Effect of the sEMG electrode (re)placement and feature set size on the hand movement recognition

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ABSTRACT

Recording electrode array may not be exactly repositioned across repeated electromyography measurements resulting in a displacement error when aiming at hand movement classification. The influence of electrode displacement on classification accuracy and its relation to the feature set size is of interest for design of hand movement recognition system.

In order to examine if the classifier re-training could reach satisfactory results when electrode array is translated along or rotated around subject’s forearm for varying number of features, we recorded surface electromyography signals in 10 healthy volunteers for three types of grasp and six wrist movements. For feature extraction we applied principal component analysis and the feature set size varied from one to 8 principal components.

Our results showed that there was no significant difference in classification accuracy when the array electrode was repositioned indicating successful classification re-training and optimal feature set selection. The results also indicate expectedly that the number of principal components plays a key role for acceptable classification accuracy ~90%. Interestingly, we showed that interaction between electrode array position and the feature set size is not statistically significant.

This study emphasizes the importance of testing the interaction of factors that influence classification accuracy altogether with their impact independently in order to attain guiding principles for design of hand movement recognition system.

KEYWORDS

forearm muscles, hand movement, pattern recognition, principal component analysis (PCA), surface electromyogram (sEMG)
1 INTRODUCTION*

The performance of surface electromyography sEMG-based hand movement recognition systems is predominately affected and limited by: (1) acquisition setup, (2) protocol design, (3) signal pre-processing, (4) feature extraction, and (5) classifier design, and to date researchers have offered numerous advances in order to enhance system functionality [1-10].

In [5], we showed that significant enhancement can be obtained by increasing the number of principal components (PCs) when Principal Component Analysis (PCA) for feature extraction is applied on benchmark sEMG data obtained from the publicly available NinaPro database with data recorded in intact subjects [11-12]. Our results [5] suggested that instead of using two PCs for dimension reduction as applied in [11] for obtaining considerably satisfactory error rates, only one PC more (three PCs in total) can significantly increase classification accuracy in three sets of movements (>10%). This compelling finding was further tested on sEMG data that we recorded in three intact subjects when electrode array was relocated in proximal direction [13] and showed that by using three PCs we were able to obtain relatively small effect (<5%) of electrode dislocation on classification accuracy. To the best of our knowledge, the optimal number of PCs and its exact relation to the sEMG electrode array dislocation to operation of hand movement recognition systems is still unknown. Hence, exploring this relation could possibly improve the knowledge on the selection of feature set size, its relationship to common problem of electrode dislocation, and on possibility to compensate for electrode dislocation.

The main idea of this paper is to test whether reasonable classification accuracy (~90%) can be reached by re-training the classifier when electrode array is dislocated in relation to the feature set size. In order to test this idea, we measured sEMG in 10 able-bodied subjects. Although NinaPro database [11-12] provides perfectly usable benchmark data, it does not incorporate the measurements with electrode dislocation, and therefore we could not use existing database. We recorded sEMG signals for two sets of hand movements three grasps and 6 wrist movements previously presented in [5, 11, 13] for three positions of sEMG electrode array with 8 channels arranged circumferentially. Three positions of electrode array were selected according to the previously reported findings of common electrode array displacement in neuroprosthesis [14]. Then, the classification accuracy was tested for all three positions, for three sets of hand movements (three grasps, 6 wrist movements, and for joined grasps and wrist movements – 9 hand movements in total), and for 1-8 PCs.

The results presented here can advance areas related to the surface electromyography (sEMG) acquisition setup that includes electrode array (re)positioning and offer optimal number of features, all being required for successful sEMG-based hand movement classification that can be used for various human machine interfaces (HMI). With this aim, we had no intention to limit the recommendations to neuroprosthesis control solely. However, we present related work mostly in the area of sEMG-based hand movement classification for neuroprosthesis control as one of the most important and oldest (> 60 years) sEMG applications for hand movement recognition [15].

