Classification of Finger Movements for the Dexterous Hand Prosthesis Control With Surface Electromyography

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***Abstract*—A method for the classification of finger movements for dexterous control of prosthetic hands is proposed. Previous research was mainly devoted to identify hand movements as these actions generate strong electromyography (EMG) signals recorded from the forearm. In contrast, in this paper, we assess the use of multichannel surface electromyography (sEMG) to classify individual and combined finger movements for dexterous prosthetic control. sEMG channels were recorded from ten intact-limbed and six below-elbow amputee persons. Offline processing was used to evaluate the classification performance. The results show that high classification accuracies can be achieved with a processing chain consisting of time domain-autoregression feature extraction, orthogonal fuzzy neighborhood discriminant analysis for feature reduction, and linear discriminant analysis for classification. We show that finger and thumb movements can be decoded accurately with high accuracy with latencies as short as 200 ms. Thumb abduction was decoded successfully with high accuracy for six amputee persons for the first time. We also found that subsets of six EMG channels provide accuracy values similar to those computed with the full set of EMG channels (98% accuracy over ten intact-limbed subjects for the classification of 15 classes of different finger movements and 90% accuracy over six amputee persons for the classification of 12 classes of individual finger movements). These accuracy values are higher than previous studies, whereas we typically employed half the number of EMG channels per identified movement.**

***Index Terms*—Electromyography, linear discriminant analysis (LDA), pattern recognition, prosthetic hand.**

I. Introduction

THERE are many disabled people who have lost limbs in wars, car accidents, and industrial accidents. In the U.K. alone, with a population of 62 million, more than 300 people suffer from different levels of upper limb amputation every single year, ranging from elbow disarticulation to upper digits amputation, with trauma being the main cause for the amputation [1]. Most of these people are yet to be provided with prosthetic devices able to meet the challenges they face in their daily life. Most prosthetic devices available today are limited to a small fixed set of gestures, and have yet to fully mimic the human hand. Advanced commercial devices such as the *Michelangelo* hand from Otto Bock [2], the *i-Limb Ultra* hand from Touch Bionics [3], and the *Bebionic 3* hand from RSL Steeper [4] typically perform hand and grip positions [5] as well as being only able to control one finger independently [3], [4]. There is also on-going research toward the development of more advanced prosthetic hands, such as the modular prosthetic limb system sponsored by the Defense Advanced Research Projects Agency (DARPA) [6], the Smart Hand [7], and the UNB hand [8].

Dexterous control is important for the performance of intricate tasks in modern life, such as using a computer mouse, typing on a computer keyboard, operating a mobile phone, and operation of other electronic and domestic devices. Thumb dexterity is also needed for the performance of different kinds of grip (e.g., fine pinch and tripod grips). A pilot study asked ten participants with an upper limb deficiency about which movements or features might be needed in a future prosthetic hand [9]. All respondents wanted to point with the extended index finger, 90% of them asked for control of individual fingers, and 70% said that it would be useful to have wrist flexion and extension movements. Such movements could improve the physical and psychological aspects of the amputee persons' quality of life.

Multifinger control is more challenging than hand movement control. Firstly, sEMG signals for finger movements are generally smaller in amplitude than those of hand movement. Secondly, the muscles controlling the finger movements (flat muscles with finger-specific compartments) lie in the intermediate and deep layers of the forearm [10]. Signals recorded at the skin surface undergo nonlinear attenuation and filtering by forearm tissues. Therefore, several electrodes are generally used to provide enough information to disambiguate the intended movement.

Previous research tried to classify finger movements for dexterous hand prosthesis control. Jiang *et al*. [11] classified six finger movements using four EMG channels with wavelet transform (WT) features. Naik *et al*. [12] identified four combinations of finger movements with fractal dimension features and independent component analysis. Tenore *et al*. [13] used 32

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EMG channels to decode 12 finger movements for five healthy subjects. For one amputee person, 19 channels were used instead. Only one piece of information (the window length time-domain (TD) feature) was extracted from each channel, with a multilayer perceptron (MLP) used for classification. Kanitz *et al.* [14] have recently classified 12 finger movements using TD features derived from 16 unipolar electrodes, a genetic algorithm optimizer, and a support vector machine classifier.

In the previous research, either the number of EMG channels is greater than or equal to the number of finger movements recognized, or only a small number of movements are considered. Having a large number of electrodes requires a large surface area on the forearm, which may be not suitable for amputee persons. Thus, it is desirable to reduce the number of channels in order to increase the usability of sEMG systems. In addition, this will reduce the cost and complexity of the required hardware, as well as reducing the processing time needed by the myoelectric controller to reach a decision [15]. At the same time, the capability to discriminate a large number of finger movements must be preserved. An assumption guiding the study presented here is that this may be achievable through using more advanced signal processing methods, extracting more information from each channel, and by carefully selecting the position of the electrodes. Furthermore, it is worth noting that, up to now, very few amputee persons have been recruited in these studies. Only [13], [14] have recruited amputee persons, and often in small numbers.

Therefore, this study tackles the following research questions: 1) How accurate is the classification of finger movements based on sEMG signals with state-of-the-art classification schemes? 2) What is the minimum number of channels needed to achieve that level of classification accuracy? 3) Is the classification performance achieved from intact-limbed subjects similar to that of amputee persons? The first question is addressed by assessing the performance of four state-of-the-art signal processing and pattern recognition schemes and it will lead us to the identification of a classification algorithm for controlling dexterous prosthesis. To answer the second question, we will utilize the best of the four processing schemes to address the selection of the minimum number of EMG channels needed to achieve high classification accuracy. This will show whether there is redundancy in the signals provided by a relatively large number of EMG channels. The answer to the third question will help to clarify whether the conclusions drawn from intact-limbed subjects about the accuracy of the best classification scheme can be extrapolated to the amputee persons. This is performed by comparing the performance for the ten intact-limbed subjects and six transradial amputee persons. Another outcome of the third question is a reflection on physical limitations in signal generation due to the nature of the injury and data collection.

