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Phasor represented EMG feature extraction against varying contraction level of prosthetic control

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ABSTRACT

This paper introduces phasor representation of electromyography (EMG) feature extraction (PRE). The well-known EMG signal analysis methods, namely root mean square (RMS), and waveform length (WL) are adopted into phasor form depending electrode placement. The values of these methods are computed from 8-channel EMG signals, and their magnitudes with respect to origin are used to construct phasor represented features in this study. The class separability of the PRE is strengthened by adding difference EMG and Euclidean distanced phasor in order to obtain improved feature set against force and electrode variations. The simulations (three schemes) are performed on publicly available EMG dataset on transradial amputees, and the results are presented in terms of accuracy and processing time considering the control strategies of a prosthetic hand. Linear (LDA), and quadratic (QDA) discriminant analysis, and k-nearest neighbor (k-NN) classifiers are trained, and tested by the PRE features. Our method outperforms previous accuracy rates in some cases, and reaches to accuracy results of the first study using this dataset without using any reduction method. In our simulations, accuracy rates up to 71.17% (PRE with QDA) for six classes hand movements with three force levels are obtained decreasing processing time by 81.83%.

1. Introduction

Surface electromyography (sEMG) signals from the muscles of a healthy limb or a residual limb have been widely used for human-machine interaction (HMI), myoelectric prostheses and rehabilitation robots [1,6,9]. The hidden information in the sEMG signals is an assistive tool to control robots, computer games, and especially prosthetic devices for amputees [1,8,13,20]. The main approach to use surface electrodes at given a muscle location is to extract the similarity between muscle activity and signal pattern. On the other hand, it is still a difficult task to extract informative features from amputee's residual limb [3,20,24]. Although the electrodes are placed onto residual limb, the informative and separable features are expected to be extracted for different movements of lost limbs with various force levels [2,20].

There are several upper limb prostheses [4,7] controlled by sEMG signals with conventional signal processing and pattern recognition (PR) methods [18]. Hence, researchers have focused on several PR approaches as well as different channel configurations and movements [11]. These can be categorized into three groups; time-domain (TD), frequency-domain (FD), and time-frequency (TF) domain analysis for mono-variate or multi-variate signal processing [5]. Root mean square (RMS), integrated EMG (IEMG), waveform length (WL), mean absolute value (MAV), slope sign changes, and the number of zero crossing rate (ZCR) can be listed as successfully proposed time-domain methods [12,13,15]. Fast Fourier transform (FFT) [10], and wavelet transform (WT) [8] based FD and TF-domain features were evaluated on EMG signals belonging to different contraction levels. k-nearest neighbor (k-NN) algorithm with aforementioned TD signal analysis was performed on four different hand posture classification. It was reported that accuracy rates up to 94% were obtained [22]. Six hand motion classification using discrete wavelet transform (DWT) with wavelet neural network (WNN) yielded average accuracy rate of 94.67% (max 100%) [8]. In another study, RMS, sample entropy (SE), and WL were adopted to the inputs of support vector machine (SVM) and general regression neural network (GRNN) to classify nine hand movements. The recognition rates were 98.64%, and 96.27%, respectively [15]. These methods are also discussed in a review paper [17]. Time-dependent power spectrum descriptors (TD-PSD) was first introduced in 2014, and evaluated on publicly available EMG signals of healthy subjects [14] using linear discriminant analysis (LDA), k-NN), SVM. It was reported that error rates have been reduced to 8% for 5 hand position with 8 class hand movements. In

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[16], deep neural network (DNN) performance (98.88%) was compared to SVM (98.66%), k-NN (90.64%), random forest(RF) (91.78%), and decision tree (88.36%) using the same database.