It has been reported that the main limitation of the state-of-the-art hand movement recognition systems for neuroprosthesis is the limited number of discernible movements that leads to reduced operational intuitiveness in spite of recent captive improvements [4, 6-7, 10]. Here, we aimed at addressing two challenges and their relation in a controlled laboratory setting: (1) sEMG electrode repositioning challenge and (2) challenge for selection of adequate number of PCs.

*Non-standard abbreviations* include types of hand postures: relaxation (R), spherical power grasp (PS), three finger sphere grasp (3F), two finger prismatic grasp (PP), wrist flexion (FL), wrist extension (EX), radial deviation (RD), ulnar deviation (UD), forearm rotation i.e., pronation (PR), and supination (SU).
1.1 sEMG acquisition set-up: Electrode repositioning challenge

Day-to-day positioning of the sEMG array electrode can produce undesirable electrode displacements. The results presented in the literature confirmed that accuracy changes due to the electrode displacement and is additionally affected by: inter-electrode spacing, the number of electrodes used, and the number of classified motions [16]. Matching sEMG records in consecutive user utilizations requires replacing the electrode array over identical recording locations. Such protocol is demanding and involves specialized knowledge of muscle anatomy and the previous positions of electrodes. Therefore, accommodation of training and/or classification strategy to sEMG electrodes repositioning has been proposed [17]. There is a need for a wide variety of examples (that result from electrode displacement) to be presented to a classifier (during a training phase) in order to apply sEMG-based pattern recognition with satisfactory performance [16]. Offered solutions include enlargement of the training set as proposed in [16-17], daily calibration aiming at accommodation to displacement changes as introduced in [8], and transfer learning approach has also been proposed to compensate for electrode dislocation with pre-trained deep learning-based classifier [18]. In order to enhance more knowledge of electrode dislocation on classifier performance, we tested the effect of feature set size on sEMG array electrode that was translated along and rotated around subject’s forearm when classifier is re-trained as we did not aim at pre-training of classifier as proposed recently in [18]. The displacements were chosen in accordance with the previously reported common misalignment in real-life setting [14].

1.2 Feature extraction: Adequate number of principal components challenge

PCA is an orthogonal data transformation method commonly used for feature extraction from multi-channel sEMG signals [4-5, 9, 11, 13, 19] in order to reduce the dimensionality of multidimensional data and to reveal data patterns. Another PCA application is directed toward multi-channel sEMG-based assessment of muscle sub-modules termed neuromuscular compartments [20], but this application is out of our scope. In this study we applied PCA for feature extraction as we assumed that the temporal-spatial information contained within muscle crosstalk on the forearm might implicitly add class discriminatory information as suggested in [4-5, 11]. In [5] we found that the proportion of variance present in the first three PCs compared to first two PCs extracted from the sEMG data from the NinaPro database provides a statistically significant increase in classification accuracy which is promising. However, we did not evaluate the optimal number of PCs and here we present in detail evaluation of an optimal number of PCs in relation to sEMG array electrode repositioning. In order to minimize other possible effects on classification accuracy, we measured sEMG signals in 10 intact subjects from three electrode array locations in a controlled laboratory setting with similar measurement paradigm as in [2].

1.3 Study objectives

With the aim to evaluate the effects of electrode array dislocation on PCA-based classification feature selection and classification accuracy, we measured 8-channel sEMG from 10 volunteers for 9 hand movements. Recorded data provided a deeper look at the exact influence of electrode array repositioning (translational and rotational) on the robustness of feature extraction for three hand movement sets.
2 METHODS AND MATERIALS

2.1 Intact subjects

We measured sEMG signals from 10 healthy volunteers with no known neuro-muscular or skeletal disorders. All volunteers signed an Informed Consent and the study was performed in compliance with the Code of Ethics of the University of Belgrade, which provides guidelines for studies involving human beings and is in accordance with the Declaration of Helsinki. The demographic data with anthropometric measurements (forearm length and forearm circumference) for all subjects are presented in Table 1.