TABLE I
DEMOGRAPHIC INFORMATION OF THE AMPUTEE PERSONS PARTICIPATED IN THIS STUDY

Person ID	Age (years)	Missing hand	Stump length	Stump Cir. (cm)	Time since Amp	Prosthesis used
A_1	24	Left	13 cm	27	3	Cos
A_2	32	Left	18 cm	24	5	None
A_3	29	Left	29 cm	23.5	27	Cos
A_4	26	Left	16 cm	23	3	BP
A_5	34	Left	23 cm	26	7	Cos
A_6	28	Left	24 cm	26	6	Cos

Cir = Circumference, Amp = Amputation, BP = Body Powered, Cos = Cosmetic.

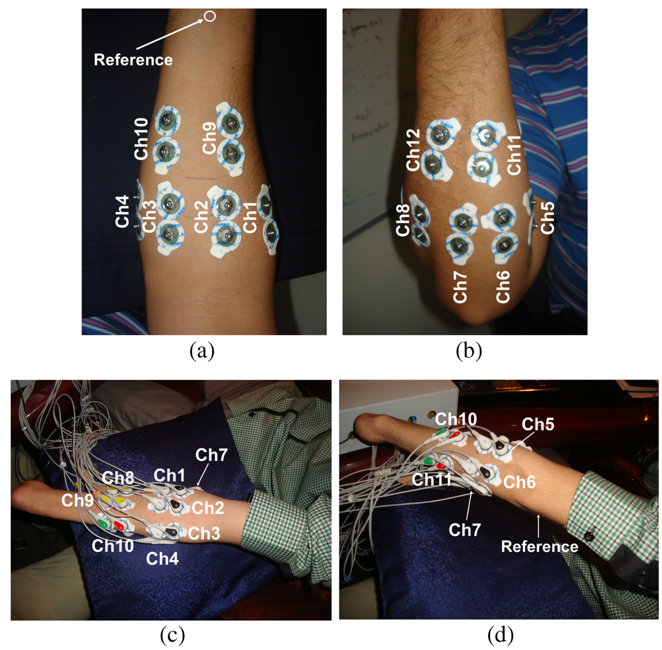


Fig. 1. Example of electrode location. (a) Anterior view of the right forearm of an intact-limbed subject. (b) Posterior view of the forearm of an intact-limbed subject. (c) Anterior view of amputee person A_3. (d) Posterior view of amputee person A_3.

II. MATERIALS AND METHODS

A. Data Acquisition Protocol

1) Participants: EMG signals were recorded from the right forearm of ten intact-limbed subjects (six males and four females) aged 21–35 years. Six traumatic below-elbow amputee persons aged 24–34 years also took part in the study. The data from intact-limbed subjects were collected at Plymouth University, U.K. The amputee persons' data were collected at the artificial limbs and rehabilitation centers in Baghdad and Babylon, Iraq. The demographic information of the amputee persons participated in the study is shown in Table I.

The study was approved by the Human Ethics Committee of the Faculty of Science and Technology at Plymouth University. All intact-limbed and amputee subjects were asked to read the participant information sheet and to give their written informed consent to participate in the study.

2) Electrode Placement and Numbers: Before placing the electrodes, the skin was cleaned with alcohol and abrasive skin preparation gel (NuPrep, D.O. Waver and Company, Aurora, CO) was applied to the forearm. The electrode locations were chosen to maximize the quality of recording. For intact-limbed subjects, 12 EMG channels were used with pairs of self-adhesive Ag–AgCl electrodes (Tyco Healthcare, Germany) placed around the circumference of the upper part of the forearm [(see Fig. 1(a)

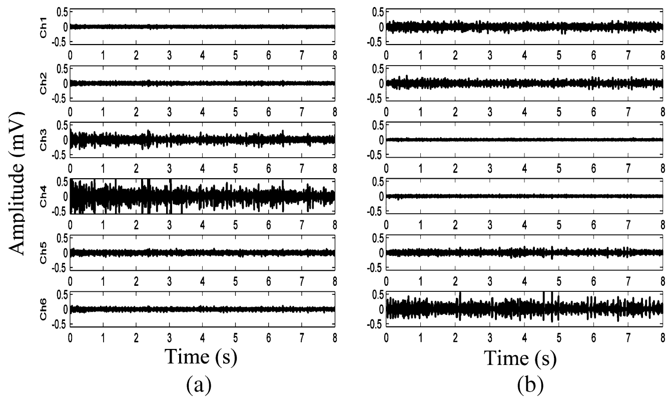


Fig. 2. Sample of six EMG channels. (a) Intact-limbed subject for middle finger flexion [see corresponding electrode locations for the same subject in Fig. 1(a) and (b)], (b) Amputee person A_3 for middle finger flexion, for electrode locations shown in Fig. 1(c) and (d).

and (b)]. Fig. 2(a) depicts six EMG channels for an intact-limbed subject. To reproduce electrode positions, European recommendations for sEMG [16] were followed by determining the electrode locations prior to electrode placement. The elbow joint was used as reference to mark the electrode locations.

Only 11 EMG channels were recorded for amputee persons due to the limited surface area in their upper forearms. The same self-adhesive Ag–AgCl electrodes (Tyco healthcare, Germany) were used to acquire the signals from amputee persons. The level of transradial amputation was different for each amputee person. For A_1, the 11 pairs of electrodes were placed around the circumference of the upper forearm. For the rest of the amputee persons (A_2–A_6), the electrodes were placed into two rows around the circumference of the upper forearm. The ground reference electrode was placed on the wrist for healthy subjects and at the Olecranon process of the Ulna for the amputee persons. The type of amputation was transradial amputation for all of the amputee persons apart from amputee person A_3, who had undergone a wrist disarticulation amputation [see Fig. 1(c) and (d)]. Fig. 2(b) illustrates an example of six channels of EMG signals for amputee person A_3. To minimize the crosstalk, bipolar EMG measurements were used with interelectrode distance of 24 mm as recommended by Young *et al.* and the SENIAM [16], [17]. It is worth mentioning that the amputee persons A_1, A_4, and A_5 have thick hair on their forearms but the hair was not shaved according to their request.