It is impossible to make a definite comparison about the success rates of the PR methods on sEMG due to different electrode placement scheme, number of channels, force level, and movement. However, it is clear that studies on healthy subjects have higher accuracy levels when compared to studies on amputees, e.g., accuracy rate up to 97.87% were obtained using EMG map image processing method [23]. However, error rates up to 30–40% were yielded using TD feature set and LDA within inter-level muscle contraction in the study on intact-limbed subjects [21]. It was decreased to 8–10% within inter-level contractions. sEMG recorded from intact-limbed subjects, and FT features were performed on three force levels of nine wrist movements [10]. It was reported that the error rate was lessened by 11% compared to TD method, but specific electrode placement was also reported as vital. Thus, implementation of this configuration has limitations to deformed amputee stump, and other residual limbs. Al-Timemy et al. [2] were acquired at least 8 channels sEMG signals from nine transradial amputees for three force levels. Feature vectors based on the TD-PSD with k-NN, LDA, Naive Bayes (NB), RF classifiers were evaluated on this data set. LDA classifier performed nine amputees' recordings within inter-level force(trained and tested using sEMG signals with same force level), unseen force level (testing without trained levels), and finally all force levels (testing and training data consists of each force level), and has approximately 8%, 10%, and 13% for inter-level error rates, between 30–70% for unseen force levels, and 17.42% for all force level. Spectral regression was the key point in this paper to reduce dimension of the TD-PSD features. Besides, the effect of four different scenarios of the residual limb position on classification accuracy of 8-channels EMG signals were investigated [19]. Acquisition while sitting, walking on a flat ground, ascending a star, and descending a star were conducted to evaluate the robustness of the EMG-PR approaches. In [25], aforementioned EMG-PR methods were performed on downsampled signals of healthy and amputee subjects. EMG acquisition using a wearable device was simulated by downsampling to 200 Hz, and the accuracy results of the five data sets compared to 1000 Hz sampled recordings. It was reported that wearable device with low sampling rate can cause drastic reduction for prosthetic hand control.

Our purpose is to propose a novel feature extraction for multi-channel sEMG signals from transradial amputees. The phasor represented EMG (PRE) feature space is introduced in this paper. Instead of applying the well-known RMS and WL based features to classifiers directly, they are formed into phasor space, and then logarithmically scaled signal and features are used to extract feature vector. The proposed PRE is performed on the EMG recordings, and the results are compared to the previous novel method called TD-PSD [2] considering prosthetic hand control strategies for different force levels. In addition to introduced phasor space in this paper, we present the results eliminating dimension reduction process to reach up to high accuracy rates. The remainder of the paper is organized as follows: Section 2 provides a description of the EMG database and related study. The proposed PRE based feature extraction is presented in Section 3. Consequently, in Section 4 simulation results of the PRE with classifiers are examined, and the conclusions are drawn in Section 5.

2. Dataset description and related work

The EMG dataset consists of 8-channel EMG recordings from nine participants suffering from unilateral transradial amputation (7 traumatic, 2 congenital). Table 1 shows the detailed information of the participants.

Table 1
The information of transradial amputees in the dataset.

Participant	Age	Gender	Amputation type
Amputee 1	25	M	Traumatic
Amputee 2	33	M	Traumatic
Amputee 3	30	M	Traumatic
Amputee 4	27	M	Traumatic
Amputee 5	35	M	Traumatic
Amputee 6	29	M	Traumatic
Amputee 7	57	M	Traumatic
Amputee 8	19	F	Congenital
Amputee 9	31	F	Congenital

Fig. 1. The electrode placement on a residual limb.

A multi-channel EMG acquisition system was mounted on the residual limb shown in Fig. 1, and then multi-channel signals were recorded during each motion at different force levels. Thus, six motions namely thumb flexion (TF), index flexion (IF), fine pinch (FP), tripod grip (TG), hook grip (HG), spherical grip (SG) classes in Fig. 2 were obtained for three variable force levels as low, moderate and high.

