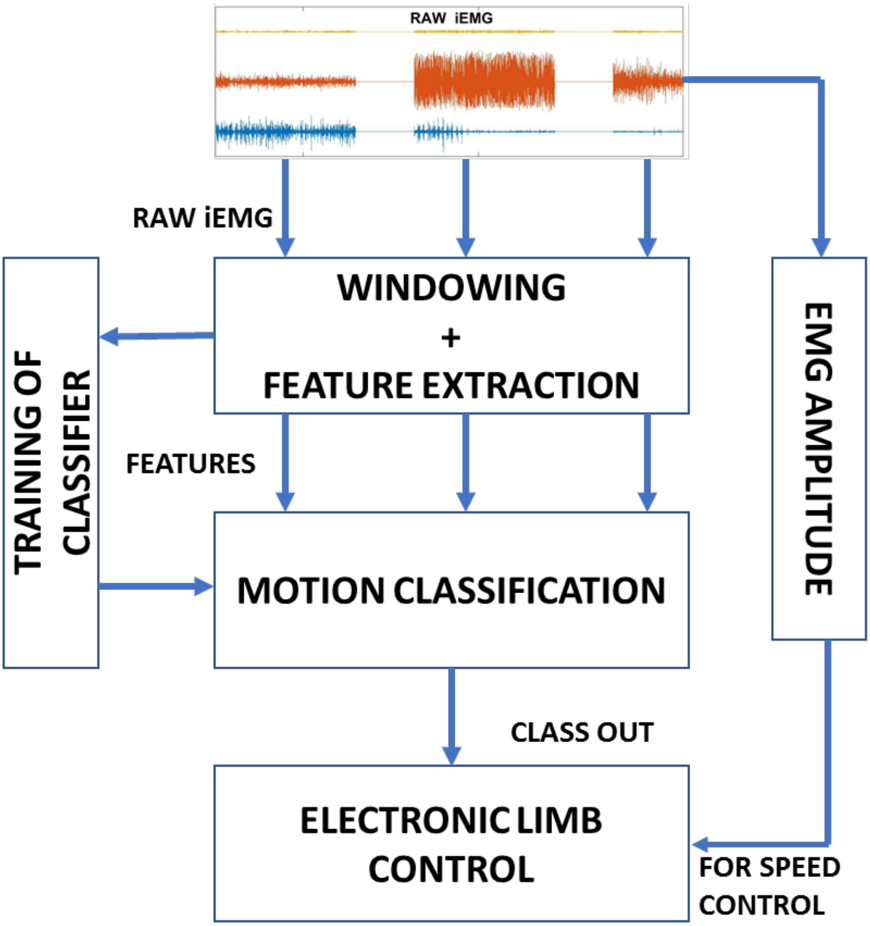


Figure 2.1: Block diagram of different steps involved in PR based myoelectric control including EMG signal acquisition, feature extraction, and classification.

2.3 Sequential control

Sequential control based on either Proportional or PR based techniques can drive only one DOF at a time. Multiple DOFs are sequentially controlled via direct control, requiring a cumbersome process of mode switching initiated by co-contractions. Plenty of research has been devoted to direct control of many DOFs via classification-based approaches (Scheme et al., 2011). The reported accuracy in these studies was high and the factors affecting the control schemes over time under real-world conditions were highlighted (Fougner et al, 2011, Hahne et al., 2012). Yet, most PR-based methods can manage only one task at a time, preventing natural control of hand motions. This also initiates additional cognitive load in planning the preconceived motions on amputees. Recently some studies showed, using the technique of classification based on parallel classifiers for multi-DOF control could provide intuitive control to amputees compared to the use of one classifier (Geng et al., 2013, Young et al., 2013). However, higher real-time combined classification error was reported.

In literature, pattern matching techniques demonstrated the ability to steer multiple DOFs intuitively than conventional direct control (Kuiken et al. 2016, Wurth et al., 2014). Although pattern matching schemes have reported higher accuracies (> 95%) in the literature but these schemes were confronted by many issues such as position of the electrodes, stability of the electrodes, adaptation over time and muscle fatigue (Hargrove et al., 2006, Scheme et al., 2010, Young et al., 2011). Similarly, a stable set of features reduces the impact of electrode location shift and varying effort level on classification by 16% (Tkach et al., 2010). Fougner et al., 2011 studied the impact of same hand motions in space at different angles on EMG pattern recognition. Results depicted strong dependence of EMG classification accuracy with limb position. It was recommended to develop a training strategy accounting for multi-position use. Other than that, the performance of this approach has also been affected in terms of controllability by environmental conditions (temperature, skin electrode impedance such as changes in electrode-skin impedance, inter-electrode distance and psychological factors (Hargrove et al., 2006, Scheme et al., 2010, Young et al., 2011, Young et al., 2012, Tkach et al., 2010, Fougner et al., 2011). Because of these constraints, only one solution based on this approach has been available commercially (COAPT complete control ® system).

2.4 Simultaneous control

As compared to other approaches, a limited number of studies has been done on extending pattern recognition control with respect to direct control of multiple DOFs. Following two methods were investigated in these studies.

2.4.1 Simultaneous control based on PR

Classification-based schemes divide movement intent into a definite set of “motion classes,” involving single DOF activity, multiple simultaneous DOFs, or no DOFs (a rest state). Statistical PR methods have been performed to concurrently and independently regulate control of two DOFs. However, this resulted in seamless transition velocity mappings between single-DOF- and multi-DOF movements (Wurth and Hargrove, 2014). This approach has provided the ability to isolate single DOFs with path efficiencies like sequential control methods.

Targeted muscle reinnervation (TMR) surgery is another technique to re-establish independent control sites for amputee having Tans humeral, forequarter and shoulder disarticulations. (Kuiken et al., 2009). The surgical technique redirects residual nerves to the residual muscles having no biomechanical function after amputation. After typical surgeries for transhumeral (Dumanian et al., 2009) or shoulder disarticulation (Kuiken et al., 2004) amputees, up to four at least four independent myoelectric control sites were utilized to provide simultaneous control of 2 DOF (Kuiken et al., 2004, Miller et al., 2008). Mode switching is not required after TMR with the benefit of reduced crosstalk. Although TMR is growing in popularity, only a few amputees have had TMR surgery.

At present, direct control is implemented for simultaneous activation of several DOFs with only amputees having TMR surgery. Recently (Hargrove et al., 2017) compared pattern recognition and direct control in a first home-based trial for trans-radial amputees who had TMR in a balanced randomized cross-over study. The outcome of the investigation shown that pattern recognition is a durable option and has functional advantages over direct control. Several other research studies have investigated the same prospect of providing simultaneous control to subject without going TMR surgery (Muceli et al., 2012, Cipriani et al., 2011, Baker et al. 2019). Average classification accuracies were 46% including individual and combined motions.

2.4.2 Simultaneous control based on regression

Regression techniques have been studied recently to investigate independent proportional and simultaneous control. The major difference to non-linear classification-based approach is that a regression model does not determine a definite class but alternatively, a continual output value is approximated for each DOF. This scheme provides simultaneous and proportional control independently and can dispense intuitive control. Researchers have studied both linear (Hahne et al., 2014, Jiang et al., 2014b, Smith et al., 2015a) and nonlinear (Jiang et al., 2012, Hahne et al., 2014, Kamavuako et al., 2012, Ameri et al., 2014, Ngeo et al., 2014, Muceli and Farina, 2012) means of mapping EMG recordings. Real-time analysis of these has though focused on linear methods and is mostly motivated by the motor control concept of muscle synergies (Jiang et al., 2009, d'Avella et al., 2006). (Jiang et al., 2014a, Jiang et al., 2014b, Smith et al., 2015a) has successfully demonstrated this method of simultaneously controlling different motions in real-time tests. (Jiang et al., 2014a) non-negative matrix factorization (NMF) which was used to extract low-dimensional neural signals. These signals were translated by the user into a kinematic variable. The comparison was also drawn between offline and online scenarios using above-mentioned control strategy with two conventionally used control algorithms. It was shown that although offline performance showed the difference between classifiers but in real-time, the subject was able to execute goal-oriented tasks similarly by using all three algorithms. Control. (Smith et al., 2015) compared linear regression simultaneous control with direct control using intramuscular wires. Motion specific training was also compared with the training of all movements, where all motions were used as inputs into regression model in which recordings not corresponding to the model's motion type were labelled as 0% speed. It was also found in an offline analysis that all-motion training had significantly better prediction accuracy than (R2, $p < 0.001$) one motion accuracy.

2.5 User adaption over time as a factor affecting PR-based myoelectric control

One of the main issues in the usage and design of myoelectric prostheses is that despite the significant improvement in technology, many amputees not adopt them as a durable solution. (Atkin et al., 1996, Biddiss et al., 2007). Three major issues were identified in the surveys-based studies (Atkin et al., 1996, Biddiss et al., 2007, Pons et al., 2005): “lack of robust intuitive control, insufficient feedback, and functionality”. Only prostheses available in the market and their usage by amputees were investigated in these survey-based studies.

Recently, it has been shown that surface EMG recording on the day is relatively different from the recordings acquired from another day for the same subject under same experimental conditions, resulting in substantially low accuracies over time (He et al., 2015). Importantly, high classification error of up to 40% was reported when testing and training data was from different days. Results indicated that changes in EMG signal characteristics over the course of 11 days became gradually smaller (He at al., 2015).

While many studies focus on other challenges mentioned above related to PR control, only a few studies have investigated time as robustness factor and its effect on intuitive control. Firstly, it is important as calibration of PR based myoelectric prosthesis is an important step before it can be used by an amputee, the question of whether training with respect to time could result in improve the performance or deteriorate with respect to time. Secondly, it is already discussed in the introduction that adaptive variations can occur in the neural functions in response to training. Question is whether these adaptive changes in neural function has some effect on the performance of PR control. Studies performed in the PhD project will help us to answer this question and tell us more about optimum techniques with optimum thresholds for each type of surface and intramuscular based PR control.

2.6 Summary of the chapter

In this chapter, we have reported factors that affect PR based myoelectric control schemes. We discussed optimal signal processing techniques with a best-suited range of band filter for both sEMG and iEMG, the optimal window size for segmentation and most importantly feature extraction. These features extracted from sEMG or iEMG signals provide the basis for separability between classes. For high separability, selected features have to be represented as distant as possible and with minimum interclass variability. To obtain the best out of these features, (Hudgins et al., 1993) suggested that threshold values must be contained in the computation of two-time domain features (ZC and SSC). Similarly, in any PR based control strategy, reliability and efficacy of pattern matching algorithms are of extreme importance as the electronic module of the prosthesis is implemented on low performance embedded systems. So, it is important to consider optimum classification techniques before implementing it in real-time especially if considering for long term solution. LDA is the most extensively employed classifier in the studies associated with PR based myoelectric due to its simplicity and low computational load.