3) Signal Conditioning and Acquisition: The EMG signals were acquired with a custom-built multichannel EMG amplifier with a gain factor of 1000 per channel. For noise reduction, two analog filters were implemented in the amplifier (fourth-order Butterworth low-pass filter with cut-off frequency of 450 Hz and second-order Butterworth high-pass filter with 10-Hz cut-off frequency). A USB bus-powered data acquisition device (USB-6210, National Instruments) was used for data acquisition. Each EMG channel was sampled at a rate of 2000 Hz with 16-bit resolution. A second stage of band-pass filtering was implemented digitally with pass-band frequencies 20–450 Hz. A fifth-order Butterworth notch filter (centered at 50 Hz) was also implemented for noise reduction. The EMG signal was visually examined to make sure that there was no contamination from other sources. A virtual instrument was developed in LABVIEW (National Instruments, Austin, TX, USA) for displaying and storing the EMG signals.

4) Experimental Protocol: The intact-limbed and amputee subjects had not been trained on EMG recording prior to the study. The amputee persons were exsoldiers and policemen (A_2, A_5, and A_6) and workers (A_1, A_3, and A_4), all with a strong muscular structure in the arm and forearm, apart from (A_3). The EMG activity was strong since none had suffered nerve damage.

While intact-limbed subjects performed actual finger movements, amputee persons were instructed to produce a specific imagined finger movement. This was sometimes helped by mirror movements of the fingers of the intact hand. The amputee persons performed 12 classes of finger movements (11 individual finger movements as well as the rest position, which is considered as one of the movement classes in this study). The intact-limbed subjects performed 15 classes of finger movements (11 individual finger movements, 3 finger movement combinations, and the rest position).

The 12 individual finger movements performed by both amputee persons and intact-limbed subjects are: little flexion (f_1), ring flexion (f_2), middle flexion (f_3), index flexion (f_4), rest position, little extension (e_1), ring extension (e_2), middle extension (e_3), index extension (e_4), thumb flexion (f_5), thumb extension (e_5), thumb abduction (a_5). The other three finger movement combinations performed only by the intact-limbed subjects are little and ring fingers flexion (f_{12}), flexion of the ring, middle, and index fingers (f_{234}); and finally, the flexion of the little, ring, middle, and index fingers (f_{1234}). In summary, the amputee persons performed 12 movement classes (f_1 to a_5) whereas the intact-limbed subjects performed 15 movement classes (f_1 to f_{1234}).

The thumb by itself is able to perform four movements. Only three thumb movements were included in the classification (flexion, extension, and abduction) since the muscles responsible for thumb adduction lie in the hand itself [10] and it cannot be decoded from the upper forearm. It is worth noting that, to the best of our knowledge, thumb abduction was decoded successfully in the current study for the first time with high accuracy for six amputee persons.

During the recording, each participant sat on a chair in front of a computer with the Labview interface screen to see all the EMG channels in real-time while performing the movements. Their arm position was fixed and it was resting on a pillow. They were asked to produce a succession of different finger movements separated by 5 s periods of rest. Participants were asked to produce finger movements with a moderate, constant force, and nonfatiguing contraction to the best of their ability. The final position of a movement was held for a period of 12 s by intact-limbed subjects but was limited to 8 s for amputee persons to avoid fatigue. Each holding phase is referred to in this paper as a "trial."

Six trials were recorded for each movement. The odd-numbered trials were used as a training set while the even-numbered trials were used as testing set. The transition regions

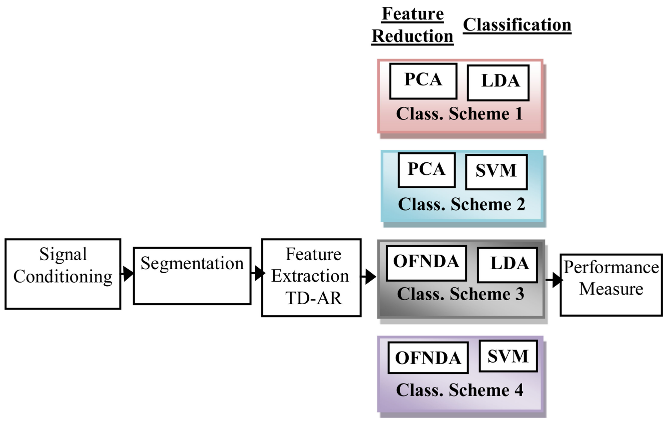


Fig. 3. Schematic diagram of the four classification schemes explored in the current study.

were removed from the signals for both the training and testing sets.

B. Data Processing Experiments

To address the research questions, three numerical experiments were designed as described in Sections II-B1, II-B2, and II-B3. The MATLAB 2010 a (Mathworks, Natick, MA, USA) software was used for the numerical processing. The SVM classifier was constructed with the sequential minimal optimization (SMO) tool in the Weka software [18]. Offline processing was used to evaluate the classification performance.

1) Numerical Experiment 1—Classification of Finger Movements and Selection of the Classification Scheme to be used in the Rest of the Study: In this experiment, we investigate combinations of feature reduction and classification techniques (denoted as "Schemes") for maximal performance. Four Schemes were tested composed of the two by two combinations of feature reduction and classification techniques (Section II-B1-c) (see Fig. 3). For a thorough review on pattern recognition studies in the last 2–3 decades, the reader is referred to [19].

a) Segmentation: The recorded EMG data were divided into overlapping windows of 200 ms length with a 50 ms increment between windows. This segmentation scheme was used for all numerical experiments in this study.

b) Feature extraction: To extract the useful information from the segmented EMG windows, time domain-auto regression (TD-AR) features [15] were used for the feature extraction. It has been shown that TD-AR features can achieve higher performance than that of other feature extraction methods such as Fourier transform and WT for the detection of *hand* movements with EMG signals [15]. Moreover, its computation is efficient, which enables its real-time implementation [19]. Additionally, it has been shown that AR coefficients are robust to displacements in electrode positions [20].

TD-AR features consist of calculating the following values for each analysis window: the coefficients of a sixth-order AR model, root mean square value, waveform length, number of zero crossings, integral absolute value, and slope sign changes. Hence, 11 features were extracted from each EMG channel. TD-AR features are used for all numerical experiments in this study.

c) Feature reduction and classification: Using a large number of EMG channels, with 11 features extracted per channel, leads to a high-dimensional feature vector. To reduce the computational cost, a feature reduction technique is used to map the feature vector to a lower dimensional space. To find the best combination of feature reduction technique and classifier, two feature reduction techniques and two classifiers were used in four combinations (referred to as "Schemes") (see Fig. 3). The classification Schemes 1 and 2 consisted of principal component analysis (PCA) [21] for dimensionality reduction; and linear discriminant analysis (LDA) and support vector machine (SVM) as classifiers, respectively. The third and fourth schemes included orthogonal fuzzy neighborhood discriminant analysis (OFNDA) [22] for feature reduction; and again LDA and SVM as classifiers, respectively (see Fig. 3). The number of features after dimensional reduction was set to 15 for both PCA and OFNDA. To summarize, the four "schemes" included in this study are as follows: 1) PCA+LDA, 2) PCA+SVM, 3) OFNDA+LDA, and 4) OFNDA+SVM.