The EMG signals belonging to each motion were recorded at five to eight trials for each force level to enhance reliability of dataset with the length of 8–12 seconds. In the original study [2], classification accuracy against varying force levels for these six classes were performed on these recordings. For this, the proposed TD-PSD [2] by modifying spectral moments to enhance discrimination power among the six classes with varying force levels. First, three even normalized moments m_0, m_2, m_4 were obtained by

$$m_k = \frac{1}{N}\sqrt{\sum_{i=0}^{N-1} \nabla^k x_i^2}. \tag{1}$$

where N is the total number of samples and k is the degree of the differentiation. Then, these were used to extract the feature vector as given by

$$f_1 = \log(m_0) \tag{2}$$

$$f_2 = \log(m_0 - m_2) \tag{3}$$

$$f_3 = \log(m_0 - m_4) \tag{4}$$

$$f_4 = \left(\frac{m_0}{\sqrt{m_0 - m_2}\sqrt{m_0 - m_4}}\right) \tag{5}$$

Fig. 2. The six classes of the hand movements in the dataset.

$$f_5 = \log\left(\frac{m_0}{m_2 m_4}\right) \tag{6}$$

$$f_6 = \log\left(\frac{\sum_{i=0}^{N-1}|\nabla x|}{\sum_{i=0}^{N-1}|\nabla^2 x|}\right). \tag{7}$$

f_4, f_5, f_6 are well-known feature extraction techniques called sparseness, irregularity factor, and waveform length ratio. Authors also extended the feature vector by repeating the same procedure to logarithmically scaled EMG signal $\log\left(x^2[n]\right)$. Finally, two feature vectors composed of six elements were obtained as $\boldsymbol{a} = [a_1, a_2, a_3, a_5, a_6]$, and $\mathbf{b} = [b_1, b_2, b_3, b_4, b_5, b_6]$ for the signal itself, and the logaritmically scaled version, respectively, and then their orientation between original signal based and non-linear scaled signal based feature vectors are estimated using cosine similarity measure function as

$$F_i = \frac{2a_i b_i}{a_i^2 + b^2}. \tag{8}$$

According to myoelectric control strategies of a prosthesis, the multi-channel EMG signals were split into segments with the length of 150 ms and 50 ms overlapping, and the final feature vector, **F** with 48 dimensionality was extracted for each parts of the signal. SR, which is an unsupervised and semi-supervised subspace learning algorithm, is used to reduce dimensionality to five. Consequently, two trials were applied to the classifiers including LDA, and k-NN as test data, and the others were retained as training for different classification schemes; (1) Training with a single force, and testing using same level. (2) Training with a single force, and testing using untrained (unseen) two force. (3) Training with all three forces, and testing it using single force at a time. In the original study on transradial amputees [2], spectral regression (SR) was used for dimension reduction of the extracted features. SR is a semi-supervised subspace learner, that can cause biasing effect on classifier performance, and requires more processing time for each sample (i.e., each testing vector should be processed within training at a time, or all testing and training data should be processed together at once, but it is not suitable for control strategies of a prosthetic hand). For this reason, we propose the PRE feature extraction method to reach the accuracy levels of the study without SR.

3. Proposed phasor represented feature extraction

In the proposed novel feature extraction method, we focus on the two crucial steps of EMG signal processing for transradial amputees. The first, it should be immune to varying contraction level (low, moderate, and high) for different types of movements (thumb flexion, index flexion, fine pinch, tripod grip, hook grip, spherical grip), and the second one is low computational cost or delay for implementation of the myoelectric control of prosthesis, while separating capability of the acquired signal from a residual limb is less than healthy subjects.

The proposed phasor representation is based on distance based modeling of all channels. The residual limb is modeled as a cylindrical part with 8 electrodes so that 8 phasors ($P_0, P_1 \ldots, P_7$) with $\pi/4$ radian spacing are constructed. The demonstration of the electrode phasors is shown in Fig. 3.