All the studies referred in Section 2.2 have investigated factors which are affecting PR based myoelectric control in offline settings. There is a lot of debate on the evaluation of PR based control strategies in offline or online settings. Although offline evaluation is a useful performance metric, studies have shown that it is not a good representative of usability (Bellingegni et al., 2017, Ortiz-Catalan et al., 2013). It has recently also been reported that results from offline and online evaluations are only loosely correlated (Lock et al., 2005, Hargrove et al., 2007). Researchers have worked also on various approaches in real-time settings to demonstrate the usability of myoelectric control but in acute settings only. (Choi et al., 2009, Rosenberg et al., 1988, Kuiken et al., 2014, Matrone et al., 2012, Smith et al., 2014, Kamavuako et al., 2014). Therefore, it has not been established how real-time performance will be affected by different train-test strategies and their performance over time. Secondly, any training model based on the data from short duration may not be representative of better clinical usability.

CHAPTER 3: THESIS OBJECTIVES

In a PR based myoelectric control, feature extraction is an important step. To the best of my knowledge, most of the methods which utilized TD features require threshold values were being extracted without reporting their threshold value. So, the question is 1) To what extent threshold values affect the time domain features and their combinations in surface and intramuscular recordings? This question was answered in study I, by finding the effect of a threshold on each feature and combined the effect of different features with an optimal threshold in sEMG and iEMG recordings.

Although in the literature it has been demonstrated that few pattern matching algorithms have a recognizable edge over others based on their performance and computational load in offline and online settings. Almost, all these studies focused on the effectiveness of features sets extracted from the time domain, frequency domain or time-frequency domain representations. But the performance of classifiers based on time as the robustness factor was not investigated in the literature. Selection of an efficient and reliable classifier for implementing them in a low performance embedded system can be crucial especially if considering for long term solution. In addition to this, from an academic point of view, the most significant drawback of the current state of the art is that only very little studies have been conducted in a setup close to clinical practice and most of the studies are limited to one or two sessions only. Similarly, studies have shown that adaptive changes over time can occur in the neural functions (maximum neural firing rates, increased excitability, down-regulation of inhibitory pathways etc) apart from the morphological changes in the muscles that will occur as other training effects in response to training (Aagaard et al., 2001, Aagaard et al., 2002, Aagaard et al., 2003, Custem et al., 1998).

So, in a pretext question arises, 2) What is the correlation between the performances of PR based myoelectric control schemes and time? To investigate this second study was performed with more trans-radial amputees and the concept of non-stationarity of sEMG and iEMG signals of PR control were studied over days with respect to training effect on amputees and able-bodied subjects. We investigated the optimum classification technique in a separate study in which multiday analysis was performed on both sEMG and iEMG recordings. We compared the performance of most widely used PR techniques over days and as well as across days.

As many studies have investigated the offline and online evaluation of PR control, it can be concluded that both evaluation techniques are loosely correlated. So, in the backdrop of our previous studies question arises, 3) How do PR training strategies influence real-time performance over time? In the fourth study, the real-time outcome of multiple train-test schemes for the classifier over time was evaluated.

Each designed study was aimed to reach **specific objectives**, which are provided below.

1. Identify the optimum threshold values for features in sEMG and iEMG recordings.

2. Quantify the effect of time on PR based myoelectric control for sEMG and iEMG recording.

3. Compare most widely used classifiers in PR based myoelectric control over days for sEMG and iEMG recordings.

4. Quantify the effect of multiple train-test strategies on sEMG and iEMG over days with real-time testings.

Study I: To identify the best threshold values for the calculated features. Best performing threshold values were selected from the set of applied range (R = 0:0.02:6) times the average root mean square of the baseline. Classification performance was compared for using LDA and KNN as classifiers.

Study II: To estimate the time effect on classification performance of function motions of hand with different train-test strategies in, sEMG, iEMG and their combination (cEMG) using standard linear regression analysis. Correlation between data types was found by comparing their classification performance over time.

Study III: Six most widely used classifier were selected and compared longitudinally for sEMG and iEMG recordings separately. With-in day and between day classification performance were used as a performance measure.

Study IV: To investigate the real-time performance of hand motions with different train-test strategies over time with classifier being considered best in the previous study for both surface and intramuscular detections separately. Effect of each train-test strategy will explain the usability of both surface and intramuscular detection techniques.

CHAPTER 4: METHODS

During the PhD project, four data sets were used in the PhD project. Each data set was recorded in accordance with the declaration Helsinki and approved by the local ethical committee (approval no: N-20160021). Pre-recorded data set was used in study I. Separate data sets were recorded and used for each study II, IV(I) and IV(II). Data set 2 was for study II and III. For detail methodology for each study, papers that are published in relation to these studies can be referred to.

4.1 Data set 4: Used in study IV part II

Participants: In total five able-bodied subjects took part in the experiment. None of the subjects had any medical condition related to muscles Average age of the subject participated in the experiment were 25.4 years. Written consent was taken from all the subjects participated in the study. The protocol of the experiments was in accordance with the Declaration of Helsinki and approved by the local ethical committee of the region of Northern Jutland (approval no: N-20160021).

Data Acquisition: AnEMG12 amplifier by OT Bioellectronica was used to record iEMG signals which were then passed through a bandpass filter (100 – 900 Hz). These filtered analogue signals were converted into digital signals using 16 bits via NI-DAQ PCI-6221, sampled at 2kHz, and amplified with gain 5000. A band electrode was placed on the wrist contralateral to the dominant one as a reference. Figure 4-1 shows the setup for this experiment. Using three pairs of wire electrodes, iEMG was recorded from three different muscles, namely: Extensor Digitorum on Channel 1, Extensor Carpi Radialis Longus on Channel 2 and Flexor Digitorum Superficialis on Channel 3. These in-vivo wire electrodes were made from 50 µm diameter Teflon-coated stainless steel. A 25-gauge sterilized needle was inserted in each muscle for each electrode. Precautionary measures against the risk of infection were thoroughly observed. Each subject's skin was disinfected with 70% isopropyl alcohol before needle insertion. Sterile electrodes and gloves were used while handling the subjects.

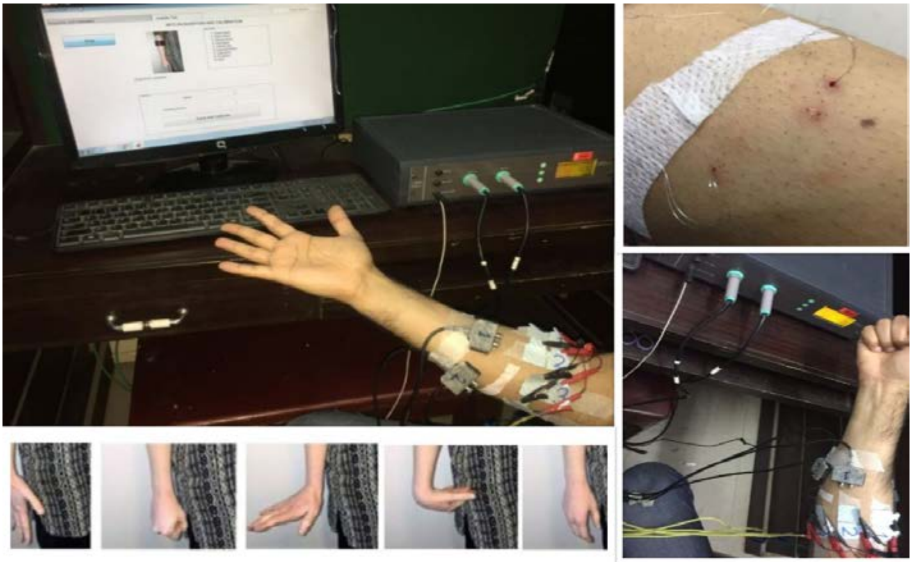


Figure 4-1 Experimental setup including the position of the electrodes, insertion points and movements included in the study.

The needle was inserted 10-15 mm below the muscle fascia and removed once the electrodes had been fixed inside the muscle. The insulated wires were unsheathed from the tip by about 3 mm to maximize the pickup area (Kamavuako et al., 2014). These pair of wires were to stay in each subject's arms for five days.

After the electrodes were inserted, a sterile bandage was taped on the wires leaving leeway for in vivo wire motion during extension and flexion and to allow connection to amplifiers. After each session, another bandage was placed to completely cover the wires before each subject left the room. This bandage served as a precautionary measure against electrode displacement. It was removed once the subject re-entered the room for further sessions. The bottom bandage was only removed upon the subject's wish to withdraw or after all the sessions had been successfully completed.

Experimental Procedure: The experiment had two main steps: firstly, data was collected to train a classifier and then the models trained on different sets of collected data were tested online. For the first step, subjects were required to produce a medium level contraction (to emulate routinely chores) from rest to motion. They were prompted by an image of a specific motion randomly generated by a customized MATLAB-based Graphical User Interface. For each motion, data were collected four times, six seconds each time. Between each sustained contraction, six seconds break was given. Data for four active motions (Wrist extension, Wrist Flexion, Hand open, Hand close) and one rest (no motion) were collected. After each set of five motions, a break of twelve seconds was given.

For the second step, a cursor at the centre of the screen was to be controlled by the hand. There were two axes on the screen: XX' and YY'. The top YY' represented Hand Closed while the bottom YY' represented Hand Opened. Similarly, left XX' represented Hand Flexion and right XX' represented Hand Extension. These four targets were measured by Distance (D) and Width (W). To be considered a successful movement, the cursor had to hit the target and remain at it for one second. The entire experiment spanned at five days. On each day, three types of online tests were carried out as shown in Figure 4-2. Firstly, within day training and testing of Artificial Neural Network (ANN) was denoted by WDT row in the table. BDT represents the online test in which the training data of the previous day was used to test the data of the present day. Lastly, the training data of all the previous days was used to test the present-day data in CDT. Three sessions of testings were performed per day. In which each motion was tested 18 times in all three sessions and 6 times per session. 24. Thus, 24 targets for four different motions were to be reached per session.

