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Multiday Evaluation of Techniques for EMG Based Classification of Hand Motions

Asim Waris^{1,2}, Imran K. Niazi^{1,3}, *Member, IEEE*, Mohsin Jamil², Kevin Englehart⁴, *Senior Member, IEEE*, Winnie Jensen¹, *Member, IEEE*, Ernest N. Kamavuako^{5*}, *Member, IEEE*

1
2 **Abstract**— currently, most of the adopted myoelectric
3 schemes for upper limb prostheses do not provide users
4 with intuitive control. Higher accuracies have been
5 reported using different classification algorithms but
6 investigation on the reliability over time for these
7 methods is very limited. In this study, we compared for
8 the first time the longitudinal performance of selected
9 state-of-the-art techniques for Electromyography
10 (EMG) based classification of hand motions.
11 Experiments were conducted on ten able-bodied and six
12 transradial amputees for seven continuous days. Linear
13 Discriminant Analysis (LDA), Artificial Neural Network
14 (ANN), Support Vector Machine (SVM), K-Nearest
15 Neighbour (KNN) and Decision Trees (TREE) were
16 compared. Comparative analysis showed that the ANN
17 attained highest classification accuracy followed by
18 LDA. Three-way repeated ANOVA test showed a
19 significant difference ($P < 0.001$) between EMG types
20 (surface, intramuscular and combined), Days (1-7),
21 classifiers and their interactions. Performance on last
22 day was significantly better ($P < 0.05$) than the first day
23 for all classifiers and EMG types. Within-day
24 classification error (WCE) across all subject and days in
25 ANN was: surface ($9.12 \pm 7.38\%$), intramuscular
26 ($11.86 \pm 7.84\%$) and combined ($6.11 \pm 7.46\%$). The
27 between-day analysis in a leave-one-day-out fashion
28 showed that ANN was the optimal classifier (surface
29 ($21.88 \pm 4.14\%$) intramuscular ($29.33 \pm 2.58\%$) and
30 combined ($14.37 \pm 3.10\%$)). Results indicate that that
31 within day performances of classifiers may be similar
32 but over time it may lead to a substantially different

33 **outcome. Furthermore, training ANN on multiple days**
34 **might allow capturing time-dependent variability in the**
35 **EMG signals and thus minimizing the necessity for daily**
36 **system recalibration.**

37 **Index Terms**— Electromyography; Pattern recognition;
38 **Classification; Myoelectric control; Prostheses;**
39 **Intramuscular**

40 I. INTRODUCTION

41 Myoelectric control schemes use muscle contractions as
42 control signals to activate prostheses [1]. During the
43 contraction of muscles, the electric activity
44 (Electromyography, EMG) is detected from selected
45 residual limb muscles of an amputee [2]. Commercial
46 myoelectric control systems employ the relatively simple
47 approach of encoding the amplitude of the EMG signal
48 measured at one or more sites to actuate one or more
49 functions of a prosthesis [3]. Single-site controlled
50 myoelectric devices are used when limited number of
51 control sites (muscles) are available in a residual limb and
52 utilize single electrode to control both motions of paired
53 activity. Dual-site controlled myoelectric control scheme is
54 commonly used in clinics in transradial amputees. This
55 system utilizes separate electrodes for paired prosthetic
56 activity from antagonistic muscles (i.e. wrist flexor and
57 wrist extensor). When multiple degrees of freedom (DOF)
58 are to be controlled, sequential and mode switches are used,
59 allowing the same pair of electrodes to control a second
60 DoF. Switching mode is performed by a brief co-contraction
61 of the muscles or by a switch to toggle between different
62 functions of a prosthesis. Although these control schemes
63 are clinically and commercially viable option for
64 myoelectric prostheses, they do not provide intuitive and
65 simultaneous control of a device having multiple DOFs [3].
66 This, among other reasons, make patient compliance to the
67 current prostheses low [4].

68 Pattern recognition (PR) schemes can be used to extract a
69 wealth of controllable information from the EMG. The key
70 assumptions of a PR myoelectric control are that repeatable
71 and distinctive signal patterns can be extracted from muscle
72 signals. These decoding algorithms have been used in
73 academia for several decades [5,6]. Since then significant
74 improvement has been made in these PR algorithms with the
75 advent of advanced signal processing techniques and high-
76 speed embedded controllers. These systems are intended to
77 be more intuitive and control a greater number of DOFs

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1 which should improve performance while keeping the
2 number of electrodes low. Furthermore, PR systems do not
3 require independent channels, which can sometimes be
4 impossible to locate due to small stump size.
5 In the context of PR of EMG signal, the first step involves
6 feature extraction from the different time windows.
7 Choosing a feature set is an important step as several studies
8 [7] have shown some feature are more representative of data
9 than others. These feature sets are then fed into the
10 classifiers for the recognition of the different hand motions.
11 The output of the classifier is used by the controller for the
12 actuation of prosthetic devices. The typical modern
13 classification algorithms used in myoelectric control are:
14 Linear discriminant analysis(LDA) [8,9], Support vector
15 machine(SVM) [10,11,12], K-nearest neighbour(KNN)
16 [13], artificial Artificial Neural Network (ANN) [14-15],
17 Bayesian classifiers [16], Gaussian mixture models [17],
18 Fuzzy logic [18] and genetic algorithms [19]. It has been
19 demonstrated in these studies that if proper methods are
20 used, high classification accuracies (>95%) can be achieved
21 on a dataset with multiple classes [20]. Despite these high
22 accuracies, only one prosthetic control system based on
23 pattern recognition is commercially available [21]. There
24 are several factors which are preventing the implementation
25 of these systems outside laboratory conditions, such as
26 adaptation over time, muscle fatigue and electrode shift in
27 offline settings [22,23,24].
28 The efficiency of classification algorithms is of utmost
29 priority as prosthetic control is implemented on low
30 performance embedded systems due to some constraints like
31 the size of residual limb and space available in a socket.
32 Many of these algorithms have been compared for short-
33 term EMG recordings [25,26]. Englehart et al. compared
34 the performances of LDA and MLP for four classes. LDA
35 exhibited better a classification performance over MLP after
36 using a PCA reduced feature set [27]. Kaufmann et al
37 applied five PR schemes on 21 days of data from only one
38 able-bodied subject to evaluate five classifiers (KNN, DT,
39 MLP, LDA, SVM) and found that the accuracy degrades
40 with increasing time difference between training and testing
41 data, and drops gradually if not retrained for all algorithms
42 but the LDA [28]. On the same data set, Phinyomark et al.
43 found that LDA outperformed the rest of the seven
44 compared classifiers with an overlapped window size of 500
45 ms and increment of 125 ms [29]. Bellingegni et al.
46 evaluated the maximum acceptable complexity of each
47 classifier, by using a constraint of a typically available
48 memory of high-performance microcontroller [30]. It was
49 found that a non-logistic regression (NLR) provided the best
50 compromise between the complexity and the performance
51 followed by multiple layer perceptron (MLP). Recently, it
52 has been shown that classification accuracies vary
53 significantly over time [31,32], as data recorded on one day
54 has different characteristics from data recorded on the other
55 day due to the real-world conditions mentioned above. The
56 central question is: why studies have focused on comparing
57 classifiers on the basis of their performance using short-term
58 scenarios while many other factors such as time can