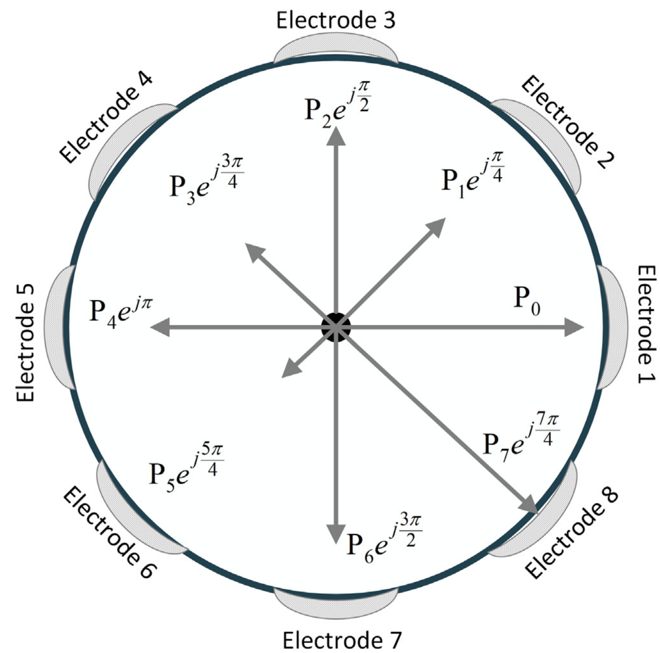

Fig. 3. The phasor representation principle of the study.

The magnitude sequences given in Fig 3 are insubstantial, but the main principle of the proposed method is based on extraction of the unique pattern for each movement with varying force levels. Due to the same electrical activity produced by muscles, a robust feature extraction techniques are required to quantify the signals from electrodes. The well-known and successfully applied root mean square (r) and the waveform length (w) are deployed to measure channel activity given by

$$r = \sqrt{\frac{1}{N}\sum_{i=0}^{N-1} x_i^2} \tag{9}$$

$$w = \sum_{i=0}^{N-1}\sum\left|x_{i+1} - x_i\right|. \tag{10}$$

where $x[n]$ is the N samples EMG signal from each channel. Now, we can start to form phasor features for EMG signal as

$$\mathrm{P^r} = \left[\mathrm{r_0}, \mathrm{r_1} e^{j\frac{\pi}{4}}, \mathrm{r_2} e^{j\frac{\pi}{2}}, \mathrm{r_3} e^{j\frac{3\pi}{4}}, \mathrm{r_4} e^{j\pi}, \mathrm{r_5} e^{j\frac{5\pi}{4}}, \mathrm{r_6} e^{j\frac{3\pi}{2}}, \mathrm{r_7} e^{j\frac{7\pi}{4}}\right] \tag{11}$$

$$\mathrm{P^w} = \left[\mathrm{w_0}, \mathrm{w_1} e^{j\frac{\pi}{4}}, \mathrm{w_2} e^{j\frac{\pi}{2}}, \mathrm{w_3} e^{j\frac{3\pi}{4}}, \mathrm{w_4} e^{j\pi}, \mathrm{w_5} e^{j\frac{5\pi}{4}}, \mathrm{w_6} e^{j\frac{3\pi}{2}}, \mathrm{w_7} e^{j\frac{7\pi}{4}}\right] \tag{12}$$

, and then the same steps are applied to $\nabla x[n]$ to increase separability of the feature set for varying force levels. Thus, pairwise Euclidean distances between phasors after difference phasor computations, ∇P^{r}, and ∇P^{w} are formulated by

$$\mathrm{D^r} = \left[\left\|\vec{r_0} - \vec{r_1}\right\|, \left\|\vec{r_0} - \vec{r_2}\right\|, \ldots, \left\|\vec{r_1} - \vec{r_2}\right\|, \ldots, \left\|\vec{r_6} - \vec{r_7}\right\|\right] \tag{13}$$

$$\mathrm{D^w} = \left[\left\|\vec{w_0} - \vec{w_1}\right\|, \left\|\vec{w_0} - \vec{w_2}\right\|, \ldots, \left\|\vec{w_1} - \vec{w_2}\right\|, \ldots, \left\|\vec{w_6} - \vec{w_7}\right\|\right]. \tag{14}$$