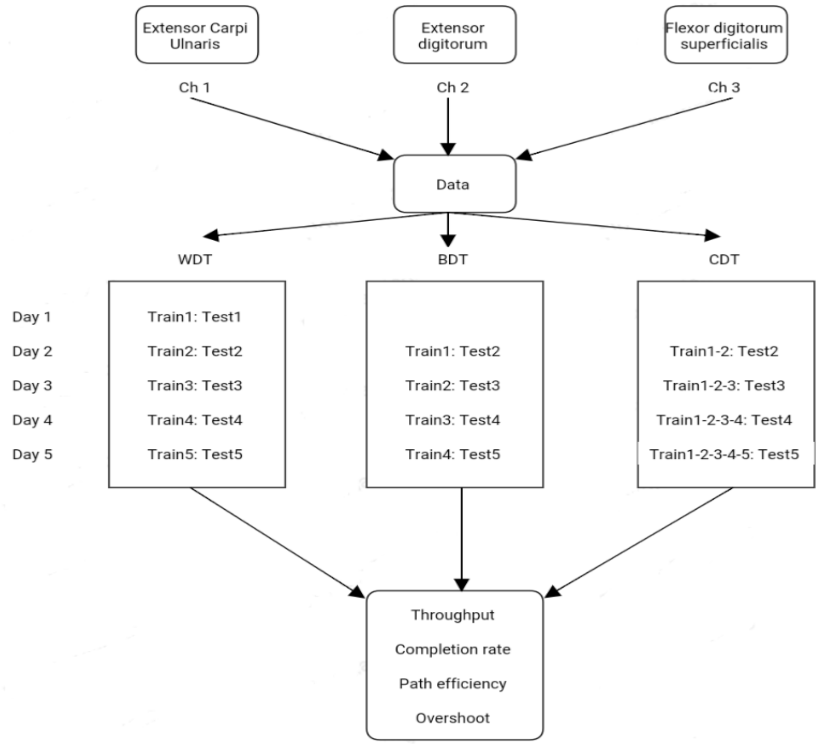


Figure 4-2 Scheme of an experiment in Study IV part II.

4.2 Data analysis

A 200ms overlapping window with an increment of 50ms was used to segment the steady-state part of four seconds of the data from every six seconds recorded signal. Six features were examined, namely: Mean Absolute Value, Cardinality, Waveform Length, Zero Crossings, Willison Amplitude and Slope Sign Changes. ANN was used as an offline and online training and testing classifier. The offline configuration was simulated in GUI such that it had a fixed number of neurons in the hidden layer. A profile specific to each subject was created in which the subject's calibrated signals were stored. The trained ANN was subjected to Fitts' law to classify the cursor-controlled hand gestures.

During the implementation of Fitts' law, participants were asked to move the cursor from rest position (origin of the axes) to a random target at a distance (D) and width (W) from the origin. Upward movement of the cursor represented an open hand, the downward movement represented a closed hand, left represented wrist flexion while the right movement represented wrist extension. Based on the distance D and width W from the origin, each target's index of difficulty (ID) was calculated. Various combinations of target distances and widths calculated by Equation (1) are tabulated in Table 2. While testing in real-time, subjects were required to remain at a target for a dwell time of one second for the movement. Motion considered unsuccessful if the cursor remained in the target for less than one second [Gusman et al., 2017, Wruth et al., 201425-26]. Similarly, if the subject was unable to hit a target after 15 seconds of the cue, the motion was considered unsuccessful and the cursor was moved back to the origin. To evaluate real-time system performance: path efficiency (PE), overshoot (OE), throughput (TP), and completion rate (CR) were examined as four performance parameters.

$$ID = \log_2\left(\frac{D}{W} + 1\right) \qquad (1)$$

Table 4-1: Description of performance metrics.

Performance metric	**Description**
Throughput	Throughput (TP) is the ratio between the index of difficulty (ID) and the time taken (in seconds) to reach the target $T_p = ID/M_t$ (Fitts', 1954)

Path Efficiency	Path Efficiency (PE) is calculated by the distribution of the straight-line distance over the travelled distance It defines the quality of the control system. $P_E = SD/AD$ (William et al., 2008)
Over Shoot	Overshoot is defined as the ability to remain on the target. It is calculated by dividing the number of events where the subject reaches the target but fails to remain at it for the dwell time of 1 second divided by the total number of targets. (William et al., 2008)
Completion Rate	Completion Rate computes the percentage of successfully completed tasks within the time limit. (Simon et al., 2011)

Offline classification performance parameters were computed using the attained data. The training strategies were like the ones applied for online classification. Error ij was calculated by dividing the number of times the system failed to classify or misclassified the target with the total number of classifications. Between-day classification error (BCE) was computed by using the training data of the previous day and the testing data of the present day. $Error_{ij}$ was calculated by day i training data and day j testing data. Within-day classification error (WCE) was computed by using training and testing data of the present day. $Error_{ij}$ was computed by implementing two-fold validation. Combined-day classification error (CCE) was calculated using training data attained on all former days and present-day testing data.

Results were descriptively compared to assess the overall performance of the offline system based on classification error. The relationship between the index of difficulty and completion time was assessed to examine the feasibility of Fitts' law for online testing. The attained data was fit into the computer-based linear model. To examine how well it fits the data, R^2 coefficient of linear model was used. Based on training strategies, performance metrics for the online system were computed and compared. Results were calculated and demonstrated as mean ± standard deviation.

CHAPTER 5: MAIN FINDINGS

5.1 Study I

5.1.1 Single feature evaluation

Results showed that classification error (CE) obtained from sEMG and iEMG were not significantly different (P=0.99). Significant difference (P=0.006) was found between features, with WAMP (0.153 ± 0.063) and CARD (0.161 ± 0.066) performing significantly better than SSC (0.21 ± 0.078. On average it was found that KNN (0.154 ± 0.063) performed significantly (P<0.001) better than LDA. Figure 5.1 showing the interaction between types of EMG and classifiers ((P = 0.047) and also between classifiers and features(P = 0.043). It was found that classifiers and features depend on the type of EMG signals.

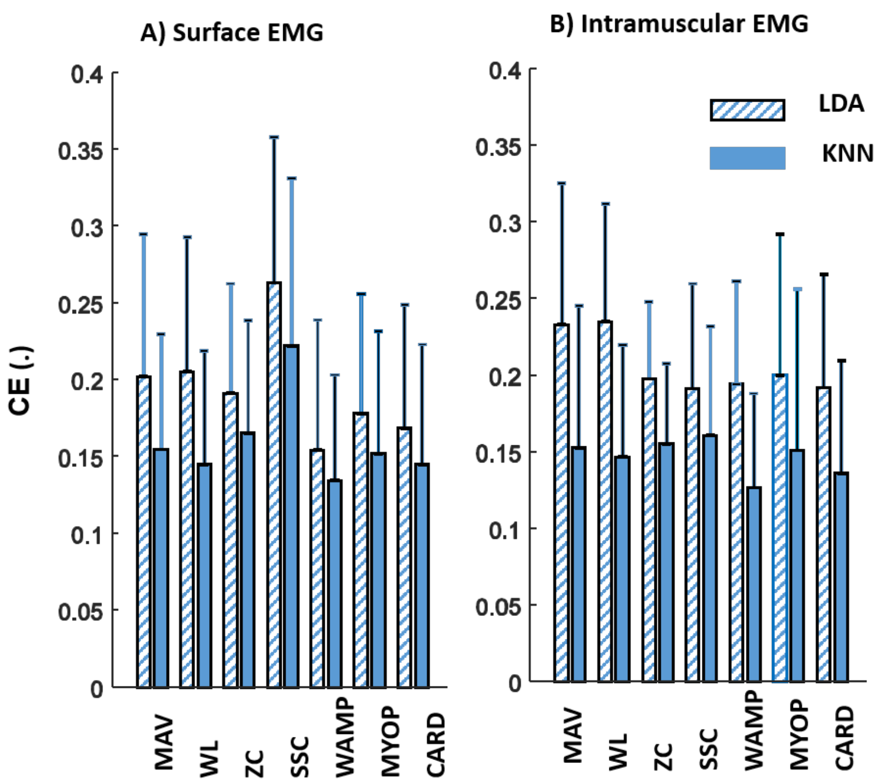
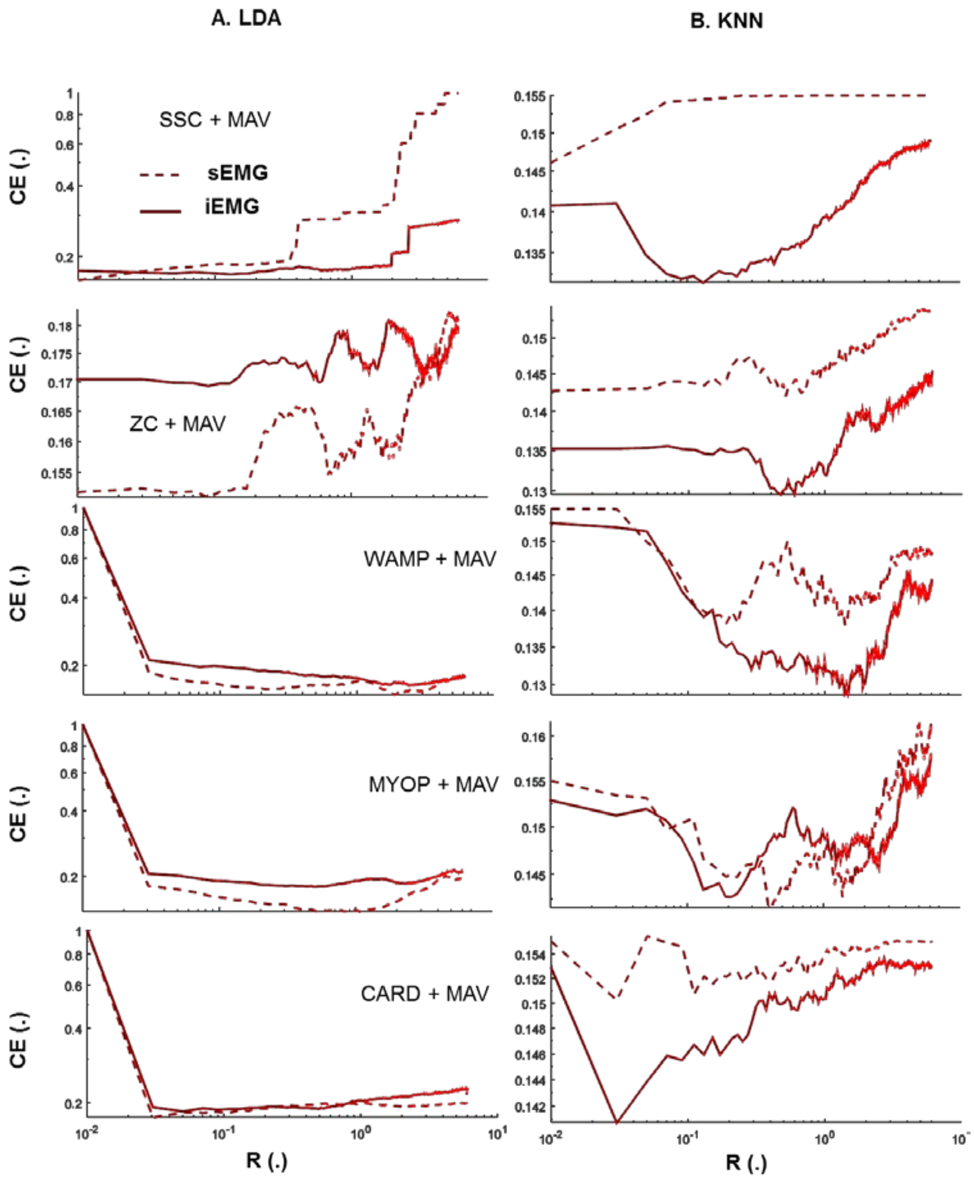


Figure 5-1: Classification performance of all features for both A. sEMG and B. iEMG with respect to threshold values R.