59 influence their performances? Hence the choice of a
60 classifier should not be entirely based on performance and
61 computational load but on a trade-off between performance
62 and robustness over time. Moreover, limitation of surface
63 EMG suggests that combining a new control strategy by
64 combining multiple channels from the surface and
65 intramuscular EMG can increase the amount of information
66 harvested from the body [33]. The combined effect of
67 surface and intramuscular EMG could improve the
68 performance of selected classifiers.

69 Weir et al. developed first implantable myoelectric sensors
70 (IMES) for prosthesis control [34]. These electrodes were
71 intended to detect and wirelessly transmit EMG signals to
72 an electromechanical prosthetic hand via an electromagnetic
73 coil built into the prosthetic socket. This system was only
74 tested on animals. Since then only a few researchers have
75 used IMES to achieve direct and simultaneous control of
76 myoelectric prosthesis on humans. Such a control is not
77 possible by using conventional surface-based myoelectric
78 control [35,36,37]. The Myoelectric Implantable Recording
79 Array (MIRA) is other solution for future advanced
80 prostheses [38].

81 Intramuscular recordings have several advantages over
82 surface EMG. The insertion of the intramuscular electrode
83 can acquire signals from the small and deep muscles
84 providing localized information, thereby greatly increasing
85 the information to control a prosthetic device. Intramuscular
86 recordings also have limited crosstalk and are less affected
87 by factors such as skin impedance and precipitation [39],
88 however, the selectivity of these recordings may constitute a
89 drawback.

90 Therefore, the aim of this study was to evaluate and
91 compare for the first time the longitudinal performance of
92 five classifiers; Linear Discriminant Analysis (LDA),
93 Artificial Neural Network (ANN), Support Vector Machine
94 (SVM), Naive Bayes (NB), K-Nearest Neighbour (KNN)
95 and Decision Trees (TREE) over seven days for surface and
96 intramuscular EMG recordings. The intention was to
97 provide insight into the behavior of the selected classifiers
98 with time as a robustness factor, an experimental design that
99 constitutes the novelty of this study. Intramuscular EMG
100 signals was recorded concurrently in an effort to increase
101 the information content. Intramuscular electrodes were kept
102 inside the muscles for seven days in ten able-bodied and six
103 trans-radial amputee subjects.

104 The rest of the paper is prepared as follows: in the next
105 section, the subjects, data collection, and experimental
106 procedure are presented. In Section III complete
107 experimental results with respect to different training and
108 testing strategies are presented. In Section IV, a discussion
109 is given on the impact of the use of surface and
110 intramuscular recordings and classification methods.
111 Finally, the conclusions are given in Section V.

112 II. EXPERIMENTAL METHODS

113 A. Subjects

114 Subjects were divided into two groups, one group

1 comprised of eight subjects who had transradial amputation
2 at different levels (all males, age range: 20-56 yrs., mean
3 age 26.56 yrs.) and the other group included 10 normally-
4 limbed subjects who had no history of upper extremity
5 deformity or other musculoskeletal disorders (all male, age
6 range: 18-38 yrs., mean age 24.6 yrs.). Subjects were
7 informed about the experiment and their participation was
8 voluntary. They provided informed written consent and they
9 had the right to leave the experiment without providing an
10 explanation. Out of the eight inducted amputees, two left the
11 experiment (after first and third day) before the completion
12 of data collection and thus were excluded from data
13 analysis. The procedures were in accordance with the
14 Declaration of Helsinki and approved by the Aalborg
15 University, Denmark local ethical committee approval
16 number N-20160021.

17 *B. Data Collection*

18 EMG signals for 11 different motions were recorded from
19 the skin surface as well as from inside the muscles. Surface
20 EMG was recorded using bipolar Ag/AgCl electrodes
21 (Ambu WhiteSensor 0415M). According to the surface area
22 available on the residual limb, five to six surface bipolar
23 electrodes were placed at equal distance from each other
24 around the circumference of the forearm. Positions of
25 surface electrodes were marked each day with a skin maker,
26 to ensure correct placement of electrodes on the following
27 day. Three to six bipolar wire electrodes were used to
28 record intramuscular EMG. These electrodes were inserted
29 to reside underneath each surface EMG electrode pair,
30 providing similar sites for surface EMG so intramuscular
31 EMG could be recorded together with the surface EMG.
32 Intramuscular electrodes in amputees were inserted using a
33 B-mode ultrasound machine, whereas in healthy subjects,
34 we relied on surface anatomy of the forearm for insertion.