PCA is an established technique frequently used in previous studies, and is included as a benchmark technique [21] for comparative purposes. OFNDA has been successfully applied to classify ten classes of *hand* movements of healthy subjects with high accuracy [22]. This is the first reported study in which OFNDA has been used to classify individual finger movements in six amputee persons. OFNDA aims to minimize the distance between samples belonging to the same class while maximizing the distance between the centers of different classes. In this way, it preserves the samples' contribution to the different classes [22].

Classification is performed with an LDA classifier for the first and third schemes (see Fig. 3). LDA was included in the study as a benchmark technique as well as being simple and proven to show good results for myoelectric control [15], [19], [23]. Also, it avoids iterative training giving less problems with under- and overtraining [21].

SVM was selected for being a state-of-the-art classifier used in the second and fourth schemes. It supports multiclass classification using the "one-versus-one" procedure to perform the classification. It has been shown that SVM works well for high-dimensional spaces since it searches for a hyperplane with the largest margin to classify different datasets.

A linear implementation of SVM was used for the classification. Additionally, the complexity parameter C of the SVM classifier was optimized for each subject within the range $-4 \leq \log_{10}(c) \leq 4$ in nine steps such that, $C \in$ [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]. A 10-fold cross-validation was used for the optimization of C on the training set only.

To identify the best classification scheme and to investigate the dependence of the results on the number of classes to be recognized, the four classification schemes were used to distinguish 5 (f_1-rest), 9 (f_1-e_4), 12 (f_1-a_5), and 15 (f_1-f_{1234}) movement classes with 12 EMG channels for the intact-limbed subjects. For the amputee persons, we classified 5, 9, and 12 movement classes with 11 EMG channels.

Finally, the statistical significance of the differences between the four classification schemes for the control subjects and the amputee persons was tested with the related-samples Friedman's two-way analysis of variance by ranks. In this and the following experiments, nonparametric tests were selected to prevent bias in the significance of the results due to potentially nonnormal distributions.

2) Numerical Experiment 2—Effect of the Number of Channels on Classification Performance: In this experiment, we use the best classification scheme identified in Section II-B1. Then, we determine the effect of the number of channels on the classification performance by using a channel elimination technique [23]. The objective is to find the smallest number of EMG channels that achieve a performance that is indistinguishable from that obtained using all available channels. This enables us to find out which subset of channels provides the best tradeoff between accuracy and number of channels for each individual participant.

The approach of channel elimination [23] was implemented for 15 finger movement classes of ten intact-limbed subjects and 12 finger movement classes for the six amputee persons. The straightforward exhaustive search algorithm [24], [25] was not used to determine the subsets of EMG electrodes because it has a very high computation load. Its computation requires investigating all possible channel combinations for a reduced number of channels. Conversely, the channel elimination used in the study [23] is less computationally intensive than the straightforward exhaustive search algorithm since it has the benefit of recursively removing the worst performing channel at a time.

For the intact-limbed subjects, 12 iterations of the channel elimination approach were performed. Within each iteration, the classification accuracy was calculated after eliminating one EMG channel at a time. Then, the channel that has the least contribution to the classification performance was removed. For the six amputee persons, since only 11 EMG channels were recorded, the channel elimination technique was applied with 11 iterations to find the best set of EMG channels.

The related-samples Friedman's two-way analysis of variance by ranks test was used to test the significance of the differences in the accuracy obtained with different numbers of EMG channels for both intact-limbed and amputee persons.

3) Numerical Experiment 3—Comparison of the Performance Between Intact-Limbed and Amputee Subjects: This experiment aims to compare the performance of the recognition of intended finger movement for intact-limbed and amputee subjects. The objective is to clarify whether the conclusions drawn from intact-limbed subjects about the accuracy of systems for the myoelectric control of prostheses can be extrapolated to amputee persons. To do so, we analyzed the best 6 and 11 channels obtained from numerical experiment 2 for the intact-limbed subjects. For the amputee persons, only 11 channels were recorded originally due to the limited area in the upper forearm. These channels were used to obtain the classification error together with the best six channels obtained from numerical experiment 2. The error rates were calculated for 5, 9, and 12 movement classes.

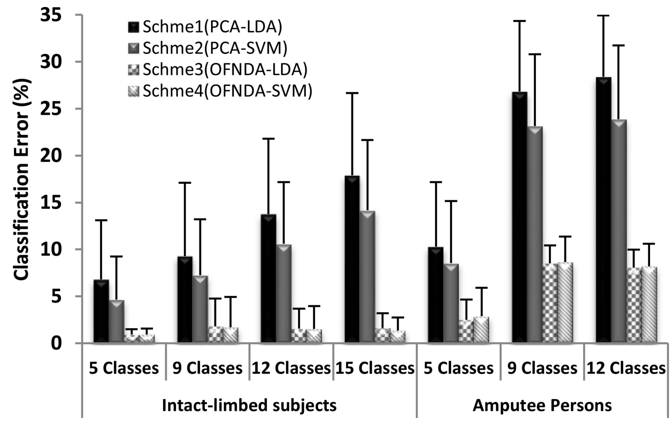


Fig. 4. Average classification errors obtained from ten intact-limbed subjects (left) for all classification schemes for 5, 9, 12, and 15 movement classes using 12 channels and from 6 amputee persons (right) for all classification schemes for 5, 9, and 12 movement classes using 11 channels.

The differences between the accuracy values achieved for controls and amputee persons with 6 and 11 EMG channels were tested for the significance with an independent-samples Mann–Whitney U test.