5.1.2 Adding MAV to each single feature

The performance of the two features was investigated in the second step of the study



The effect of *Figure 5-2: Classification performance of MAV feature combined with each feature with respect to threshold values for both sEMG (dashed line) and iEMG (plain line) using LDA and KNN.*

increasing the value of the threshold for each feature combined with MAV is represented in Figure 5.2. Both classifiers showed that all features are threshold dependent. The result showed that for sEMG low threshold value is required for WAMP, CARD and MYOP while no threshold is required for ZC and SCC. A similar trend is observed for iEMG when using LDA as a classifier. Low threshold values may improve the performance of SSC and ZC when KNN is used as a classifier.

5.1.3 Best combination of features

This part of the study depicted the combination of best-performing features depending on their threshold values. Figure 5.3 shows the best performing combination for each EMG type and classifier when employing one to four features in the clockwise direction. Results suggest that for both sEMG and iEMG best performing features are different.

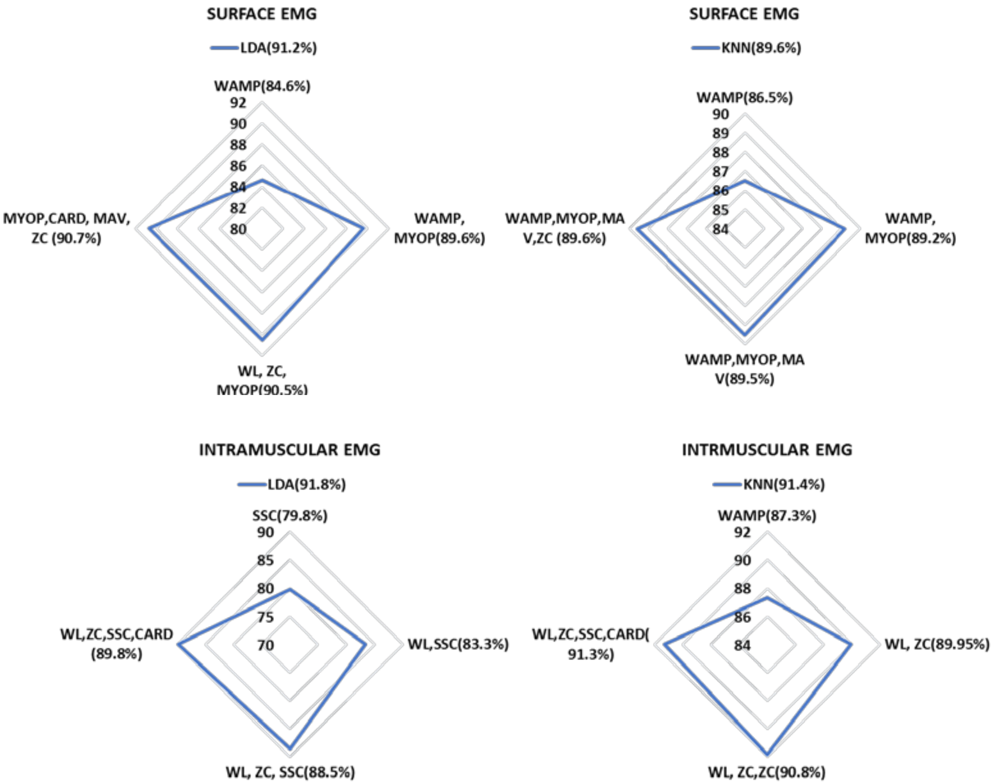


Figure 5-3. Best performing features (in the group of one, two, three and four features) after comparing all features for both EMG (surface and intramuscular) in LDA and KNN

5.2 Study II

5.2.1 Within-day classification

WCE for amputees and able-bodied with seven functional motions are shown represented in Figure 5.4. In amputees across days, combined EMG (7.8 ± 4.5%) was not significantly different from surface EMG (12.7.0 ± 6.2%, P = 0.5) and Intramuscular EMG (17.2 ± 11.3 %, P = 0.6). For both EMG types, on average WCE was 16.5 ± 8.2% (sEMG) and 20.2± 9.3% (iEMG) on first day, which reduced to 10.0 ± 5.6% (sEMG) and 15.9 ± 12.3% (iEMG) respectively. Combined WCE was 10.5 ± 5.5% on the first day which reduced to 7.7 ± 4.4% on the seventh day. No interaction was found between EMG types and Days (P=0.2). In able-bodied, results exhibited that iEMG (8.3 ± 1.6 %) was significantly different (P < 0.001) from sEMG (3.5 ± 0.96 %) and cEMG (2.2 ± 0.3 %) across days.

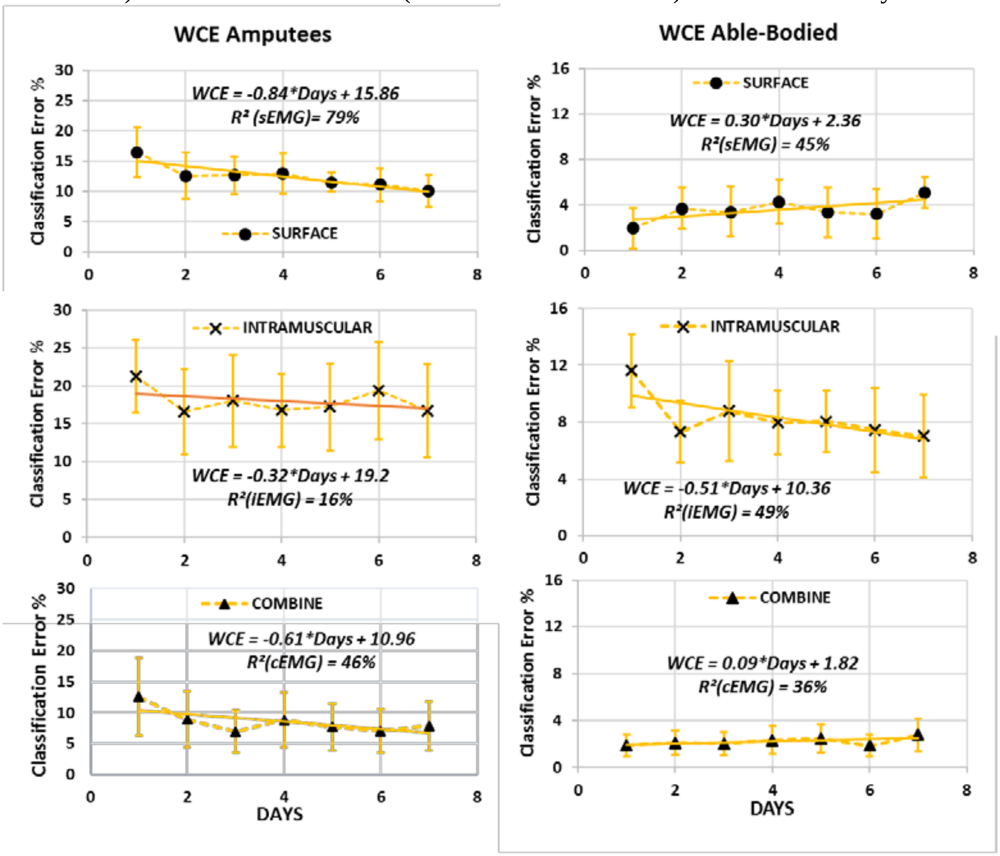


Figure 5.4 Fixed lines are representing the linear regression model for surface (sEMG), intramuscular (iEMG) and cEMG along the course of seven days in amputees with SD.

5.2.2 Correlation between residual limb and performance

A close correlation was found between the length of residual limbs and WCE. In iEMG regression slope was significant $F(1,5) = 58.71$, $P = 0.001$, R^2 (iEMG) = 0.94, 95% CI [-1.74, -0.82] indicating improved performance in amputees have bigger stump Figure 5.5. A weak correlation was found for sEMG.

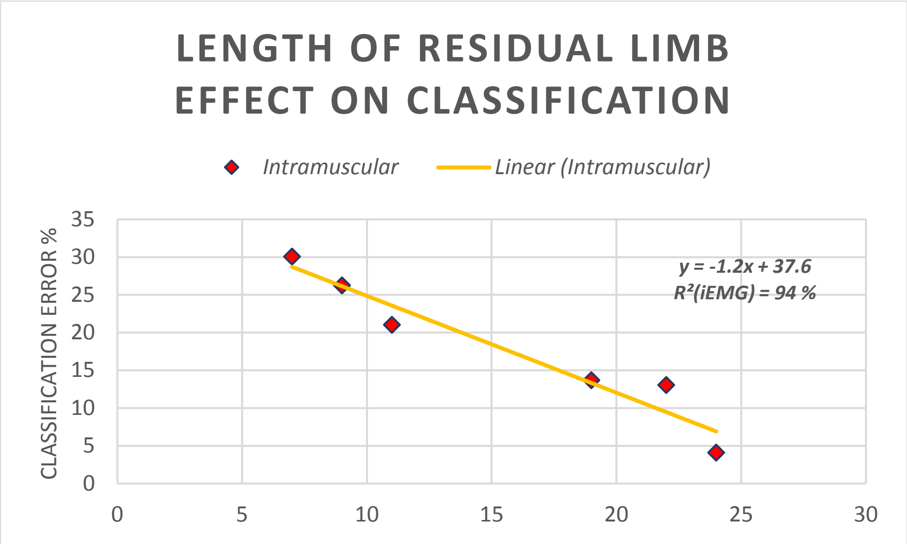


Figure 5.5: Regression line representing the relationship between classification performance and the size of the residual limb.