35 Intramuscular wire electrodes were made of Teflon-
36 coated stainless steel (A-M Systems, Carlsborg WA
37 diameter 50 μ m) and were inserted into each muscle with a
38 sterilized 25-gauge hypodermic needle. Antiseptic measures
39 were used to minimize the risk of infection. Skin of subjects
40 was prepared by using 70% isopropyl alcohol before
41 inserting the needle. All the electrodes used were sterile and
42 unpacking of needle and electrodes took place using sterile
43 gloves. The needle was inserted to a depth of approximately
44 10-15 millimetres below the muscle fascia and then
45 removed to leave the wire electrodes inside the muscle. The
46 insulated wires were cut to expose 3mm of wire from the tip
47 to maximize pickup area [40]. Intramuscular electrodes
48 were kept inside the muscles for seven days while surface
49 EMG electrodes were placed on a daily basis on the same
50 location, with the help of the marks placed on the skin on
51 the previous day.

52 After the electrodes had been inserted, a sterile bandage
53 was placed to cover all the insertion sites and only the tips
54 of the wires were left outside the bandage to allow
55 connection to the amplifiers. After each session, a second
56 bandage was placed to cover the wires before the subject

57 could leave the room, to minimize the risk of electrode
58 displacement. The top bandage was removed to allow wire
59 connections at the subsequent session. The bottom bandage
60 was only removed after the completion of all sessions or if
61 the subject wished to withdraw from the experiment.

62 EMG signals were acquired using a commercial myoelectric
63 amplifier (AnEMG12, OT Bioelettronica, Torino, Italy).
64 Signals were analog bandpass filtered (10 – 500 Hz for
65 surface EMG and 100 – 4400 Hz for intramuscular EMG),
66 A/D converted using 16 bits (NI-DAQ PCI-6221), and
67 sampled at 8 kHz. Recorded signals were amplified with the
68 gain of 2000 for surface and 5000 for intramuscular EMG.
69 A reference wristband electrode was placed on the opposite
70 hand close to the carpus.

71 *C. Experimental Procedures*

72 Subjects were prompted to execute comfortable and
73 sustainable contractions corresponding to 11 classes
74 containing 10 active motions: Hand Open (HO), Hand
75 Close (HC), Wrist Flexion (WF), Wrist Extension(WE),
76 Pronation,(PRO) Supination(SUP), Side Grip (SG) (all
77 fingers are flexed around the object which is usually at a
78 right angle to the forearm and thumb is wrapped around the
79 object), Fine Grip (FG) (Metacarpophalangeal and proximal
80 inter-phalangeal joint of the fingers are flexed, thumb is
81 abducted and the distal joints of both are extended, bringing
82 the pad of the thumb and finger together), Agree (AG)
83 (thumb abducted and fingers flexed, with thumb pointing in
84 upward direction), Pointer Grip (PG)(index finger is
85 extended while middle, ring, and little fingers are flexed,
86 with the thumb in adducted position) and Resting state or no
87 motions (RT).

88 For data collection, BioPatRec [41], an open source
89 acquisition software was used. Data of four repetitions of
90 five seconds each were collected. One experimental session
91 was conducted in one day. The complete duration of the
92 experimental session was around one hour. The time
93 interval between two experimental sessions on consecutive
94 days was approximately 24 hours. The amputee subjects had
95 never used a prosthesis, except for one subject who had
96 been using a body-powered prosthesis. Experimental
97 sessions were conducted for seven consecutive days.

98 During the experiment, over the course of seven days,
99 some of the intramuscular electrodes were pulled out. In
100 amputee subjects, about three electrodes remained in the
101 muscles and functioned properly for seven days. In normally
102 limbed subjects, at minimum four intramuscular electrodes
103 remained inside muscles until day seven. Thus, data from
104 only functioning electrodes were used for analysis. The
105 number of surface channels used for analysis was reduced
106 accordingly on a per subject basis to allow a fair
107 comparison. Although absolute classification rates will be
108 reduced by eliminating channels, the time effect on
109 classification, the key element of this study, is the essential
110 observation. Therefore, the number of viable channels can
111 be considered a subject-specific parameter, and

1 consequently is embedded in the *subject* effect in the
2 statistical analysis.

3 *D. Data Analysis*

4 EMG surface signals were digitally high-pass filtered
5 (third order Butterworth filtered) with a cut-off frequency of
6 20 Hz as well as low pass filtered with a cut-off frequency
7 of 500 Hz. A notch filter at 50 Hz was used to reduce power
8 line interferences. Intramuscular EMG signals were
9 digitally high-pass filtered (third order Butterworth filtered)
10 with a cut-off frequency of 100 Hz and low-pass filtered
11 with a cut-off frequency of 1500 Hz. From every five
12 seconds of contraction time, one second was provided for
13 onset phase and one second for offset phase to avoid non-
14 stationarity. Subsequently, three seconds of the steady-state
15 phase was used for the extraction of features. Seven time-
16 domain features were extracted from incrementing (by 35
17 ms) windows of 160 ms duration. These features were Mean
18 Absolute Value (MAV), Zero Crossings (ZC), Slope Sign
19 Changes (SSC), Willison Amplitude (WAMP), Waveform
20 Length (WL), Myopulse Rate (MYOP) and Cardinality
21 (CARD).

22 Data with high dimensionality tend to be prone to
23 overfitting and loss of information as an overfitted model
24 can lead to classification errors [42]. PCA was used to
25 overcome the curse of dimensionality. The classification
26 error (ratio between misclassification and total
27 classification) was used as a performance index. Within-day
28 classification error (WCE) was defined as training and
29 testing data on the same day. Four-fold cross-validation was
30 used to quantify WCE. Each fold comprised of assigning
31 one repetition of testing data and the remaining three
32 repetitions as training data; the mean of the four
33 classification errors was reported. To investigate the long-
34 term effects on classification performance, classification
35 between days was computed on the corresponding seven
36 days of data collection. Between-day classification error
37 (BCE) was defined as training and testing data from two
38 different days. BCE was quantified using a 7-fold validation
39 procedure where six days were used for training and one
40 day for testing. This was repeated seven times and the
41 results were averaged.