Table 1, Demographic data with anthropometric measurements for 10 healthy volunteers (ID1-ID10). The abbreviations are M - Male, F - Female, L - left, and R - right.

| Subject ID | Height [cm] | Weight [kg] | Sex [M/F] | Age [years] | Forearm length [cm] | Forearm circumference [cm] | Dominant arm [L/R] |
|------------|-------------|-------------|-----------|-------------|---------------------|---------------------------|-------------------|
| ID1        | 168         | 58          | F         | 23          | 24                  | 20.0                      | L                 |
| ID2        | 175         | 65          | F         | 28          | 25                  | 24.0                      | R                 |
| ID3        | 193         | 85          | M         | 27          | 29                  | 26.0                      | R                 |
| ID4        | 180         | 68          | M         | 26          | 28                  | 27.0                      | R                 |
| ID5        | 168         | 53          | F         | 25          | 24                  | 23.0                      | R                 |
| ID6        | 186         | 83          | M         | 23          | 27                  | 26.5                      | R                 |
| ID7        | 164         | 50          | F         | 22          | 23                  | 22.0                      | R                 |
| ID8        | 178         | 67          | M         | 22          | 27                  | 24.5                      | R                 |
| ID9        | 175         | 66          | M         | 27          | 28                  | 24.0                      | L                 |
| ID10       | 165         | 51          | F         | 25          | 24                  | 19.0                      | R                 |
| All        | 175.2±9.4   | 64.6±12.2   | 5M+5F     | 24.8±2.2    | 25.9±2.1            | 23.6±2.7                 | 8R+2L             |

2.2 sEMG measurement set-up

An array of 8 circular Ag/AgCl electrode pairs arranged uniformly and circumferentially around the forearm of the dominant arm was used for the measurement of bipolar sEMG signals following SENIAM recommendations [21].

sEMG signals were recorded from 8 channels having in mind our previous results [5] in PCA application for feature extraction from sEMG signals recorded from 10 channels where 8 electrode pairs were placed circumferentially as described in [11]. It is assumed that 8 channels would be sufficient for adequate feature extraction and classification accuracy, especially as our electrode array was placed more distally than in [11] in order to cover the muscle bulge – more similar to the [4]. Our approach presents a compromise between array location presented in [11] and [4] having in mind the SENIAM recommendation to place sEMG electrodes over “the most prominent bulge of the muscle belly” [21] and the fact that muscle cross-talk would occur.

The electrode array was arranged from disposable, pre-gelled, and self-adhesive sEMG Skintact F-TC1 (Leonhard Lang GmbH, Innsbruck, Austria) electrodes (2 x 8). The position of the electrode array was chosen according to the proximate bulks of extensor carpi radialis and flexor carpi ulnaris muscles which corresponds to one-third of the distance between the elbow and wrist as used in [4]. Prior to electrode placement, the skin was cleaned with the Nuprep abrasive gel (Bio-Medical Instruments, Inc., Warren, MI, USA). A Skintact F-TC1 reference electrode was placed over the articulatio cubiti bone.
The signals were digitized with the USB AD converter NI6212 (National Instruments, Inc., Austin, USA) with 16 bits resolution and sampling rate of 1000 samples per second. The signals were amplified using Biovision amplifiers (Biovision, Inc., Wehrheim, Germany) with gain of 1000. A recent study [22] compared acquisition setups and concluded that no significant difference was observed between low- and high-priced systems. We used the Biovision sEMG system in the mid-price range. For signal acquisition, we adopted a custom program previously created in the LabVIEW (National Instruments, Inc., Austin, USA) environment [23]. Subjects were prompted to follow the software feedback instructions with LED and audio cues. Each movement repetition lasted for 5 s with LED indicator set to the “ON” state and it was followed by 3 s long rest position with LED set to the “OFF” state.

2.3 Measurement protocol

Prior to each measurement session, an instruction video was presented on a computer screen. The instruction video consisted of a recorded scene showing the desired posture for the subject, the reference arm position, and the movement being performed.