5.1.2 Between-day classification

"BCE was computed from Df = 0 (training and testing of the classifier on the same day) to Df=6 (training on day one and testing on day 7) i.e. the difference between training and testing day was increased from 0 days to 6 days. Figure 5.6 shows the regression fit between BCE and Df (0-6) for EMG (surface and intramuscular) in amputee and able-bodied. The slopes with amputees were 3.6, 95% CI [0.42, 1.04] and 4.6, 95% CI [0.69, 1.16] for sEMG and iEMG respectively. The slopes for able-bodied were 1.55, 95% CI [-0.02, 0.64] and 4.3, 95% CI [0.26, 1.45] for sEMG and iEMG respectively. The slopes for cEMG were 1.91, 95% CI [-0.06, 0.82] and 1.59, 95% CI [0.14, 0.48] for amputees and able-bodied respectively. Results indicated that performance continuously degraded as the time difference between training and testing day increased" (Waris et al., 2018).

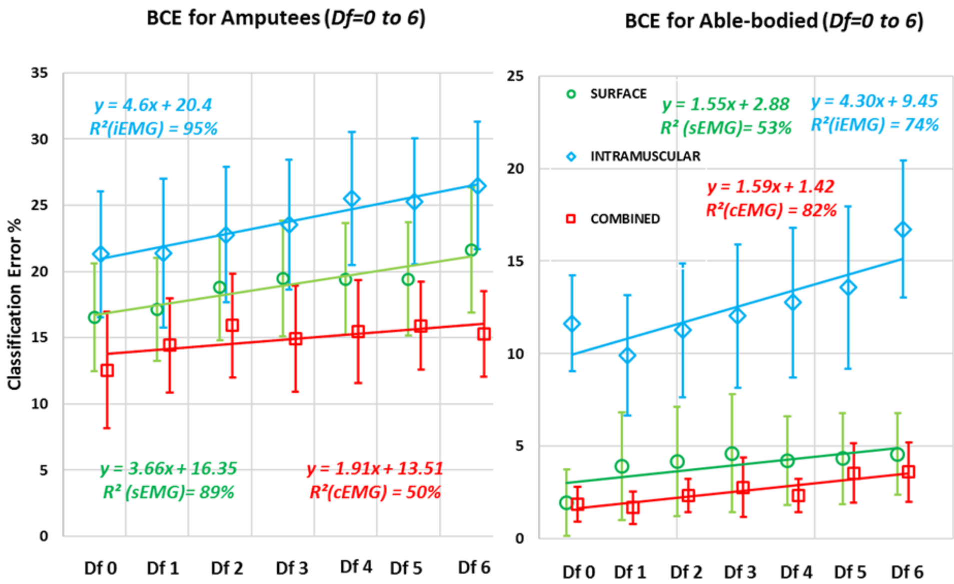


Figure 5.6: BCE for sEMG, iEMG and cEMG for amputees (right) and able-bodied on the (left) representing polynomial fit for Df= 0 to 6.

5.3 Study III

“Figure 5.7 showed the geometrical changes in feature space for first two principal components of three classes (Pronation, Supination, and Fine Grip) on day one, three, five and seven in one amputee subject. Three classes were used to exhibit changes in the genetic distance between populations in 2-dimensional embedding over time. PCA transformation ensures horizontal axis PC1 has the most variation, vertical axis PC2 the second most. Factor scores for both components improved over time distinctly for all classes till days seven. On the first, a cloud of data (Pronation, Supination and Fine Grip) could be seen. Genetic distances between populations also increased by day seven as three classes could be seen as an individual class showing adaptation of subject over time.

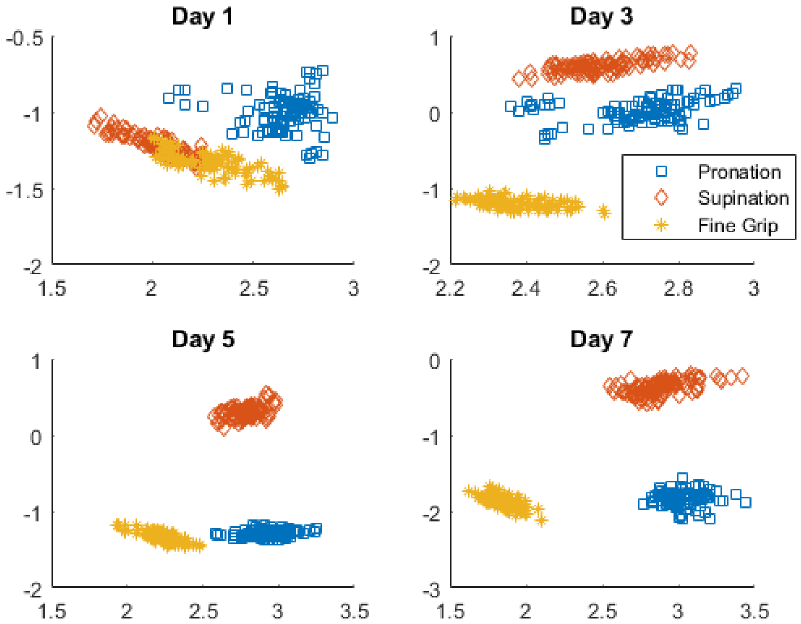


Figure 5.7: Surface EMG feature space representing two principal components for three classes Pronation '□', Supination '◊' and Fine Grip '' in an amputee.*

5.3.1 Within-day comparison

Three-way repeated ANOVA test showed significant difference (P<0.001) between EMG types (surface, intramuscular and combined), Days (1-7), classifiers (TREE, LDA, SVM, NB, KNN, ANN) and their interactions ([Days * classifier], [Days*Type], [Type*Classifiers].

Classifiers: No significant difference (95% of CI [-0.39 0,64], P = 0.97) was found between NB and SVM. The remaining classifiers were significantly different from each other. ANN was best and TREE was the worst on (95% of CI [17.20 18.24], P < 0.01). **Days:** Day 7 was significantly better P<0.01 than the rest of the days, Day five, six and seven were significantly different from all other days. Day1 and Day3 found no significance between each other (95% of CI [-0.38 0.77], P = 0.94) and so as Day 2 and Day 4 (95% of CI [-0.28 0.88], P = 0.70). Interactions between each factor (type*days), (type*classifiers) and (days*classifiers) found that type (combined ANN), day (seven) and classifier (ANN) was statistically better than any other type, day and classifier.

The results of WCE across all subjects: sEMG, iEMG and cEMG are summarized in Figure 5.8. Each group represents the performance of all classifiers on each day for seven consecutive days.

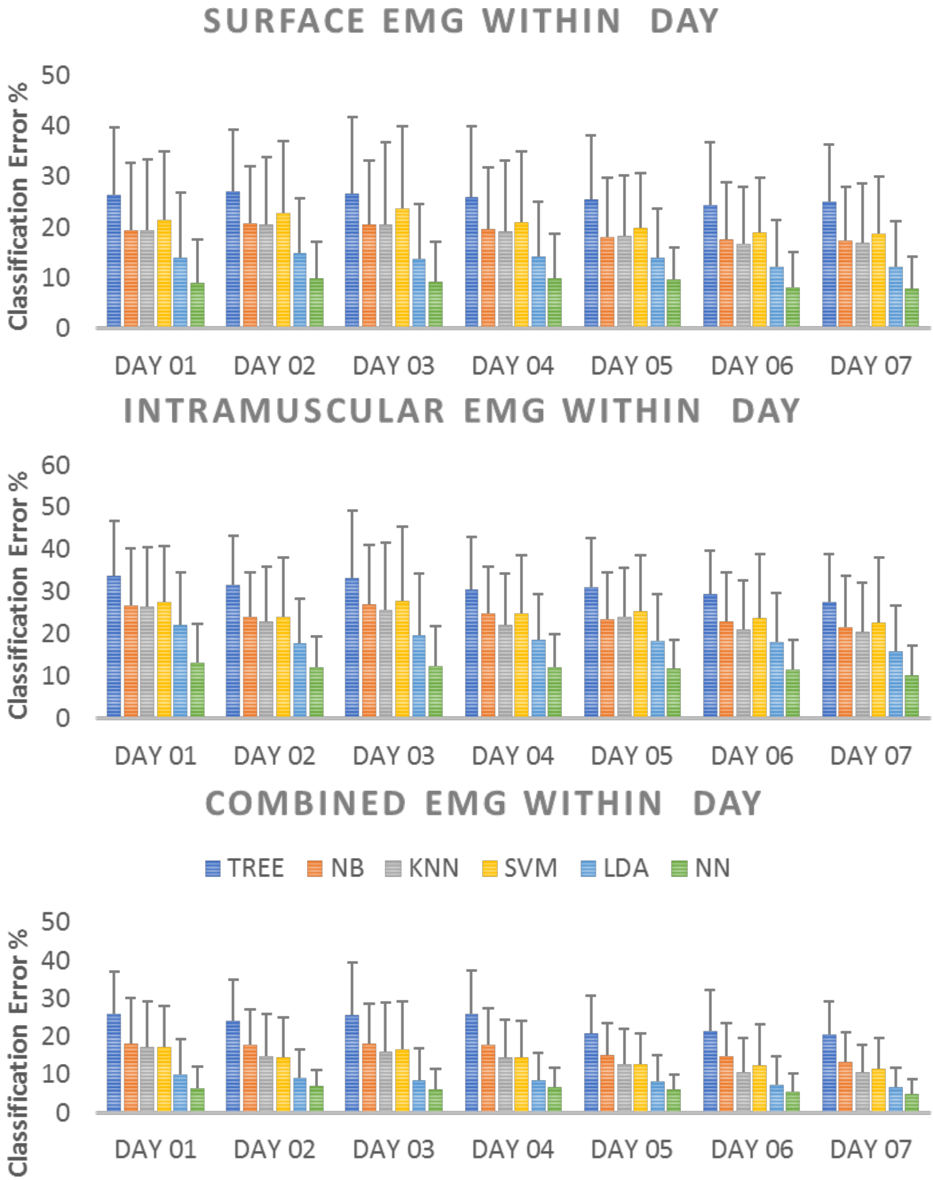
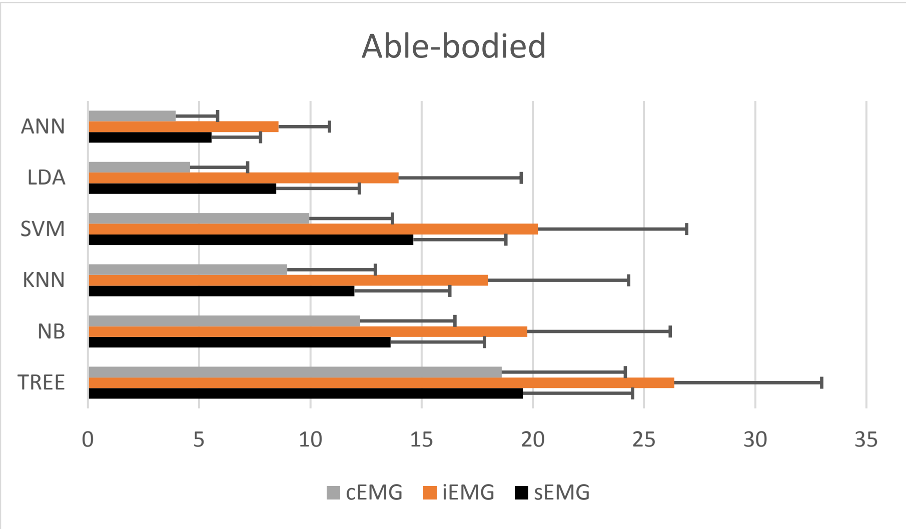


Figure 5.8: WCE for all classifiers for all types sEMG, iEMG and cEMG averaged across all subjects.