42 The analysis was carried out on each EMG type (surface
43 and intramuscular) and their combination. Feature vector
44 from training data was transformed into lower-dimensional
45 subspace by application of principal component analysis
46 which has an effect of linearizing the discrimination tasks of
47 the classifier. Principal components contributing to 99%
48 variance, were used for classification purposes. To assign
49 the number of neurons used in the hidden layer of the
50 Artificial Neural Network, a comparison of the
51 classification error was performed. The classification error
52 was therefore compared to each subject with different
53 numbers of neurons going from 2 to 15. The net architecture
54 with highest classification accuracy was selected. To
55 implement K-NN, several architectures were implemented,
56 varying the number of neighbours from 1 to 15 (only the
57 odd numbers). The criterion to select the optimal K-NN
58 configuration was the mean classification error. The net

59 architecture with highest classification accuracy was
60 selected.

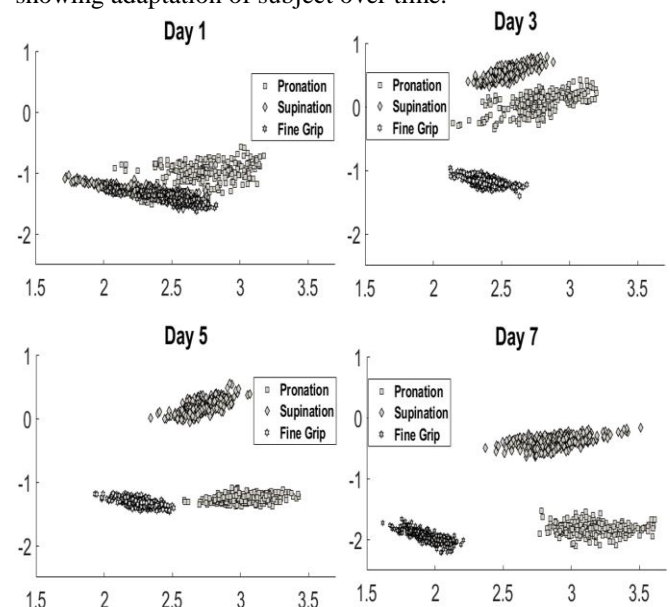
61 *E. Statistical Analysis*

62 For overall performance based on classification
63 accuracies, a three-way repeated analysis of variance
64 (ANOVA) with factors signal types (surface, intramuscular
65 and combined), Days (1-7) and Classifiers (TREE, NB,
66 KNN, SVM, LDA, and ANN) was used for comparison. A
67 two-way ANOVA was used to compare between within a
68 day classification error (WCE) and between days
69 classification error for the best performing classifier that
70 was ANN. P-values less than 0.05 were considered
71 significant.

72 III. RESULTS

73 *A. Feature Space with principal components*

74 Figure 1 showed the geometrical changes in feature space
75 for first two principal components of three classes
76 (Pronation, Supination, and Fine Grip) on day one, three,
77 five and seven in one amputee subject. Three classes were
78 used to exhibit changes in the genetic distance between
79 populations in 2-dimensional embedding over time. PCA
80 transformation ensures horizontal axis PC1 has the most
81 variation, vertical axis PC2 the second most. Factor scores
82 for both components improved over time distinctly for all
83 classes till days seven. On the first, a cloud of data
84 (Pronation, Supination and Fine Grip) could be seen.
85 Genetic distances between populations also increased by
86 day seven as three classes could be seen as individual class
87 showing adaptation of subject over time.



88 **Figure 1.** Surface EMG feature space representing two principal
89 components for three classes Pronation '□', Supination '◇' and Fine Grip
90 '**' in an amputee.
91

92 *B. Within-Day Comparison*

93 Three-way repeated ANOVA test showed significant
94 difference ($P < 0.001$) between EMG types (surface,
95 intramuscular and combined), Days (1-7), classifiers

1 (TREE, LDA, SVM, NB, KNN, ANN) and their
 2 interactions ([Days*classifier], [Days*Type],
 3 [Type*Classifiers] in able-bodied and amputees.

4 **Classifiers:** In amputees, no significant difference (95% of
 5 CI [-1.52 0.23], [-0.75 1.00], [-0.10 1.65], $P = 0.27, 0.99,$
 6 0.11) was found between KNN, SVM and NB. The
 7 remaining classifiers were significantly different from each
 8 other. ANN was best and TREE was the worst on (95% of
 9 CI [20.60 22.35], $P < 0.01$). In able-bodied, no significant
 10 difference (95% of CI [-0.83 0.31], $P = 0.75$) was found
 11 between NB and SVM. The remaining classifiers were
 12 significantly different from each other. ANN performed best
 13 and TREE performed worst (95% of CI [14.90 16.05], $P <$
 14 0.01). **Days:** In amputees, all days were significantly
 15 different ($P < 0.01$) from each other except Day 2 and Day 4
 16 (95% of CI [-0.132 0.64], $P = 0.94$). Day 7 was
 17 significantly better $P < 0.01$ than rest of the days.

18 In able-bodied, day five, six and seven were significantly
 19 different from all other days. Day 2 and Day 3 found no
 20 significance between each other (95% of CI [-0.69 0.58], P
 21 = 0.94). Day 7 was significantly better than Day 1 (95% of
 22 CI [7.22 9.19], $P < 0.01$)

23 Interactions between each factor (type*days),
 24 (type*classifiers) and (days*classifiers) found that type
 25 (combined ANN), day (seven) and classifier (ANN) was
 26 statistically better ($P \leq 0.01$) than any other type, day and
 27 classifier in amputees and able-bodied.

28 *1) Surface EMG*

29 The results of WCE across amputees and able-bodied
 30 with surface EMG are summarized in Figure 2. Each group
 31 represents the performance of all classifiers on each day for
 32 seven consecutive days. On average, for all classifiers,
 33 WCE reduced consistently for seven consecutive days.