The subjects were asked to perform the following three grasps and 6 wrist movements from the reference resting position – relaxation, R: (1) spherical power grasp, PS, (2) three finger sphere grasp, 3F, (3) two finger prismatic grasp, PP, (4) wrist flexion, FL, (5) wrist extension, EX, (6) radial deviation, RD, (7) ulnar deviation, UD, and then forearm rotation i.e. (8) pronation, PR, and (9) supination, SU, [11, 24]. For the PP, we provided a plastic cylinder (height of 9 cm with a diameter of 3 cm). The PS and 3F movements were performed with a ball (weight of 95 g with diameter of 6 cm). An image of a subject's position during relaxation (R) and grasping movements is presented in Fig. 1. All movements were performed in a sitting position with the forearm placed on a table (Fig. 1).

We recorded 10 trials for each of the 9 tasks for the following three positions of the electrode array presented in Fig. 2:

Position #1: "standard" position where the electrode array was placed on the forearm longitudinally in the proximal/distal direction; for details see sEMG measurement setup,

Position #2: 1 cm translation (3.9±0.3% of the forearm length in all subjects) of the electrode array from Position #1 in the proximal direction, and

Position #3: 2 cm rotation (8.6±1.0% of the forearm circumference in all subjects) of the electrode array in the medial direction relative to Position #1.

![Figure 1, Photo impression of subject's posture: 1) relaxation (R); and for the three grasp modes: 2) two finger prismatic grasp (PP), 3) spherical power grasp (PS), and 4) three finger sphere grasp (3F).](image)

Based on the following findings from [14]: (1) 2 cm shift represents one of the worst possible conditions when using a socket sEMG electrode array and (2) 1 cm shift or less is likely caused by the method of fitting the sEMG electrode array, we chose shifts of 1 cm in the proximal and of 2 cm in the medial direction.
The distance between two electrodes in an array is constrained by the design of the electrode and by forearm circumference. We kept the electrodes equally spaced in the medial/lateral direction and at a fixed distance of 2 cm in the proximal/distal direction. For all Positions #1-3, sEMG electrodes were taken off and re-placed. All signals for each subject were recorded in a single recording session. In order to avoid fatigue, frequent 5-20 min breaks were provided. The total recording duration for obtaining Information Consent, sEMG array electrode positioning, movement execution, and repositioning was approximately 2 hours.

2.4 sEMG data processing and feature extraction

All processing steps were performed in Matlab ver. 2013b (Mathworks Inc., Natick, USA). The sEMG signals were filtered with a notch filter (50 Hz) in order to filter out power line interference, followed by the first-order modified differential infinite impulse response (IIR) filter in order to remove the baseline offset. The sEMG signals were then rectified and filtered with 3rd order low-pass Butterworth filter with cut-off frequency of 5 Hz in order to generate sEMG envelopes. Subsequently, we applied segmentation and averaging as proposed in [5, 11]. Each repetition of the movement (termed posture) and the following relaxation (termed pause) was divided into three equal segments, in order to retain the most representative samples from the central segment. Samples from the central segment were averaged in order to obtain a single sample per movement, resulting in 20 samples (10 per posture and 10 per pause) for each subject/movement/electrode array position combination (20 x 10 x 9 x 3 = 5400 samples i.e., features in total). The data for individual subjects were normalized in order to obtain a zero mean and unit standard deviation. Next, PCA was applied to the normalized samples.

2.5 Classification and statistical analysis

Statistical analysis and classification were performed in Matlab. The simple Quadratic Discriminant Analysis (QDA) approach was used for classification as suggested in [5, 8]. The feature dataset was split into a training (80%) and a test set (20%).

The accuracy of the classifier was compared for 8 different feature sets (1-8 PCs). Simultaneously, we examined the classification accuracy for three movement sets: (1) three grasps, (2) 6 wrist movements, and (3) all movements (i.e., 9 hand movements = 3 grasps + 6 wrist movements). Muscle relaxation was used as an additional input for each movement set. For all combinations of features (1-8 PCs) and three movement sets, we performed classification for three electrode Positions #1-3. We re-trained the classifier for Positions #1-3 in order to select the optimal feature set size for different electrode array positions. Overall, 24 (8 x 3) classifiers were constructed with separate datasets i.e., the QDA classifier...
was retrained 24 times in total. The outcome measure of the classification performance was classification accuracy i.e., the percentage of correctly classified repetitions of the movements for each of the 10 subjects, three sets of movement, 8 sets of features, and three electrode array positions.