On average, for all the classifiers, WCE reduced consistently for seven consecutive days. Multiple comparisons revealed all classifiers were significantly (P<0.05) better than Decision trees (WCE 26.43 ± 13.12% on the first day, 24.03 ± 11.48 % on the seventh day). LDA and ANN outperformed (P<0.05) rest of the classifiers with error decreased consistently until day seven to 12.13 ± 8.98 % and 7.92 ± 6.16 % for LDA and ANN respectively. Classification accuracy improved over time as day six and seven were significantly better than day one to four.

In iEMG, ANN outperformed (P<0.05) all other classifiers with WCE 10.27 ± 7.04% on the seventh day. Overall LDA and ANN showed a change of 6.3 % and 2.9 % respectively till seventh. Day seven was significantly (P<0.05) better than the rest of the days, implying learning and stabilization of the implanted electrodes.

In combined EMG, attributes from the surface and intramuscular EMG were combined to analyse the overall change in the performance of different classifiers (Figure 5.8). By combining the attributes, significant improvement in WCE performance was seen in all classifiers with respect to the surface and intramuscular. All the classifiers were significantly different from each other for combined EMG expect KNN (10.75 ± 7.03%) and SVM (11.75 ± 7.03%, P=0.97). ANN in combined EMG outperformed all the classifiers implemented (P<0.05) with the lowest classification error 4.96 ± 6.34% for ANN until the seventh day. WCE for day five, six and seven were significantly (P<0.05) better than day one, two and three. Figure 5.9 represents the average WCE for able-bodied and amputees"(Waris et al., 2018).



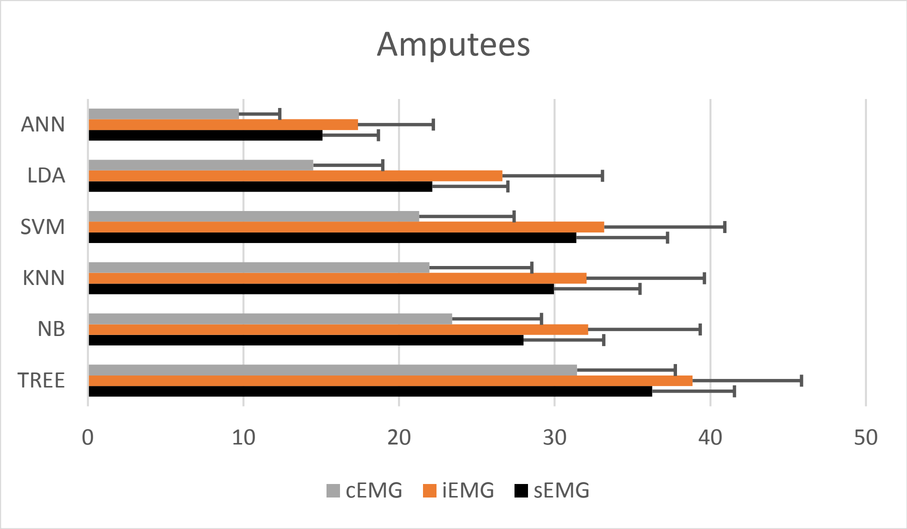


Figure 5.9 Averaged performance of each classifier across all days.

5.3.2 Between day comparison

ANOVA with factor EMG types (sEMG, iEMG and cEMG) and classifiers (TREE, NB, KNN, SVM, LDA and ANN) revealed that combined EMG was significantly (P<0.001) better than sEMG and iEMG. It was also found that ANN performed significantly better (P<0.001) than other classifiers Figure 5.10.

Surface EMG: Comparison of BCE between all classifiers for surface EMG was lowest (21.8 ±2.1%) in ANN and it was significantly better than (P<0.05) all other classifiers. LDA as a classifier performed significantly better (P<0.05) than the KNN, NB, and TREE but not significantly different from SVM (95% CI [-0.64 7.1], P = 0.14). TREE classifier was found to be least effective in classifying motions with BCE (45.82 ± 3.72%).

Intramuscular EMG: It was found that classification accuracies of iEMG were lower than cEMG and cEMG averaged across all days. ANN was significantly better than other classifiers. BCE of LDA outperformed both TREE and NB significantly (P<0.001). Performance of LDA, KNN and SVM was statistically similar.

Combined EMG: In cEMG, improved performance was observed in all classifiers in comparison to sEMG and iEMG. ANN on average (14.37 ± 1.43 %) was significantly better (P<0.05) than the rest with lowest BCE. cEMG had improved BCE effect on LDA turned out to be second best in term of classification performance as it was significantly better (P<0.05) than the rest of the classifiers. KNN was significantly better (P<0.05) than TREE but not different from NB (95% of CI [-3.80 5.83], P = 0.98) and SVM ((95% of CI [-0.89 8.74], P = 0.16).

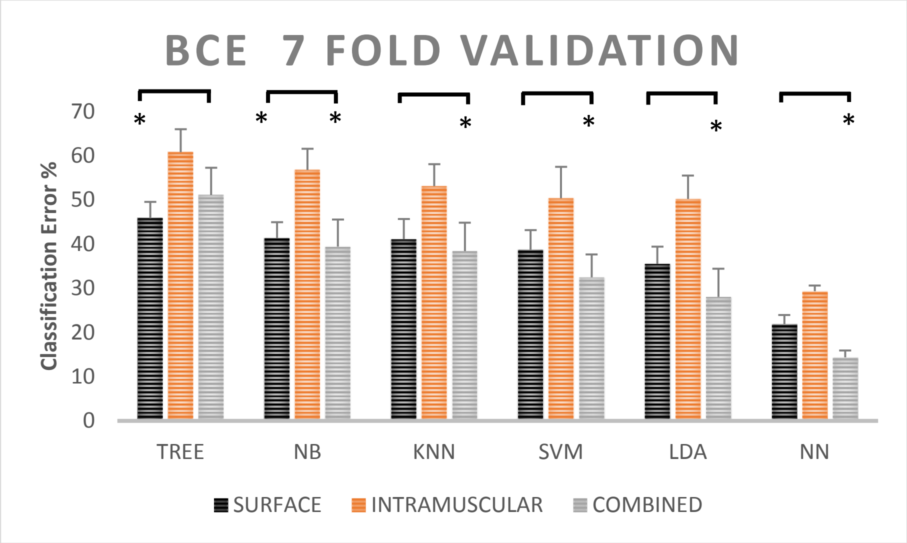


Figure 5.10: Changes in BCE for all tested classifiers and EMG types (sEMG, iEMG and cEMG).

5.4 Study IV (part I) real-time tests with sEMG

5.4.1 Offline performance

Results of the offline analysis revealed that training schemes were significantly ($P \leq 0.01$) different and performance varied over days ($P \leq 0.01$). Multiple comparison showed no significance (P = 0.55) between average WCE (0.98 ± 0.57 %) and BCE (1.55 ± 1.25%). Averaged WCE and BCE were significantly ($P \leq 0.01$) lower than CCE (4.99 ± 1.63%). Classification performance of CCE improved over time but no significance. WCE remained statistically the same over days Figure 5.11.

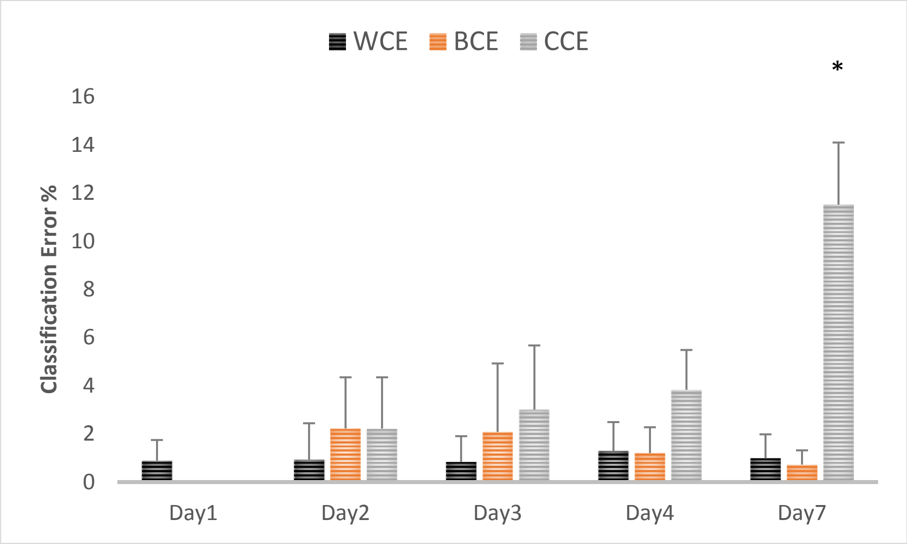


Figure 5.11: Offline Classification performance comparison between WCE, BCE, and CCE over a week. Star (*) indicate the case where there is a significant difference.

5.4.2 Online performance

It was found that completion time increased with the increase of index of difficulty for all train-test strategies (coefficient of determination $R^2 \geq 0.91$) representing a strong linear relationship between two parameters. This phenomenon indicates the efficacy of Fitts law. Table 5.1 shows the completion time with respect to IDs

Table 5.1: Average completion time with respect to the index of difficulty for BDT, WDT and CDT.