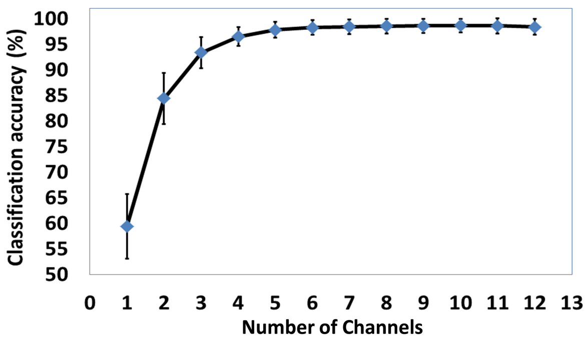
III. Results

A. Numerical Experiment 1: Classification of Finger Movements and Selection of the Classification Scheme to be Used in the Other Numerical Experiments

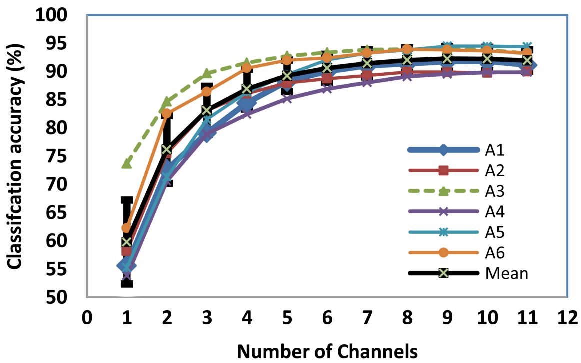
Fig. 4 shows the average classification errors across ten intact-limbed subjects with all four classification schemes for the classification of 5, 9, 12, and 15 movement classes and for the six amputee persons when classifying 5, 9, and 12 movement classes. The standard deviation of intersubject variability is shown.

Fig. 4 suggests that Schemes 3 and 4 perform better than Schemes 1 and 2. This was confirmed by the statistical analysis. All p-values obtained from the controls' results were significant (p-value < 0.001 in all four cases). This indicates that, for the intact-limbed subjects, there are significant differences in the accuracy level of the four schemes. Pairwise comparison tests indicated that, in all cases, Schemes 3 and 4 performed better than 1 and 2. For the amputee persons (six amputees), the p-values also reached significance (p-value $= 0.015 < 0.05$ for 5, p-value $= 0.002$ for 9, and p-value $= 0.001$ for 12 movement classes). Again, pairwise comparison tests point toward the superiority of Schemes 3 and 4 over 1 and 2.

From the results displayed in Fig. 4, it could be noted that Scheme 3 (OFNDA+LDA) slightly outperforms Scheme 4 for 5, 9, and 12 movements for the amputee persons. This led us to select the Scheme 3 (based on LDA) to be used in the numerical experiments (see Sections III-B and III-C). Fig. 4 also indicates that the error rates are much higher for the amputee persons than the intact-limbed subjects. This will be examined further in Section III-C.



(a)



(b)

Fig. 5. Average classification accuracy for different numbers of EMG channels using Scheme 3. (a) For ten intact-limbed subjects for the classification of 15 movement classes. (b) For each of the six amputee persons over all 12-movement classes.

B. Numerical Experiment 2: Effect of the Number of Channels on Classification Performance

Fig. 5(a) and (b) illustrate the results for the second numerical experiment for ten intact-limbed participants and the six amputee persons, respectively. This experiment elucidates the effect of the number of channels on classification performance in order to decide which minimum number of channels is required to classify finger movement classes. Fig. 5(b) also depicts the results for all amputee persons individually for a more comprehensive view of the results.

Of note is that during the second numerical experiment, there was a variation in the subset of the best six channels that achieved the highest accuracies for both intact-limbed participants and amputee persons. This might be due to the variation in the anatomy across the participants. The most common best 6 channels for the intact-limbed subjects were channel number 4, 7, 8, 9, 10, and 12 [see Fig. 1(a) and (b)]. Since the level of amputation was different for each one of the six amputee persons, the best six EMG channels were different for each one of amputee persons.

Fig. 5(a) and (b) suggests that approximately six EMG channels are needed to reach a plateau in the accuracy of the finger movement classification. Statistical analysis showed significant differences in the accuracy among different number of EMG channels for both intact-limbed and amputee subjects (p-value < 0.001 in both cases). Pairwise comparisons and homogeneous subset tests confirmed that, for both control and amputee persons, six EMG channels provided an accuracy that was not significantly different from that achieved with more EMG channels.

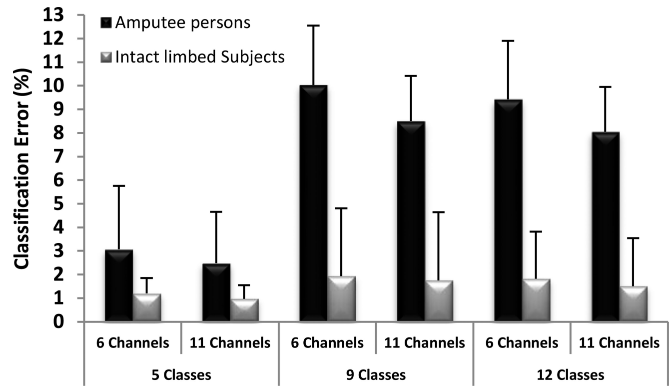


Fig. 6. Comparison of the performance of the intact-limbed subjects and amputee persons with Scheme 3.

C. Numerical Experiment 3: Comparison of the Performance Between Intact-Limbed and Amputee Subjects

In this experiment, we compared the classification performance between intact-limbed control subjects and amputee persons. Fig. 6 shows the mean error rates for ten intact-limbed subjects and six amputee persons. The analysis was performed with Scheme 3 with the best 6 and 11 channels obtained from the second numerical experiment for 5, 9, and 12 movement classes.

All results for 9 and 12 classes' problems (for both 6 and 11 EMG channels) indicated that there were significant differences in the classification performance between the intact-limbed subjects and the amputee persons (p-value < 0.05 in all four comparisons) (see Fig. 6). However, for five movement classes, the results showed that there were no significant differences between the intact-limbed subjects and the amputee persons when 6 or 11 channels were used (p-value $= 0.329$ and p-value $= 0.06$, respectively), which indicates that for a small number of finger gestures (f_1-rest), the amputee persons' and the intact-limbed subjects' performances may be indistinguishable (see Fig. 6).

Table II shows the average classification rates for six amputee persons for all classes investigated with their standard deviations. It can be seen that the relatively high error rate on extension movements is a cause for a lower overall performance for amputee persons. It is noteworthy that the recognition rate for thumb movements, including abduction, is as high as that of that of other finger movements.