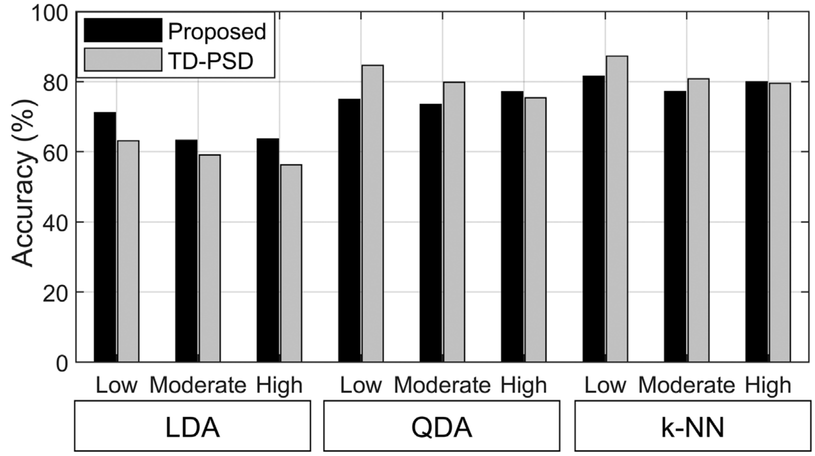

Fig. 4. Classification accuracy for nine amputees depending on experimental scheme 1 (training and testing with the same force level).

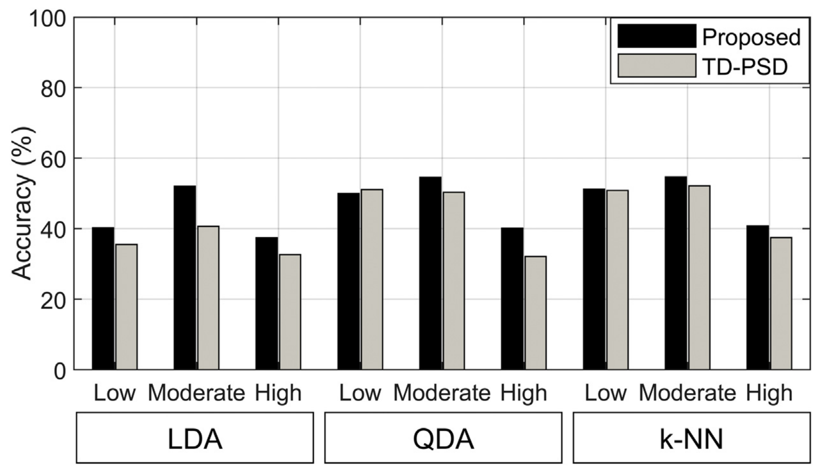

Fig. 5. Classification accuracy for nine amputees depending on experimental scheme 2 (testing with the unseen two force levels).

Likewise, pairwise distances $\nabla \mathbf{D}^r$, and $\nabla \mathbf{D}^w$ within ∇P^r, and ∇P^w are computed to construct logarithmically scaled final feature vector by

$$\mathbf{F} = \left[\log\left(\mathrm{D}^r\right),\ \log\left(\mathrm{D}^w\right),\ \log\left(\mathrm{D}^r/\nabla\mathrm{D}^r\right),\ \log\left(\mathrm{D}^w/\nabla\mathrm{D}^w\right)\right]. \quad (15)$$

With the help of the aforementioned combination of multichannel EMG processing, it is expected to extract 112 dimensional feature vector being immune to force and channel variations. We also adopted the same segmentation and data partitioning (testing and training trials) in the original study of the dataset [2] for performance comparison within scheme 1–3 in terms of accuracy and processing time. In addition, we investigated QDA classifier performance on the dataset comparing to LDA and *k*-NN.