ID	BDT	WDT	CDT
1.81	5.5±1.3	5.1±0.7	4.9±0.2
2.58	8.3±2.7	8.219±2.7	7.8±1.7
3.46	8.6±2.8	8.5±2.5	8.3±1.5
4.39	11.5±1.2	11.3±1.5	10.9±1.3

A summary of all performance metrics per session across all days is provided in Table 5.2. Table 5.2 represents the performance of all metrics per session averaged across all days. It was shown that CR decreased over sessions for both CDT and BDT. For WDT it remained statistically similar.

Table 5.2: Session wise comparison of all performance metrics in all train test strategies (WDT, BDT and CDT). A significant difference in each session of performance metric was presented in star (*) in Table 5.2.

Within-Day Testing (WDT)			
	Session 1	**Session 2**	**Session 3**
CR	94.42±4.09	93.17±3.64	95.08±3.35
OS	14.86±4.14 (*)	11.84±6.01	11.35±5.25
PE	86.86±1.75	87.50±2.70	86.69±2.51
TP	0.41±0.02(*)	0.39.71±0.02	0.38±0.02
Between Day Testing (BDT)			
	Session1	**Session 2**	**Session 3**
CR	89.06±5.45(*)	86.56±5.53	83.13±6.50
OS	14.26±4.27(*)	11.06±4.73	10.39±4.60
PE	85.55±2.37	86.78±4.61	86.18±4.89
TP	0.39±0.01(*)	0.39±0.01	0.36±0.02
Combined Day Testing (CDT)			
	Session 1	**Session 2**	**Session 3**
CR	99.79±0.29(*)	98.85±1.22	96.45±3.69
OS	14.75±4.31(*)	10.61±4.45	10.38±4.79
PE	87.03±1.31	86.93±1.01	88.55±5.03
TP	0.41±0.01(*)	0.40±0.01	0.38±0.02

Figure 5.12 represents the average performance of each train-test strategy and the overall comparison between all performance metrics. It was found that CR of CDT (98.37 ± 1.47 %) outperformed significantly (P<0.01) than BDT (86.25 ± 3.46 %) and WDT (94.22 ± 2.74 %). No significant difference (P>0.3) was found between PE and OS. Throughput (0.40 ± 0.03 bits/s) of CDT was significantly better (P=0.001) than BDT (38.07±0.03 bits/s).

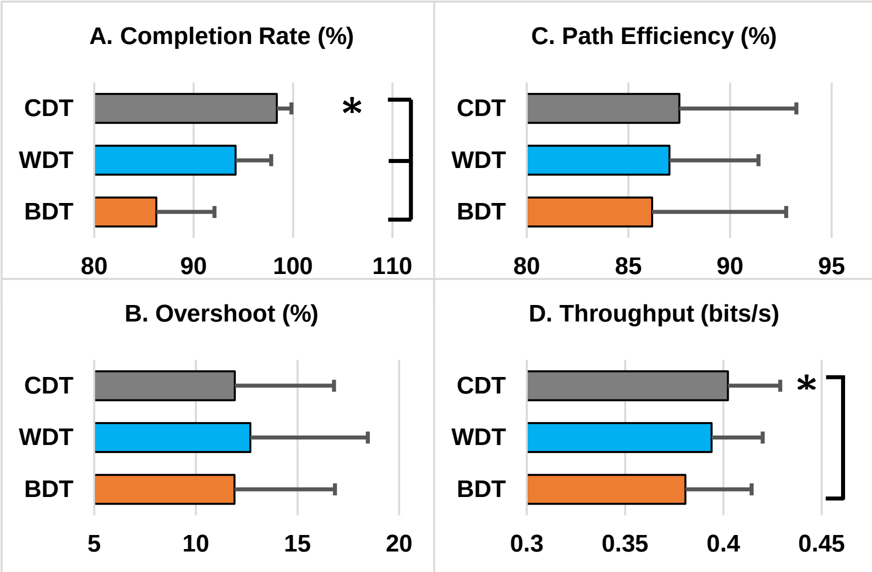


Figure 5.12: Comparison of all three train-test strategies with respect to all Performance metrics (A. Completion Rate (%), B. Overshoot (%), C. Path Efficiency (%), D. Throughput (bits/s))averaged across all days. Stars (*) indicate the case where there is a significant difference.

5.5 Study IV (part II) real-time tests with iEMG

5.5.1 Online performance

Intramuscular EMG based real-time test exhibited that completion time increased with the increase of index of difficulty for all train-test strategies (coefficient of determination $R^2 \geq 0.90$) representing a strong linear relationship between two parameters. These phenomena indicate the efficacy of Fitts law. Table 5.3 shows the completion time with respect to ID.

Table 5.3: Average completion time with respect to the index of difficulty for BDT, WDT and CDT.

ID	BDT	WDT	CDT
1.81	5.4±1.4	5.3±0.8	4.8±0.5
2.58	8.4±2.6	8.2±2.7	8.0±2.4

3.46	8.6±2.7	8.6±2.5	8.4±2.4
4.39	11.7±1.3	11.27±0.7	10.9±1.3

Table 5.4. Session wise comparison of all performance metric averaged across all days.

WITHIN DAY TESTING (WDT)			
	Session 1	**Session 2**	**Session 3**
CR	90.3±10.5	88,5±10.2	88.7±11
OS	15.6±8.5	14.5±8.6	15.2±9.1
PE	83.4±3.2	84.4±3.3	82.7±3.6
TP	38.1±1.8	37.7±2.6	37.6±2.4
BETWEEN DAY TESTING (BDT)			
	Session 1	**Session 2**	**Session 3**
CR	77.9±14.0	72.3±15.9	71.9±17.6
OS	33.2±10.8	33.5±11.2	28.5±5.8
PE	88.9±16.9	83.1±9.1	81.1±7,9
TP	35.8±3.2	36.1±3.2	35.1±3,5
COMBINED DAY TESTING (CDT)			
	Session 1	**Session 2**	**Session 3**
CR	94.0±6.7	91.5±9.5	89.4±10.3
OS	14.1±11.0	13.0±10.7	14.3±11.6
PE	85.6±3.1	86.7±3.6	84.1±3.1
TP	39.2±2.4	38.5±2.9	38.0±3.3

Figure 5.13 represent the comparison between training-testing strategies based on the data concatenated for different days. Completion rate (91.6 ± 3.6 %) of CDT was on average higher than BDT (74.0 ± 5.8 %) and WDT (88.2 ± 3.6 %). Difference between Path efficiency, Throughput, and Overshoot on average was low between strategies.

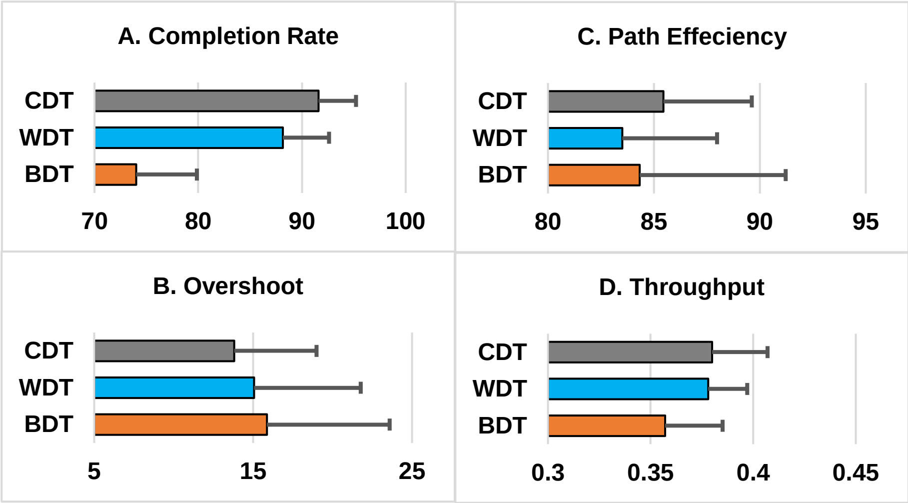


Figure 5.13: Comparison of all three train-test strategies with respect to all Performance metrics (A. Completion Rate (%), B. Overshoot (%), C. Path Efficiency (%), D. Throughput (bits/s))averaged across all days.

CHAPTER 6: DISCUSSION

In the start of this thesis, the nature of sEMG and iEMG recordings were presented in the context of multifunctional prostheses control. State of the art and challenges to were discussed as compliance of these devices are low for any type of myoelectric control. Lack of robustness and intuitiveness in previous methods were identified. Therefore, in this thesis, four studies were designed with a focus on PR based myoelectric control to investigate the robustness of these systems in a multiday analysis. With the aim to advance the state of the art in PR based myoelectric control.

6.1 Effect of optimum threshold values of features

Among various available combinations of feature sets, TD features (ZC, MAV, RMS, SSC, WAMP, MYOP and CARD etc) are commonly used. Some features require threshold values to lower the influence of the background noise (Zardoshti-Kermani et al., 1995). Most of the studies using these didn't report threshold values or applied predetermined threshold values which may have been too high resulting in degradation of the discriminative power of the threshold based features. In the first study, these features (ZC, SSC, WAMP, MYOP, and CARD) were studied individually for the range of threshold values, in combination and performance comparison was drawn between sEMG and iEMG.

Each feature investigated individually. As it was shown that MAV value provides the most discriminative information of signal for classification (Phiyomark et al., 2013). This statement didn't prove right in our study as other features performed better than MAV (Figure 5.1) when the threshold is optimized. It was also seen that each participant in the experiment has a global minimum supporting the initial suggestion made by (Hugdgin et al., 1993). Interestingly sEMG and iEMG recordings in comparison showed different features which performed optimally when the threshold was optimized. When compared in pairs, for sEMG it was found that WAMP and MYOP were the feature pair with the lowest error. For iEMG, WL and SSC showed the optimum performance. This showed that in the real case, both sEMG and EMG can be combined to excerpt more discriminative information from the signal. LDA as a classifier showed the outcome of each feature with respect to the threshold value is similar between the surface and intramuscular. The improved performance was seen in for low threshold values when tested to iEMG with KNN, this represents that KNN or other non-parametric classifiers can dominate LDA when the boundary is highly non-linear. So, the selection of an optimal classifier whose performance remained robust for both surface and intramuscular EMG is essential.

6.2 Performance over time

Recent studies have shown that the performance of PR control deteriorates significantly over time when the classifier is trained once for sEMG(He et al., 2015, Chen et al., 2013, Amsuss et al., 2014). However, it was still not known that the classifier can retain its performance if it is calibrated on daily basis or not and can its performance be improved over time if the classifier is trained on combined data from all previous days. Secondly, how the performance of these training schemes will affect iEMG recordings. So, in the second study, the performance of EMG pattern recognition was quantified by comparing classification accuracies over seven days to assess the learning characteristics of users with sEMG and iEMG.