37 Naïve Bayes, K-Nearest Neighbour, Support Vector Machine, Linear
 38 Discriminant Analysis, Artificial Neural Network) within a day.
 39 Multiple comparisons revealed all classifiers were
 40 significantly ($P < 0.05$) better than Decision trees in both
 41 amputees and able-bodied (WCE ($40.76 \pm 4.01\%$, $17.83 \pm$
 42 3.22%) on the first day, ($32.03 \pm 5.74 \%$, $20.71 \pm 4.78 \%$)
 43 on the seventh day) respectively.

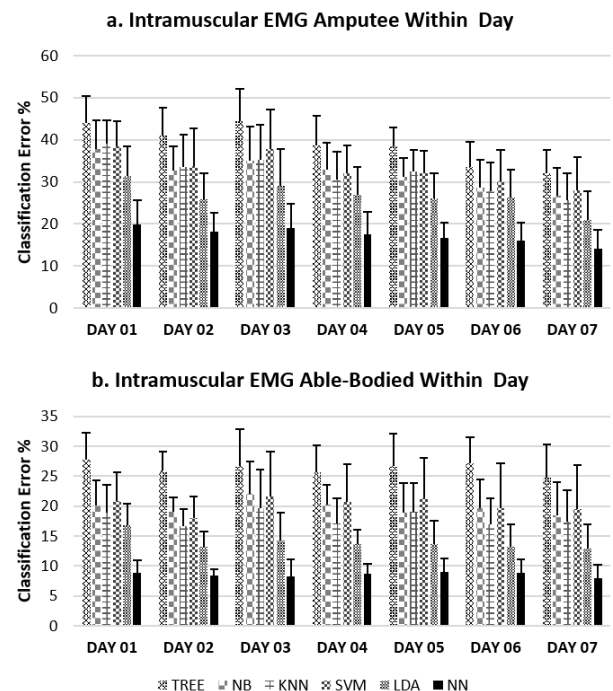
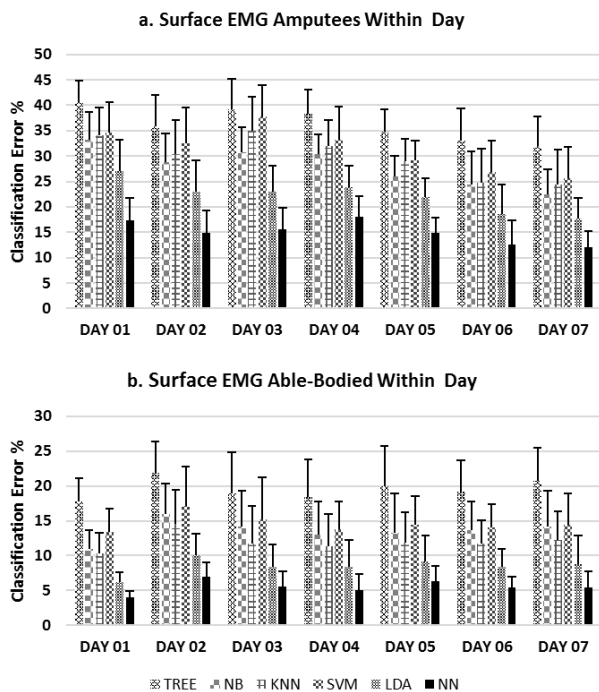
44 In amputees, ANN outperformed ($P < 0.05$) rest of the
 45 classifiers with error decreasing consistently until day seven
 46 to $12.07 \pm 3.17 \%$. No significant difference ($P = 0.32$) was
 47 found between KNN and SVM. A similar effect ($P = 0.08$)
 48 was seen between KNN and NB. Overall LDA and ANN
 49 showed a change of 9.31 % and 5.32 % respectively till the
 50 seventh day.

51 In able-bodied subjects, LDA and ANN outperformed
 52 ($P < 0.05$) rest of the classifiers with error decreasing
 53 consistently until day seven to $8.81 \pm 4.05 \%$ and $5.43 \pm$
 54 2.37% . No significant difference ($P = 0.15$) was found
 55 between KNN and SVM. Classification accuracy improved
 56 over time as Day 6 and 7 were significantly better than day
 57 one to four.

59 *2) Intramuscular EMG*

60 Figure 3 shows the changes in WCE over seven days
 61 using intramuscular EMG for all subjects (able-bodied and
 62 amputees). In amputees, Day 7 was significantly better
 63 ($P < 0.05$) than rest of the days implying learning and
 64 stabilization of the implanted electrodes. ANN
 65 outperformed ($P < 0.05$) all other classifiers with WCE 14.15
 66 $\pm 4.54 \%$ on the seventh day. Overall LDA and ANN
 67 showed a change of 10.45 % and 5.83 % respectively till the
 68 seventh day.

69 In able-bodied, ANN outperformed ($P < 0.05$) rest of the
 70 classifiers with $7.95 \pm 2.27 \%$ error till the seventh day. All
 71 classifiers were significantly different from each other



34 **Figure 2.** Mean classification error averaged across a. Amputees and b.
 35 Able-bodied subjects with surface EMG for all classifiers (Decision Tree,
 36

1 **Figure 3.** Mean classification error averaged across a. Amputees and b.
 2 Able-bodied subjects with intramuscular EMG for all classifiers (Decision
 3 Tree, Naïve Bayes, K-Nearest Neighbour, Support Vector Machine, Linear
 4 Discriminant Analysis, Artificial Neural Network) within a day.
 5 ($P < 0.05$) expect SVM and NB ($P = 0.86$). Day 7 was
 6 significantly better ($P < 0.05$) than Day 1. No significance
 7 difference ($P = 0.97, 0.62, 0.92$) was found between Day 4,
 8 5 and 6.