4. Results and discussion

The proposed PRE is performed on publicly available multichannel EMG recordings from nine transradial amputees [2]. The recording stage consists of 8-channel signals with 8–12 s length repeating the same movement at least 5 times. Thus, six movement classification (TF, IF, FP, TG, HG, and SG) with three force levels (low, moderate, and high) was evaluated using two of them as testing with 150 ms segmentation and 50 ms overlapping. Stick to the schemes of the original study, we performed our PRE method on this dataset to provide the impact of feature extraction and training on EMG.

Scheme 1 is also known as disregarding the effect of force variations, the classifiers are trained and tested using the same force level. Experiments are performed on nine amputees recordings using LDA, QDA, and *k*-NN. The results of scheme 1 are shown in Fig. 4.

Generally, the classifiers with low computational cost namely, LDA and QDA have lower accuracy rates when compared to *k*-NN. LDA at all force levels with the proposed PRE method outperforms TD-PSD, while QDA and *k*-NN at high levels do. The average accuracy rates in scheme 1 can be summarized as 66.00%, 75.16%, 79.52% for the proposed PRE, and 59.48%, 79.93%, 82.55% for TD-PSD, respectively.

The next scheme is to classify untrained two force levels while single force level is applied as testing data. The accuracy levels of the classifiers are decreased dramatically for both methods given in Fig. 5.

The proposed PRE method is more successful than TD-PSD method referring Fig. 5. The average results are 48.23%, 43.21%, and 46.02% for PRE, 44.50%, 36.28%, and 46.80% for TD-PSD. Moreover, the highest scores (54.64%, 54.61%) are obtained when PRE with *k*-NN and QDA classifiers are fed by moderate force level as training data. Thus, our proposed method can be alternative approach to different force level variations for EMG classification.

The 3rd scheme is the most effective way to analyze the signal processing and machine learning algorithms together. In this scheme, the classifiers are trained using all level force variations, and then tested by a force level at a time in order to provide detailed

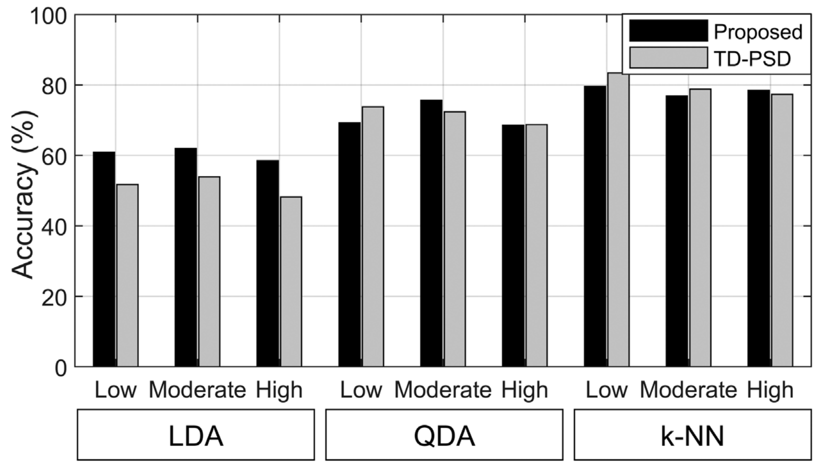

Fig. 6. Classification accuracy for nine amputees depending on experimental scheme 3 (testing the classifier with a single force).

Table 2
The accuracy rates (%) of the proposed PRE method.

Experiment	Method	Classifier	Low	Moderate	High	Average
Scheme 1	Proposed PRE	LDA	77.11	63.23	63.68	66.00
		QDA	74.91	73.48	77.09	75.16
		k-NN	81.52	77.13	79.92	79.52
	TD-PSD	LDA	63.12	59.09	56.24	59.48
		QDA	84.65	79.78	75.38	79.93
		k-NN	87.28	80.82	79.55	82.55
Scheme 2	Proposed PRE	LDA	40.26	52.00	37.37	43.21
		QDA	49.96	54.61	40.1	48.23
		k-NN	51.25	54.64	40.79	46.02
	TD-PSD	LDA	35.53	40.65	32.67	36.28
		QDA	51.10	50.27	32.14	44.50
		k-NN	50.82	52.14	37.46	46.80
Scheme 3	Proposed PRE	LDA	60.88	61.95	58.52	60.45
		QDA	69.30	75.66	68.53	71.17
		k-NN	79.62	76.88	78.5	78.34
	TD-PSD	LDA	51.74	53.92	48.15	51.27
		QDA	73.77	72.40	68.74	71.63
		k-NN	83.44	78.78	77.33	79.85