All statistical tests were performed individually for each set of movements. Two-way analysis of variance (ANOVA) and Tukey’s honestly significant difference criterion for multiple comparison tests were performed with a variable number of features (1-8 PCs) and for all electrode array positions (Positions #1-3) as factors. In order to determine the optimal number of features, statistically significant differences in mean classification accuracy among 8 sets of features for each electrode array position were tested using one-way ANOVA and Tukey’s honestly significant difference criterion for post-hoc pairwise comparisons. The number of features resulting in a classification accuracy that does not differ statistically from classification accuracies resulting from using larger sets of features was considered to be the optimal number of features i.e., PCs. An equivalent analysis was performed to explore the differences between the electrode array positions for each number of PCs used as classification features. The threshold for the statistical significance was set at p < 0.05.

3 RESULTS

3.1 Optimal number of PCs and results of statistical tests for three movement sets

For the set of three grasps, the optimal number of features (PCs) is three in case of Position #1 and average classification accuracy for all subjects is 83.8±14.5%, while it increases to four for both Position #2 and Position #3, with average accuracies of 83.8±15.7% and 80.0±15.8%, respectively. Two-way ANOVA revealed that feature set size (p < 0.01) and the sEMG electrode array location (p = 0.03) are statistically significant factors while their interaction was non significant (p = 0.97).

An optimal number of features for the set of 6 wrist movements is 5 for Position #1, Position #2, and Position #3 with average classification accuracies of 90.0±9.6%, 91.4±4.5% and 87.1±11.1%, respectively. For this set of 6 wrist movements, two-way ANOVA revealed that feature set size is statistically significant (p < 0.01), while the sEMG electrode array position was not statistically significant (p = 0.75) so as the interaction of these two factors (p = 0.85).

For all 9 hand movements (6 wrist + three grasping movements) the optimal number of PCs in this case is 5 for Position #1 with classification accuracy of 85.5±11.4% and 6 for Position #2 and Position #3, with average classification accuracies of 89.5±8.3%, and 90.0±11.5%, respectively. For this set of movements, two-way ANOVA showed that only feature set size was statistically significant (p < 0.01) while electrode array location (p = 0.24) and interaction of these two factors (p > 0.99) were non-significant.

The one-way ANOVA for all feature sets (1-8 PCs) showed no statistically significant difference in mean classification accuracy for three electrode positions #1-3 for all movement sets (9 hand, 6 wrists, and three grasping movements).

3.2 Visualization of averaged classification accuracy and confusion matrices

Averaged classification accuracies with standard deviations relative to the number of PCs for all movement sets for all three array electrode positions are presented in Fig. 3. The results of the hand movement classification using optimal number of PCs are represented by confusion matrices, for three sets of movements and three electrode array positions in Fig. 4.
Figure 3, Averaged classification accuracies with standard deviations relative to the number of features i.e., number of PCs for hand, wrist, and grasping movements. Note that “hand movements” refers to all movements (both wrist and grasping). Positions #1-3 signify array electrode locations (see text for more details).
Figure 4, Confusion matrices for hand, wrist, and grasping movements. Note that “hand movements” refers to all movements both wrist and grasping. Abbreviations are PS - spherical power grasp, 3F - three finger sphere grasp, PP - two finger prismatic grasp, PR - pronation, SU - supination, RD - radial deviation, UD - ulnar deviation, FL - wrist flexion, EX - wrist extension, and R - resting position. Positions #1-3 signify the array electrode locations. The shade bar for classification accuracy normalized from 0 to 1 is displayed in the lower right-hand panel.