9 **3) Combined EMG**

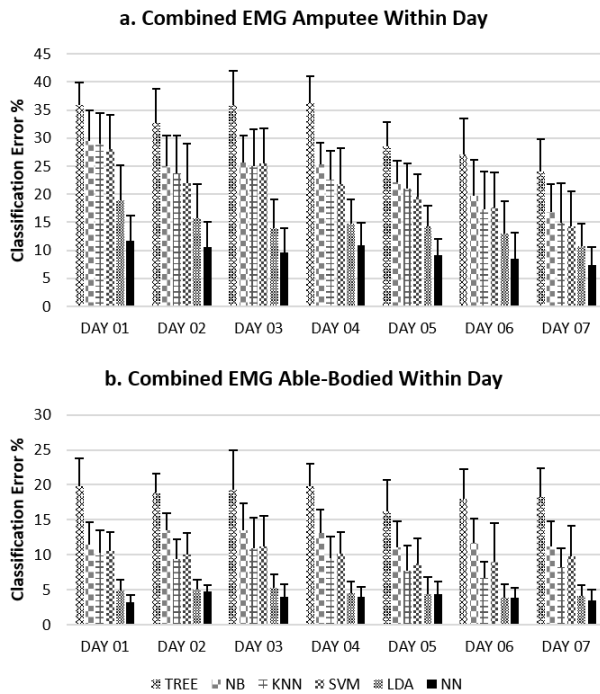
10 In combined EMG, attributes from the surface and
 11 intramuscular EMG were combined to analyse the overall
 12 change in performance of different classifiers (Figure 4). By
 13 combining the attributes, significant improvement in WCE
 14 performance was seen in all classifiers with respect to the
 15 surface and intramuscular.

16 In amputees, ANN outperformed ($P < 0.05$) rest of the
 17 classifiers as error reduced to 7.44 ± 3.17 % until the
 18 seventh day from 11.70 ± 4.41 % on the first day. No
 19 significant difference ($P = 0.98, 0.63, 0.24$) in performance
 20 was observed between KNN ($14.91 \pm 6.99\%$), SVM (14.32
 21 ± 6.26 %) and NB ($16.77 \pm 5.05\%$). Overall KNN, SVM,
 22 and NB showed a change of 14.01 %, 14.32 %, and 12.7 %
 23 respectively until the seventh day. Day 7 was significantly
 24 better ($P < 0.05$) than rest of the days except Day 6 ($P =$
 25 0.20).

26 In able-bodied, ANN in combined EMG outperformed all
 27 the classifiers implemented ($P < 0.05$) with lowest
 28 classification error $3.47 \pm 1.52\%$ until the seventh day.
 29 WCE for day five, six and seven were significantly ($P < 0.05$)
 30 better than day two and three. Table 1 represents the
 31 average WCE for able-bodied and amputees.

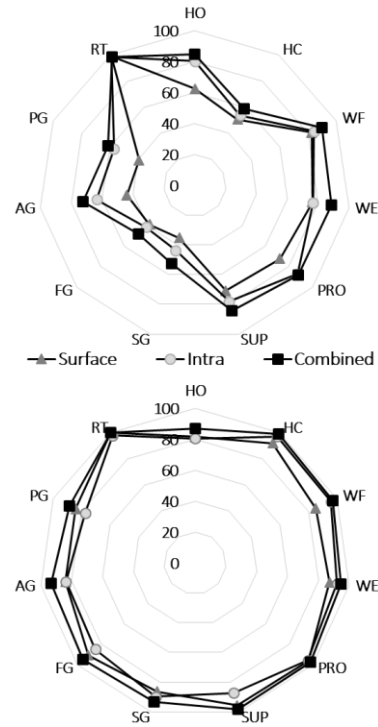
ABLE-BODIED			
	SURFACE	INTRAMUSCULAR	COMBINED
TREE	19.55±4.94	26.36±6.63	18.60±5.56
NB	13.61±4.22	19.75±6.43	12.24±4.26
KNN	11.98±4.29	17.99±6.32	8.96±3.96
SVM	14.63±4.16	20.23±6.69	9.95±3.74
LDA	8.468±3.74	13.96±5.52	4.59±2.59
ANN	5.55±2.21	8.578±2.29	3.95±1.88
AMPUTEES			
	SURFACE	INTRAMUSCULAR	COMBINED
TREE	36.27±5.28	38.86±7.00	31.44±6.31
NB	27.99±5.16	32.14±7.21	23.41±5.74
KNN	29.94±5.54	32.04±7.58	21.95±6.58
SVM	31.39±5.86	33.18±7.75	21.29±6.10
LDA	22.13±4.86	26.64±6.43	14.49±4.46
ANN	15.08±3.59	17.35±4.85	9.70±2.63

39 Figure 5 depicts a representative average performance
 40 (LDA) for a poor amputee subject (top plot) with three
 41 inserted wires and a good amputee subject (bottom plot)
 42 with six inserted wires. It can be seen that certain classes
 43 (from the poor subject) were affected due to absence of
 44 electrodes in the anatomical position related to flexor
 45 muscles.



32
 33 **Figure 4.** Mean classification error averaged across a. Amputees and b.
 34 Able-bodied subjects with combined EMG for all classifiers (Decision
 35 Tree, Naïve Bayes, K-Nearest Neighbour, Support Vector Machine, Linear
 36 Discriminant Analysis, Artificial Neural Network) within a day.

37
 38 **Table 1.** Average classification errors for seven days across all subjects.



46
 47
 48 Figure 5. Class performance for a poor amputee subject (top) with three
 49 inserted wires and a good amputee subject (bottom) with six inserted wires
 50 using linear discriminant analysis. Performance is given for surface (Δ),
 51 intramuscular (\circ) and combined EMG (\square).

52 **B. Between Days Comparison**

53 For overall performance based on BCE (Figure 6 a, b), two-
 54 way repeated measures analysis of variance (ANOVA) with
 55 factors EMG signal types (surface, Intramuscular and
 56 combined) and Classifiers, showed that combined EMG is
 57 significantly ($P < 0.001$) better than the surface and
 58 intramuscular EMG. ANN was still the best classifier and its
 59 performance was ($P < 0.001$) significantly better than the rest

1 of the classifiers and TREE was the worst one. LDA was the
 2 second-best classifier significantly better than KNN, NB,
 3 and TREE.