Results from trans-radial amputees exhibited learning during the experiment which helped them to produce discriminative contractions. This learning augmented on succeeding days of training and testing. The performance of sEMG and iEMG were statistically similar. When both types of EMG were combined, the average WCE was improved by 6.9% till the seventh day for 11 classes. Results indicate significant slope between WCE and days for sEMG, the average over all subjects indicates otherwise. This suggests that with daily calibration, daily performance remains the same. We anticipate that this adaptation process could improve further if the length of the experiment was increased.

In Study I, we analyzed the changes in performance continuously for seven days as robust PR control is one of the main challenges for long term use. Although in case of amputees results of BCE were indeed poor when the classifier was trained on the first day tested on rest of the days, the error rate reduced continuously until last day indicating more and more coherence in signal characteristics over time due to learning. In amputees for combined EMG, the BCE between days 1 and 2 was 19.8% which reduced to 10.0% when training on the sixth day and testing on the seventh day. "This observation has an important implication on real-world myoelectric based on pattern recognition, which provides the possibility of reducing the level of system recalibration for prostheses training. Similar variations in BCE were observed in able-bodied subjects but with a much lower level of error rate. The relatively large change in performance with amputees as compared to normally-limbed individuals may be attributed to a more substantial learning effect, as the level of training to perform required motions, most of whom were performing the targeted contractions for the first time since amputation. Consistent improvement in the performance was observed due to the neuromotor adaptation of the amputees in the form of learning. Therefore, it is implied that changes in signal characteristics and performance were mainly due to the improved ability of the subjects to produce consistent EMG patterns for each movement" (Waris et al., 2018).

6.3 Robust optimal pattern recognition techniques

LDA is the most widely used classifier in studies related to PR based myoelectric control. It is believed to be most robust classifier when not being trained recurrently (Kaufmann et al.,2010) while other techniques are popular for benchmarks like high performance within a day, more stable to complex motion etc. It is difficult to generalize as multiple studies have explored different aspects of PR based techniques. Type of amputation, stump size(Li et al., 2010, Li et al., 2017), feature selection (Rechy-Ramirez et al., 2017, Ahmad et al., 2009, Phinyomark et al., 2014) feature extraction (Phiyomark et al., 2014, Ahsan et al., 2011, Tkach et al., 2010) classification parameters (Chen et al., 2013, Chu et al., 2007, Boschmann et al 2009, Phinyomark et al., 2013, Englhart et al., 2005) and number of recruited subjects (Chen et al., 2013, Chu et al., 2007, Boschmann et al 2009) are some of the factors that can affect the overall outcome of a technique. But one factor which was missing in these studies was their performance over time, especially under variable real-world conditions. It was shown in study III that while many classifiers may exhibit similar classification accuracies over time, but their underlying confidence profile may be substantially different. It was suggested that how these classifiers behave over time may lead to the selection of a control scheme with characteristics that are more suitable for robust control.

Results have indicated in amputees for WCE, NN performed significantly ($P<0.05$) better than all other adopted classifiers and its performance improved over time as a significant difference was found in performance between Day1 and Day 7 ($P=0.014$) for the surface, intramuscular and combine EMG. Performance of surface and intramuscular EMG in amputees found no significance for all classifiers (LDA $P=0.54$, KNN $P=0.75$, SVM $P=0.54$, TREE $P=0.54$, NB $P=0.12$, NN $P=0.54$) but in contrast, combined EMG acquisitions were significantly better($P<0.05$) than the surface and intramuscular EMG for all classifiers. This implied that if myoelectric control system could interface both surface and intramuscular EMG signal, to date which has not been practical to use invasive electrodes for prosthetic control, can provide more robust and stable control with cross talk free signals providing very local information.

Results indicated that combining the two EMG modalities had a positive effect on performance as it not only improves the information but also provides the local or global outlook to the attributes.

.6.4 Patient-specific strategies

Study II and III have shown that selecting an optimum set of motions may improve performance; such as significant improvements were seen in functional motions of hand such as the opening of the hand, wrist flexion and wrist extension and little to no improvement in performance was seen in grip motions. This class performance may vary with time allowing quantification of the degree of motion preference that is patient specific. Results showed that the degree of motion preference depends on the patient and that some motions are not preferred. This is clinically relevant to the patient’s specific adaptive systems.

6.5 Real-time effect of training schemes over time

Historically researchers have quantified EMG PR performance by comparing classification accuracies of different pattern recognition algorithms in offline or in online settings. Most of these studies had used only short-term scenarios under one train-test scheme. However, the one-time train-test scheme is not a reliable measure to estimate real-time behaviour as it provides an ideal condition for reporting performance and can produce unrealistically repeatable contractions. In study IV (Part I and II), multiple train-test schemes were assessed over seven days in the context of real-time usability test using Fitts' Law as it is well defined and well documented metric for the evaluation of motor control schemes. For the overall performance based on throughput and completion rate, two-way ANOVA revealed a significant difference between combined day testing (CDT), within day testing (WDT) and between day testing (BDT) in both parts of study IV.

Overall out of three sessions performed per day, for all train-test combinations reduction in all performance metrics were observed until the third session. The outcome of the different methods over sessions within a day implies that EMG characteristics change, and the same motions may become uncorrelated over time leading to the need to recalibrate or retrain the classifier. So, in all train-test schemes classifier was trained on each day, which resulted in improved performance for all train-test schemes as no significant difference was found between days.

6.6 Combined sEMG and iEMG based myoelectric control

"Limitation of surface EMG suggests that combining a new control strategy by combining multiple channels from the surface and intramuscular EMG can increase the amount of information harvested from the body (Kamavuako et al., 2013). The combined effect of surface and intramuscular EMG could improve the performance of selected classifiers. iEMG recordings can provide independent control this can enable amputees to control multiple DOFs simultaneously. In case of sEMG, the downside of this simultaneous and proportional control is past pointing, isolating 1 DOF targets and ballistic nature of movements during positioning (Smith et al., 2015, Smith et al., 2016). Since both acquisition types (surface and intramuscular) and their control schemes (sequential and simultaneous) have limitations, a control scheme based on both surface (isolate single DOF) and intramuscular (provide simultaneous and proportional control of multiple DOF's) could be devised for providing faster, intuitive and natural control.

6.7 Limitations

One major factor about the performance of intramuscular is related to the use of wire electrodes and their loose connections to the muscles. This is a limitation that may signify to generalize with care our results to all implantable systems. First, this configuration caused wires to be pulled out and second, displacements in the implanted depth may have changed due to the pulling force of connecting cables. Therefore, we cannot guarantee that the implanted electrodes were measuring from the same area throughout the seven days of the experiments. This is a limitation that is worth mentioning because the results of future studies could be different. An efficient way of testing such a system would be to use wireless implantable sensors, but to date, they are not commercially available. Considering the specificity of the intramuscular channels, the reduction in the number of channels can result in poor classification performance for certain classes. These certain classes were affected due to the absence of electrodes in that anatomical location. However, it should also be useful to note that the removal of the surface EMG channels that correspond to the failed intramuscular EMG channels causes a correlated decrease in performance on the same classes".

6.8 Future perspectives

Long term stability of techniques used for myoelectric control is a major issue. As of today, PR based algorithms and hardware for real-time control are available. It was found in our results that, ANN was the best performing classier for all EMG types (surface, intramuscular and combined). "The comparison of BCE and WCE for the optimum classifier (ANN) revealed that increasing the amount of training data can significantly reduce BCE and might converge to WCE, however, this may require the use of deep networks s such as convolutional neural networks (CNN)". Such an approach can be tested on amputees for real-time tests in the future with an expectation that training of such a deep network on the big data from many days will enable the possibilities to capture the EMG natural variabilities of each motion and thereby limit the necessity for system recalibration. Secondly, such a network can be tested on raw data without the steps of filtering, data segmentation, and feature extraction.

The concept of PR based approach is more appealing than other approaches because of patterns are actual natural representative of muscle behaviours before amputation. So, the use of these patterns is intuitive to the amputee and have the ability to control multiple DOF. But a PR based system is susceptible to more issues (electrode shift, doffing and donning) than a DC control. In a real case where amputee wants to put the prosthesis and go home and don't want to have an extended and repeated session of training. A system can be devised, where both sequential control-based algorithms such as LDA, ANN and simultaneous and proportional control based on the regression model can be combined. As both controls have strengths and weaknesses. For robust and accurate positioning in single DOF targets, sequential control is a suitable choice. In case of multi DOF gross positioning and intuitive control simultaneous and proportional control is most suitable. Combination of both these controls for variable DOFs can be an interesting study in the future.

The noise-free and stable signal is strongly related to the recording method and source. The origin of the signal source impacts on how easy it is for the patient to yield the information needed for the given movement. PR based techniques or control can be designed to be more robust and noise free but still dependent on consistent and stable input. So, recording EMG signals intramuscularly can provide physiological appropriate locations for natural and stable control. Implantable electrodes (MyoNode, Ripple) can solve the problems of signals stability affecting PR based control. As results of both offline and online studies indicate that intramuscular can be used as an alternative to sEMG. These electrodes can be placed superficially, deep and in small innervated muscles to investigate the performance of PR control for an elongated period of time and to find the solutions of problems associated with surface electrodes.

CHAPTER 7: CONCLUSION

Currently available myoelectric prosthesis lack intuitive and robust control over time mainly because these devices have limited DOF and independent controls sites making compliance of these devices low (Shenoy et al., 2008). PR based myoelectric has potential to have more robust multi-functional control. In the PhD project, three important questions related to PR control were answered. 1) To what extent threshold values affect the time domain features and their combinations in surface and intramuscular recordings? 2) What is the correlation between the performances of PR based myoelectric control schemes and time? 3) How do PR training strategies influence real-time performance over time? were answered. Following were the conclusion of each study.

1. In study I, it was found that threshold values affect the time domain features and their combination in sEMG and iEMG recordings. For both types (sEMG and iEMG), best performing features vary.

2. In study II, it was found that trans-radial amputees learned to produce discriminative motions over days. Performance of sEMG and iEMG over days remain statistically the same. Between days performance degrades over days leading to system recalibration.

3. In study III, it was found that ANN was the most robust and stable classifier over days for both sEMG and iEMG recordings.

4. In study IV, for both real-time test of sEMG and iEMG using Fitt's law, it was found from BDT and CDT, that difference between both train-test schemes was reducing indicating an adaptation of subject. This implies that if the classifier is used with an increased amount of data the performance of both schemes will be the same.

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