Fig. 7(I) and (II) shows the confusion matrix for the worst performers of the amputee persons (A_2 and A_4) for 12 movement classes with Scheme 3. The data suggest a tendency for errors between extension movements.

TABLE II
OVERALL AVERAGE CORRECT CLASSIFICATION RATES IN PERCENT (AND THEIR RESPECTIVE STANDARD DEVIATION) FOR SIX AMPUTEE PERSONS WITH THE BEST SIX EMG CHANNELS

Classes investigated	Classification accuracy (%)
Little flexion (f_1)	96.29 ± 3.8
Ring flexion (f_2)	92.96 ±8.0
Middle flexion (f_3)	89.62 ± 7.9
Index flexion (f_4)	97.21 ± 2.5
Rest	99.05 ± 1.2
Little extension (e_1)	79.65 ± 18.1
Ring extension (e_2)	80.18 ± 7.7
Middle extension (e_3)	84.68 ± 14.0
Index extension (e_4)	86.13 ± 7.4
Thumb flexion (f_5)	97.40 ± 1.8
Thumb extension (e_5)	92.40 ± 11.8
Thumb abduction (a_5)	93.13 ± 6.4

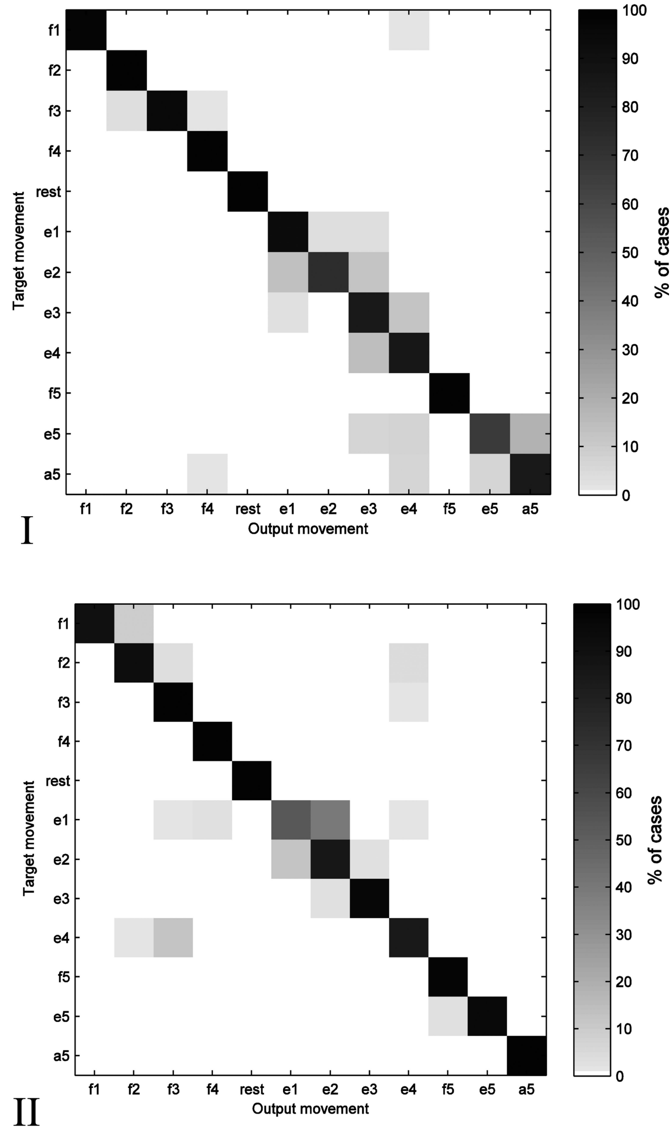


Fig. 7. Confusion matrix showing the error distribution for the Scheme 3 with all EMG channels. In a confusion matrix, the results in the diagonal are the correct classification rates while the results outside the diagonal line are the errors. (I) Amputee person A_2. (II) Amputee person A_4. The symbols represent the following movement classes: little flexion (f_1), ring flexion (f_2), middle flexion (f_3), index flexion (f_4), rest position, little extension (e_1), ring extension (e_2), middle extension (e_3), index extension (e_4), thumb flexion (f_5), thumb extension (e_5), and thumb abduction (a_5).

IV. DISCUSSION

A. Numerical Experiment 1

Numerical experiment 1 evaluated four Schemes for finger movement classification. In Fig. 4, for intact-limbed subjects, the classification error increased with the number of movements to be recognized. Fig. 4 also showed a similar trend for amputee persons. The error increases with the number of classes from five to nine for all schemes. However, the error saturates for 9 and 12 classes. Of note is that, in both groups, the error was much larger when PCA was used for the feature reduction as compared with OFNDA. As for the classification stage, there was little difference between LDA and SVM. LDA was preferred here as it showed marginal improvements for larger numbers of finger movements for the amputee persons. Additionally, it has a lower computational complexity and fewer tunable parameters than the other classifiers [15]. Given that the difference was small between the SVM and LDA classifiers, this might suggest that the feature reduction technique is more important than the classifier to achieve a high accuracy when a large number of EMG channels are considered.

Regarding the feature reduction stage, previous work has shown that OFNDA is an effective feature reduction method in *hand* movement classification experiments [22]. It must be noted that here, in contrast to other studies, our results for OFNDA point to the ability of this technique to contribute to a highly accurate recognition of *finger* movements in both intact-limbed and amputee subjects. The better performance of OFNDA compared to PCA, can be explained as follows. PCA projects the original feature vector to a new representation that maximizes the feature variance for low-order dimensions, while keeping the same number of features as the original one. Selecting a reduced number of low-order PCA components for the classification stage (e.g., 15 features in our case) can cause the loss of crucial information because the class information is ignored in the projection process, as it is driven by variance alone. In contrast, the objective of OFNDA is to minimize the distance between samples with the same class label while maximizing the distance between different class centers. In order to do so, OFNDA projects the feature vector into a new set with a reduced dimension (e.g., 15 dimensions in our case) while maximizing the class separability [22]. As a result of this, the orthogonal projection matrix provided by OFNDA tends to preserve the separation among classes better than the PCA principal components. This difference has little impact for a small number of classes, but becomes increasingly apparent for a large number of movements. For instance, Khushaba *et al*. [22] classified ten *hand* movement classes and OFNDA produced an improvement over PCA of 7%. Here, we classified 15 *finger* movement classes for the intact-limbed subjects and 12 *finger* movement classes for the amputee persons, and OFNDA outperformed PCA by 12% and 16%, respectively. The larger number of movement classes in this study explains a bigger improvement than reported by Khushaba *et al.* [22].