4 DISCUSSION

4.1 Classification accuracies in relation to the electrode position and the results applicability

Our results showed that the rotation of 2 cm (Position #3) produced somewhat higher dispersion of classification accuracies in relation to the initial Position #1 and compared to the 1 cm translation (Position #2). Discrepancies of average accuracy between Positions #1 and #3 were in a relatively small
range from -3.8% to 4.5% for three hand movement sets, while absolute differences between Positions #1 and #2 were always positive leading to slightly higher classification accuracies for Position #2 (in a range 0-4%). This somewhat better effect of electrode translation (Position #2) than electrode rotation (Position #3) on classification accuracy might be a consequence of incorporating other forearm muscles more proximal such as brachioradialis in relation to our initial Position #1 targeted to the bulks of extensor carpi radialis and flexor carpi ulnaris muscles. The number of muscles covered by electrode array remains the same when rotation is introduced and might change after translation covering non-identical anatomical landmarks in respect to the underlying musculature (see Fig. 2). Specifically, after rotation, the sEMG array covers the same anatomical circular landmarks with similar crosstalk compared to the translation which has been confirmed in the study that thoroughly assessed sEMG crosstalk in the forearm muscles [25]. Hence, we expected that rotation of the sEMG array electrode would introduce smaller changes in classification accuracy in comparison with translation that did not happen, although for majority of cases those changes were not significant. Two-way ANOVA revealed significant effect of electrode array only in a set of three grasping movements (p = 0.03). For this set, averaged classification accuracy was significantly higher for Position #1 (85.8±17.6%) than for Position #3 (79.5±20.8%). We believe that this result for classification of three grasp movements should be taken with precaution as the relative difference was <8%, the difference of classification accuracies between these two positions for optimal number of PCs showed even smaller relative difference <5%, p value was relatively close the boundary of 0.05 (p = 0.03), and one-way ANOVA for individual sets of features being more important in this study showed no statistically significant differences. These relatively higher discrepancies for the set of three grasping movements are noticeable in bottom panel in Fig. 3 as larger deviation between curves corresponding to the electrode Positions #1 and #3.

Our method might be applicable to a system involving daily calibration and aiming at accommodation to changes in electrode dislocation as we did not use the data from various electrode array positions to form the training data set. In [8] main challenges with possible solutions for sEMG-based pattern recognition application in clinics were presented and it was suggested that daily calibration can compensate for sEMG electrode impedance, muscle hyper- or hypotrophy, and learning effects. Other successful approaches incorporating sEMG data recorded for electrode shifts in training set for the classifier have been proposed, too. For instance in [17], it is reported that when perpendicular and parallel shifts (1 cm and 2 cm) are accounted in the classification feature set during the training phase, the classification error decreases, in some cases reaching substantial error decline of up to ~18 times (from 35.3% to 1.9%). Another interesting approach has been applied in [26] where the effect of the rotation of a circumferentially placed electrode array in clockwise and counterclockwise directions by 1 cm on classification accuracy was investigated. The authors found that a system trained with features detected from all displacement electrode locations performed better (approx. error 10-20%) than one in which only a single electrode location was used (approx. error 30-40%). In this study, we tested the effect of dislocation on classification accuracy and feature extraction modality, presenting suggested possible scenario from [8].

### 4.2 Classification accuracies in relation to the feature set size and selected movements

Fig. 3 provides relationship between classification accuracy, feature set size, and the number of movements revealing dependency of the feature set size to the classification accuracy and confirming our result that the optimal feature set size can be chosen independently of sEMG electrode array position when re-training is implemented and it varies from three to 6. Here, optimal number of features was proportional to the movement set size which is in accordance with the previously published results in [4].
It can be assumed that hand movement set size together with hand movement types within each set influenced the optimal number of PCs.