4 1) Surface EMG

5 To investigate changes in signal characteristics during the
 6 7-day experiment and its effect on pattern recognition based
 7 control algorithms, all possible combinations between days
 8 were analyzed. Figure 6 represents all possible
 9 combinations of BCE for surface and intramuscular EMG
 10 for seven functional motions in amputees and able-bodied.
 11 BCE for both surface and intramuscular EMG improved
 12 along the course of the experiment. For surface EMG, a
 13 classifier trained on the data from the first day and tested on
 14 the data from the second day showed BCE of 23.8% which
 15 reduced to 14.4% when the classifier was trained on the
 16 data from the sixth day and tested on the data from the
 17 seventh day. Results indicated that performance
 18 continuously improved for the system trained on the
 19 previous day and tested on the next day, indicated by the
 20 outlined cells. BCE in surface EMG reduced to $(33.23 \pm$
 21 8.27% in amputees and $10.54 \pm 0.69 \%$ in able-bodied) for
 22 the classifier trained on the sixth day and tested on the
 23 seventh day.

24 2) Intramuscular EMG

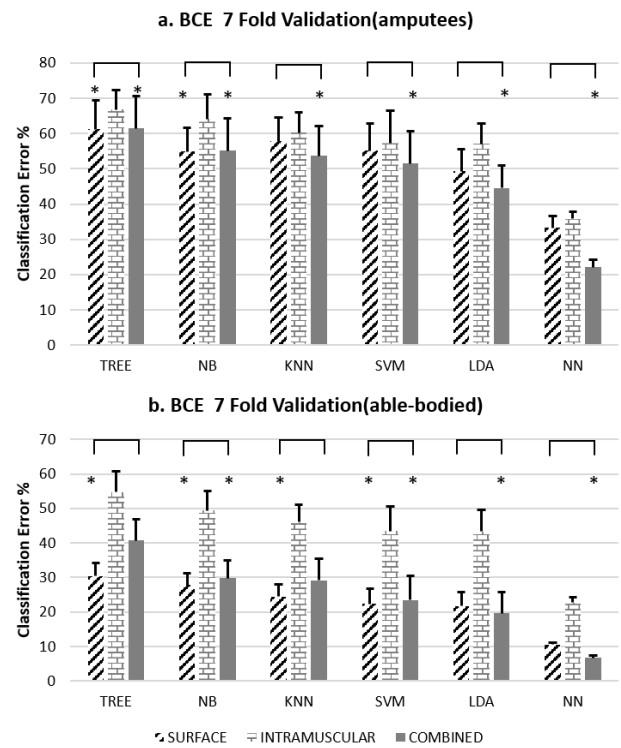
25 On average across all classifiers, the performance of
 26 intramuscular EMG was lower than surface EMG.
 27 Performance of ANN was significantly better ($P < 0.05$) than
 28 rest of the classifiers. LDA was the second-best classifier
 29 significantly better ($P < 0.05$) than TREE and NB in both
 30 amputees and able-bodied.

31 In amputees, no significant difference (95% of CI [-3.09
 32 8.60], $P = 0.70$) was found between TREE and NB.
 33 Similarly, no significance was revealed in the comparison of
 34 KNN and SVM (95% of CI [-2.98 8.71], $P = 0.67$).

35 3) Combined EMG

36 For the combined features from the surface and
 37 intramuscular EMG, improvement in BCE performance was
 38 observed in all classifiers except TREE with respect to the
 39 surface and intramuscular. Performance of ANN ($22.06 \pm$
 40 2.25% in amputees, $6.68 \pm 0.82 \%$ in able-bodied) was
 41 significantly better ($P < 0.05$) than rest of the classifiers.
 42 Combined EMG showed improved BCE on LDA as it was
 43 significantly better ($P < 0.05$) than SVM, KNN, NB, and
 44 TREE in amputees and able-bodied. Combined BCE which
 45 outperformed both surface and intramuscular BCE and
 46 reduced to $(22.05 \pm 2.25 \%$ in amputees and $6.68 \pm 0.82 \%$
 47 in able-bodied) for the classifier trained on the sixth day and
 48 tested on the seventh day.

49 In amputees, KNN was significantly better ($P < 0.05$) than
 50 TREE but not different from NB (95% of CI [-5.40 8.34], P
 51 $= 0.98$) and SVM ((95% of CI [-4.71 9.04], $P = 0.92$).



52
 53
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 57

Figure 6. Changes in BCE (a. Amputees, b. Able-bodied) for all classifiers (Decision Tree, Naïve Bayes, K-Nearest Neighbour, Support Vector Machine, Linear Discriminant Analysis and Artificial Neural Network) and all type (surface, intramuscular and combined EMG). Significant difference in types is represented by '***'.

58 IV. DISCUSSION

59 There is an extensive discussion in the literature about
 60 performance of classifiers, with each having variable
 61 number of amputees (trans-radial [43] or trans-humeral
 62 [44], feature selection methods [45,46,47], features (Time
 63 Domain [46, 48, 49], Frequency Domain [50, 51, 52] and
 64 Time-Frequency Domain [53,27]), feature reduction
 65 techniques [54, 20], classification parameters (no. Of
 66 neurons, no of neighbours) [8,9,12,20,27] and number of
 67 recruited subjects (healthy and amputees)[8,9,12]. But one
 68 fundamental missing factor in these studies is their
 69 performance over time for long-term usability assessment.
 70 In this study, Classification performance of most adopted
 71 classifiers for surface and intramuscular EMG signals were
 72 evaluated for seven days and showed that within day
 73 performances of classifiers may be similar but over time it
 74 may lead to a substantially different outcome. Results have
 75 indicated that subjects with upper limb amputation and able-
 76 bodied subjects can learn to produce discriminative
 77 contractions which improved on successive days of training
 78 and testing. Performance of classifiers varies within-day and
 79 between days. For within day classification error (WCE),
 80 ANN performed significantly ($P < 0.05$) better than all other
 81 tested classifiers and its performance improved over time.
 82 LDA is the most recommended classifier in the literature
 83 and accuracies up to 98% are reported in able-bodied
 84 subjects for surface recording [20, 27, 49]. Accuracies in
 85 LDA method were obtained up to 96.1% per day for surface

1 EMG. TREE was the worst classifier with average
2 classification error of 19.55% (Figure 4), previous studies
3 reported low performance up to 30% classification error
4 [55]. In general, the performance of each classifier was
5 similar to previously reported results [53, 56].