B. Numerical Experiment 2

Numerical experiment 2 addressed the question of how many EMG channels are actually needed for dexterous prosthetic hand control. Fig. 5(a) and (b) showed that the classification accuracy increases sharply as the number of channels increases from one to six and remains stable afterward. Statistical analysis for the ten intact-limbed subjects and for the six amputee persons also suggested six as a suitable number of EMG channels for the finger movement classification.

With six channels, an accuracy of 98% for the 15 movement classes problem was obtained across ten intact-limbed participants [see Fig. 5(a)], whereas for the amputee persons, six EMG channels provided enough information to classify 12 classes of individual finger movements with an accuracy of 90% [see Fig. 5(b)].

These results are an improvement over those reported by Tenore *et al.* [13], where 12 classes of finger movements were classified using 19 EMG channels, with an accuracy of 93.3% for five intact-limbed controls. Increasing the number of channels to 32 channels for five intact-limbed controls increased the accuracy to 94.1%. For the only amputee person recruited, the reported accuracy was 87.8%. In Tenore *et al.* [13], the processing chain comprised of TD feature extraction and a MLP for classification. They used only one TD feature per channel: the waveform length feature with 200 ms analysis window size. In our study, we used more TD-AR features (11 features). These, together with OFDNA/LDA appear to allow for a reduction of the number of channels as well as for a higher accuracy for more movements.

In Khushaba *et al.* [22], a processing chain similar to the one in this study was used. Thirteen TD-AR features were used to classify *hand* movements but not individual *finger* movements for the amputee persons. They obtained an accuracy of 88% for ten hand movements with only two channels. This performance is similar to our own findings on *finger* movements when using two channels [see Fig. 5(a)]. However, it is noteworthy that *hand* movements generate strong EMG signals, which are understood to be easier to classify than *finger* movement activity. Our results show that the weaker *finger* movement signals can also be classified with the same method as [22]. The results also show that increasing the number of channels from two channels as Khushaba *et al.* [22] did to six channels as in our work improves the performance.

The comparisons aforementioned confirm our assumption that extracting more features from each channel, such as TD-AR features, alongside dimensionality reduction, provides the necessary information required to recognize a large number of movements. This approach resulted in a much higher N_m/N_{ch} ratio (where N_m is the number of finger movements and N_{ch} is the number of sEMG channels) than in previous studies. Table III presents a summary of the previous research showing the N_m/N_{ch} ratio in the last column. Here we achieved a ratio of 2.5 for intact-limbed subjects and 2.0 for amputee persons, in comparison with previous values ranging from 0.4 to 1.5 in Table III. Furthermore, Khushaba *et al.* [22] showed that the computational load of OFNDA is actually suitable for real-time implementation, which would enable our suggested shift from hardware complexity (N_{ch}) to computational complexity as a means of reducing the number of channels.

TABLE III
SUMMARY OF PREVIOUS RESEARCH ILLUSTRATING THE NUMBER OF EMG CHANNELS USED, THE NUMBER OF FINGER MOVEMENTS CLASSIFIED, THE CLASSIFICATION ACCURACY, THE NUMBER OF PARTICIPANTS AND THE RATIO OF THE NUMBER OF MOVEMENTS DECODED (N_m) DIVIDED BY THE NUMBER OF EMG CHANNELS (N_{ch})

Ref.	N_{ch}	N_m	Clas. accuracy	Number of subjects	N_m/N_{ch}
[11]	4	6 IF	87%	10 H	1.5
[12]	4	4 CF	96%	7 H	1
[13]	32	12 IF & CF	94.1%	5 H	0.4
	19	12 IF & CF	87.8%	1 A	0.6
[14]	16	13 IF	80%	5 H and 1 A	0.81
[26]	8	7 IF & CF	89%	5 H	0.86
			79%	5A	0.86
This work	6	15 IF & CF	98.25%	10 H	2.5
		12 IF	90.57%	6 A	2

Clas = Classification, IF = Individual Finger movements, CF = Combined finger movements, H = Healthy subject, A = Amputee person.

To find the optimal six channel locations, we have followed a computational procedure starting with a large number of channels, and then progressively removing the least useful channel. Using this procedure and subsequent statistical tests, we confirmed that six was a good tradeoff between classification accuracy and number of channels for our finger movement classification task. It is noted that a similar procedure could be applied in real-world prosthesis fitting, whereby electrode numbers and placement are optimized for each subject, thus obtaining the maximum performance for any given individual (see Section IV-D).

C. Numerical Experiment 3

This experiment compared the results for intact-limbed and amputee subjects. This is a difficult task, since there are large individual differences between the subjects, including the level of amputation, injury, and rehabilitation training. However, the statistical tests showed that for 9 and 12 movement classes and both subsets of channels (see Fig. 6), there were significant differences in the classification performance between the intact-limbed subjects and the transradial amputee persons. This is an expected result as the muscle structure of the amputee person's limb after amputation is different from that of an intact-limbed control subjects. For a small set of five movement classes, there were no significant differences between the controls and the amputee persons either when 6 or 11 channels were used. This indicates that, for a small number of finger gestures, the performance for amputee persons and the intact-limbed subjects are statistically indistinguishable. This could suggest that, the lower the number of finger movements to be classified, the more comparable the accuracy between controls and amputees. This could also reflect the fact that the set of five movement classes used did not include extension movements for which amputee persons have especially high error rates (see Table II). Overall, this is an expected result of injuries, lack of use and possibly muscle atrophy, and it highlights the importance of recruiting amputee persons for this kind of studies. It is worth noting that subject A_3 was the best performer among the amputee persons, despite the long time since amputation. Thus, the time factor alone may not explain lower performances.

Our results are in contrast with a previous study [13] where no significant differences were found between the performance of five intact-limbed controls and one amputee person for classifying 12 finger movements. However, such results might be limited by their sample size. In another study, Cipriani *et al.* [26] showed that there is no statistical difference in accuracy among five intact-limbed subjects when classifying seven finger movements, but the performance of five amputee persons varied significantly. This might be explained by different factors such as stump length and age. However, their study did not compare intact-limbed and amputee persons.