Different sets of hand movements would naturally result in different misclassifications. In this study, the chosen sets of hand movements led to confusion probably as a result of similar muscle activation for movement execution. Confusion matrices presented in Fig. 4 visualize information with regard to the specific hand movements for the three electrode array positions, three movement sets, and for an optimal number of PCs. The majority of the confusions in Fig. 4 for hand movements is related to EX and UD for Position #1, 3F and PR for Position #2, and PS and UD for Position #3. Fig. 4 (bottom panel) presents a relatively large number of confusions for the three grasping movements, though the classification accuracies are relatively acceptable >80% (see bottom panel in Fig. 3). The greatest amount of confusions for all array electrode positions was found for EX and SU for wrist movements. PR was detected in 100% of cases for Positions #1-3. Overall, our results indicate that both simple wrist movements and functional grasping movements can lead to both higher and lower confusions. This might be a consequence of muscle anatomy and of the type of chosen hand movement complexity as for example 3F (three finger sphere grasp) incorporates FL (wrist flexion). Previously, SU and PR were proven to be more sensitive to electrode shifts [27]. In our study, PR had relatively higher classification accuracies compared to other hand movements and SU was never confused with FL/EX as might be expected. This disagreement is probably the consequence of the classification procedure since our classifier was re-trained in comparison to the classifier in [27]. In addition, PS was classified with higher accuracies and that can be explained by the fact that the sEMG during PS had a different sEMG activation compared to the sEMG for other movements. Recently sEMG-based, kinematic, and general taxonomies for human hand movements are presented in [28] revealing, among other results, similarities of sphere grasps, which is confirmed by confusions presented between PS and 3F. Nevertheless, comprehensive comparison with [28] is not possible due to the differences in sEMG measurement setup.

4.3 Limitations of the presented study

Although, we proved that classifier re-training can reach acceptable classification accuracy ~90% with application of optimal feature set size and that interaction between electrode array location and the feature set size is not statistically significant, our approach has limitations. In a nutshell, the limitations of the presented study are:

(1) The presented classifier and its robustness in the sense of electrode displacement and optimal set size for sEMG-based pattern recognition have not been checked nor designed for real-time applications. We aimed at exact impact and relation between feature set size and electrode dislocation on classification accuracy that required other measurement conditions to be kept constant in the laboratory setting as their presence could affect the classifier performance similar to approach in [2]. Therefore, we did not check real-time performance nor hand posture or other effects and these have been tested elsewhere [1-2, 10, 29-31] being out of our scope.

(2) The sEMG data from amputee subjects were not provided for this study as we focused our research on sEMG-based hand recognition in general, not solely for neuroprosthesis with approach similar to [2]. Having in mind previous findings that showed no significant differences between healthy subjects and amputees for decoding movements when using sEMG electrodes [1, 32-33], we believe that the presented results might be used in the field of neuroprosthetics. Nevertheless, precautions should be taken into account in high-level or partial wrist amputees with insufficient remaining musculature together with other clinical parameters such as phantom limb sensation intensity as it was suggested in [3, 10, 34].
(3) Classification optimization was not introduced as it was not the focus of this paper and comparisons presented by other researchers in this area can be found elsewhere [1, 18, 35].

(4) We did not consider sensor fusion. However, it is noteworthy that accelerometry data and sEMG were found to be complementary modalities and significant gains were achieved as reported in [31, 36], its application was out of scope of our study as we prioritized solely sEMG-based system.

(5) We did not check various electrode configurations as we used bipolar which has been previously recommended in [27, 37].

5 CONCLUSION
The main finding of this study is that an optimal feature set size and classifier re-training can lead to satisfactory classification accuracy. Therefore, by selecting an optimal number of PCs and with daily re-calibration, the sEMG electrode array can be repositioned (rotated and translated) with no statistically significant effect on hand gesture recognition.

AUTHOR CONTRIBUTIONS
N. Miljković: Conceptualization, Methodology, Data Curation, Writing- Original draft preparation, M. S. Isaković.: Conceptualization, Data Curation, Methodology, Investigation, Writing- Review & Editing.

DECLARATIONS OF INTEREST
None.

ACKNOWLEDGEMENTS
Funding: The work on this project was partly financed by the Ministry of education, science, and technological development, Republic of Serbia.

Special appreciation the authors owe to Professor Mirjana B. Popović from the University of Belgrade for her kind support, precious guidance, and advice regarding this research which significantly improved the manuscript. Also, the authors would like to thank Dr Matija Štrbac from Tecnalia Serbia Ltd. for providing advice throughout the study. The authors thank all volunteers for their participation.

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