6 Combined EMG was significantly better ($P < 0.05$) than
7 the surface and intramuscular EMG as a combined feature
8 set improved the information level from muscles containing
9 both local and global content. By using implantable
10 electrodes, signals from deep muscles can be extracted
11 which otherwise are not accessible or attenuated for surface
12 EMG. This is in agreement with [34] where it was shown
13 that intramuscular and surface EMG have complementary
14 information.

15 Intramuscular signals provide independent control sites
16 that can enable simultaneous and proportional control of
17 multiple DOF's [56]. The downside of this simultaneous
18 and proportional control is past pointing, isolating 1 DOF
19 targets and ballistic nature of movements during positioning
20 [56,57]. Since both acquisition types (surface and
21 intramuscular) and their control schemes (sequential and
22 simultaneous) have limitations, a control scheme based on
23 both surface (isolate single DOF) and intramuscular
24 (provide simultaneous and proportional control of multiple
25 DOF's) recordings could be devised for providing faster,
26 intuitive and natural control. The main drawback of such
27 implantable system would be the risk of infection and
28 securing stable position for electrodes over a longer period.
29 Wireless implantable systems [34,38] could be one of the
30 solutions to ensure stable and secure electrodes in deep and
31 superficial muscles. In the effort to mitigate the problems
32 related to wireless technology, an gateway using osseo-
33 integration has been proposed for long-term motor control
34 of artificial limbs [58].

35 As the performance of amputees continuously improved
36 with time, we anticipate that it may have improved further if
37 the duration of the experiment was increased. The trend of
38 improvement for WCE in able-bodied subjects for all EMG
39 types (surface, intramuscular and combined EMG) was
40 similar to amputees; though the error rate was higher in
41 amputee subjects (Table1). The consistent improvement in
42 the performance (WCE) also describes the improvement in
43 the learning ability or the adaptation of the subjects. A daily
44 calibration of the system will still be needed for surface or
45 intramuscular EMG recordings because the BCE was higher
46 than WCE.

47 The poor performance between days has been one of the
48 main challenges in the long-term use of pattern recognition
49 based myoelectric prostheses [31]. Variations in BCE were
50 analyzed by maximizing the amount of training data without
51 including any data from a testing day in a leave-one-day-out
52 fashion. It was found that ANN performed best in
53 comparison to the other classifiers (Figure 6) for all EMG
54 types (surface, intramuscular and combined). The
55 comparison of BCE and WCE for the optimum classifier
56 (ANN) revealed that increasing the amount of training data
57 can significantly reduce BCE and might converge to WCE,
58 however, this may require the use of deep networks as

59 provided by deep learning architectures. The decrease in the
60 BCE performance implies that EMG characteristics change
61 and same motions may become uncorrelated over time
62 leading to the need to recalibrate or retrain the classifier.
63 Nevertheless, we expect that training a network classifier on
64 multiple days will enable the possibility to capture the EMG
65 variabilities of each motion and thereby limit the necessity
66 for system recalibration.

67 It should be noted that classifiers were compared for only
68 an offline PR based myoelectric control system and it is not
69 known how well these algorithms would perform in real-
70 time scenarios. Offline performance measures have been
71 challenged in many studies and the consensus is that they do
72 not provide a realistic measure of usability [59,60,61].
73 Future work would focus on the long-term real-time testing
74 including simultaneous and proportional control. Real-time
75 control using invasive EMG is feasible as already
76 demonstrated by others [57,62,63]. One major factor about
77 the performance of intramuscular is related to the use of
78 wire electrodes connected at the skin surface to the
79 amplifier. This is a limitation that may signify to generalize
80 with care our results to all implantable systems. First, this
81 configuration caused wires to be pulled out and second,
82 displacements in the implanted depth may have changed due
83 to the pulling force of connecting cables. Therefore, we
84 cannot guarantee that the implanted electrodes were
85 measuring from the same area throughout the seven days of
86 the experiments. This is a limitation that is worth
87 mentioning because the results of future studies could be
88 different. An efficient way of testing such system would be
89 to use wireless implantable sensors, but to date, they are not
90 commercially available. Considering the specificity of the
91 intramuscular channels, the reduction in the number of
92 channels can result in poor classification performance for
93 certain classes. As shown in Figure 5, certain classes were
94 affected due to absence of electrodes in that anatomical
95 location. However, it should also be useful to note that the
96 removal of the surface EMG channels that correspond to the
97 failed intramuscular EMG channels causes a correlated
98 decrease in performance on the same classes. The
99 overarching point however, is that while the absence of
100 certain channels may be problematic in classifying specific
101 classes, this does not detract from the focus of this
102 experiment: the observation of the temporal effect upon
103 performance.

104 V. CONCLUSION

105 The study presented a comparison of classification
106 algorithms using surface and intramuscular EMG signals for
107 myoelectric control of upper limb prosthesis. Within-day
108 performances in literature showed the near-perfect
109 performance of these algorithms 95% to 98%. Paper
110 investigated the behavior of the machine learning algorithms
111 for longer periods with different training schemes of data.
112 Significant differences were found attributing differences in
113 each adopted classifier. Results showed that a classifier
114 having deep architecture is robust over time.

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