Additionally, it can be seen in Fig. 6 that the amputee persons' error rates for nine movement classes are slightly higher than for 12 movement classes. This may be due to the fact that the errors appeared mainly in the extension movements of the little, ring, middle, and index fingers (within the first nine movement classes). However, the three thumb movements added in the set of 12 movement classes have fewer errors than the previous movements (see Table II), which can explain why classifying 12 movement classes has a slightly smaller error than classifying nine movement classes.

It also worth noting that the processing time required to classify the 12 movement classes for the six amputee persons was 2.4 ms on a Pentium-4 computer with an Intel Core 2 Duo processor, 2.2 GHz, 4 GB RAM with MATLAB 2010 a. The processing time was the time needed to perform the feature extraction, feature projection, and classification for each window of the EMG of length of 200 ms once the system had been trained.

From an examination of the errors in the confusion matrix for amputee persons (see Fig. 7), it can be observed that the errors occurred mainly with the extension movements of the little, ring, middle, and index fingers. Furthermore, the amputee person A_4 has many more errors in the flexion of little, ring, and middle fingers. As for the thumb movements, subject A_4 showed a small confusion between thumb extension (e_5) and thumb flexion (f_5). There was a good performance for thumb abduction, which is unique to this study.

Within the amputee person group, amputee person A_2 was the worst performer with classification accuracy of 86.9% compared to 95.3% accuracy for the amputee person A_3 who was the best performer. This is in agreement with [13], where the errors in the confusion matrix for the only amputee person recruited were also in the extension movements of the little, ring, and middle fingers. More specifically, extension movements are generally confused with other extension movements, and in the case of Fig. 7(II), flexion movements are confused with other flexion movements. Extension movements are physically difficult movements to execute for the intact-limbed subjects. For amputee persons, this is even more challenging, so it is less clear whether the subjects intended actions mapped to the same muscular effect. These considerations call for further investigation, possibly in view of a subject-specific restriction of the number of movements covered in order to increase the accuracy.

D. Limitations and Future Work

Our study has some limitations. The first one is that only offline pattern recognition was used. The participants (both intact-limbed and amputee subjects) did not demonstrate control in real time using a virtual environment or an actuated prosthesis. Specifically, a virtual environment [19], [27] could be used to perform functional testing to relate the usability and classification accuracy of a given finger movement or gesture. It should be noted that Li and Kuiken [25] and Li *et al.* [24] reported the same performance in an offline and real-time experiment with a virtual hand for ten wrist and hand motions with "no movement" class. Our results showed that amputee persons produced 90% of accuracy with 6 EMG channels for 12 individual finger movement classes in offline mode. We do believe that the functional performance may drop slightly when using a virtual prosthesis to measure the functional performance in real time even with the benefit of visual feedback. However, further research is needed.

Another limitation is that the work examined only finger movements without including hand movements. Adding more movements might cause confusion between the movements. This issue will be subject of future work to determine the performance of a classifier that combines the recognition of hand and finger movements for the transradial amputee persons. A full study needs to include wrist movements and combined as well as individual finger movements. The current results only show that better performance will be obtained with the proposed scheme over the other three alternatives. The indicated accuracies have a comparative value among the schemes. We acknowledge that reliability is a major issue and it is likely that a reduced set of movements may have to be used in a real-world prosthesis control system. Of key interest in this study is that a larger set of movements may become more practical than is currently possible with the systems available today. Electrode shift [17], [28], different arm positions [29]–[31], and the potential nonstationarity in EMG [32] have also been shown to influence the performance of myoelectric control. However, our experiments did not investigate these factors. Moreover, reproducibility needs to be examined. Overall, there is a need for a new focus on improving the robustness of the pattern recognition-based systems to make real clinical and commercial impact rather than further improving the classification accuracy by small percentage [19]. In addition, there is a research need to investigate real deficiencies in current pattern recognition systems such as the lack of simultaneous and proportional control and lack of adaptation to the changes in EMG signal characteristics [33]. Tackling these challenges will help us to improve the practical robustness and usability of prostheses controlled by pattern recognition systems.

The results of numerical experiment 3 highlight the importance of recruiting amputee persons in this type of studies and investigating a *personalized* approach to the classification task. No two amputee persons are the same, with differing degrees of injury to nerves and muscles, and differing ability to make gestures without feedback. We suggest that each amputee person may have a subject-specific optimum performance. The number of gestures, channels, and even choice of signal processing scheme may need to be optimized to such obtain optimum performance that best enhances their quality of life. This individualized approach, alongside real-time implementation, will be the focus of our future work.

V. Conclusion

This paper presented a study of the use of multichannel sEMG to classify individual and combined finger movements for dexterous prosthetic control. We analyzed sEMG dataset from ten intact-limbed subjects and six amputee persons recorded by a custom-built sEMG acquisition system. This dataset constitutes an amputee persons' database larger than those previously reported in the literature [13]–[15], [17], [22], [24], [26], [34]. Our results emphasize the crucial role played by the feature reduction method in the EMG signal processing and pattern recognition chain. In particular, the results identify the superiority of the OFNDA feature reduction method for finger movement classification, and this is consistent with previous work that showed similarly good performance for hand movement classification.

This paper has achieved higher accuracies than reported in previous work with 98% for ten intact-limbed subjects in the classification of 15 independent and combined of finger movements and 90% for six amputee persons in the classification of 12 independent finger movements. The best performing process chain consisted of TD-AR feature extraction, OFNDA for feature reduction, and LDA for classification.

We have used a method to identify the most informative channels for each subject and have consistently found that optimal performance can be maintained by using only six EMG channels. With fewer channels, the performance significantly decreases. Overall, our approach allows a high N_m/N_{ch} ratio, which may be due to the initial extraction of a large number of features from the signal using TD-AR. This N_m/N_{ch} ratio is 2.5 for intact-limbed subjects and 2.0 for amputee persons. To personalize the number and location of the electrodes for the amputee persons in real-world prosthesis fitting, the approach investigated in numerical experiment 2 in this study can be applied to improve the quality of life of the amputee persons on an individualized or subject-specific basis.

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