description about the processes, and their performances. For this reason, the simulations are conducted, and the accuracy rates of the three classifiers for nine amputees are shown in Fig. 6.

As given in Fig. 6, our proposed PRE method outperforms TD-PSD at all force levels with LDA, moderate with QDA, and high with *k*-NN classifier. For example, PRE LDA yields 60.88%, 61.95%, and 58.52% (average is 60.45%) while TD-PSD LDA scores are 51.74%, 53.92%, and 48.15% (average is 51.27%), respectively. At moderate force level, PRE-QDA has accuracy rate of 75.66%, when TD-PSD QDA has the rate of 72.40%. On the other hand, the success rates of the proposed method are decreased by 0.21% (from 68.74% to 68.53% for high level), and 4.47% (from 73.77% to 69.30% for low level). *k*-NN results are similar to QDA, but it has slightly higher scores than QDA. It yields 78.50%, and 77.33% for PRE, and TD-PSD at high force level, respectively. This increase is not available for low and moderate forces, accuracy rates are dropped by 1.9% and 3.82%. To summarize the results of the proposed method and the classifiers, Table 2 is given.

As stated before, proposed PRE with LDA is the most successful method for all schemes, when compared to TD-PSD with LDA classifier. TD-PSD with QDA or *k*-NN outperforms PRE in scheme 1, but PRE with all classifiers combination can successfully distinguish six hand movements at three force levels. Generally, scheme 3 is the more realistic application in myoelectric control of transradial amputees, and the proposed PRE has near accuracy rates to

Table 3
Processing time of the feature extraction with the classifiers for all force levels.

Method	Processing time (s)
Only PRE	133.13
Only TD-PSD	732.83
LDA with PRE features	8.73
LDA with TD-PSD features	3.68
QDA with PRE features	9.70
QDA with TD-PSD features	3.78
k-NN with PRE features	4037.24
k-NN with TD-PSD features	1390.56

TD-PSD method (decreased by 1.51%, and 0.46% for high and moderate, increased by 9.18 for low). However, the processing time of the algorithm is as vital as the accuracy of the method. For this reason, we should consider the time processing requirements of the methods including EMG signal analysis, and machine learning. The processing times on a laptop computer with an Intel 2.5 GHz i7 processor and 8 GB RAM are given in Table 3.

The processing time computations are conducted on 476,990 EMG samples (150 ms segmented 8-channels), and presented. Our proposed PRE requires 133.13 s to extract EMG features for all samples, but TD-PSD needs 732.83 s to complete it. On the other hand, the PRE increases the classification time by 5.05 s (from 3.68 to 8.73) for LDA, 5.92 s (from 3.78 to 9.70) for QDA. *k*-NN requires huge amount of processing time, at least 1390.56 s for TD-PSD, and 4037.24 for PRE. From this point of view, *k*-NN is not a preferred classifier for myoelectric control due to its high delay, but QDA is also higher accuracy rates causing low delay rate. PRE has low computation time (reducing 732.83 s to 133.13 s) with the accuracy rate of 71.17%, and adds extra 5.92 s to all samples classification with QDA due to 112-dimensional feature vector. Thus, the proposed PRE feature extraction method with QDA classifier can be a successful method for prosthetic limb control, considering accuracy and delay. The details of the LDA, and QDA classification for each hand movement are presented in Fig 7 .

In the original study on transradial amputees [2], spectral regression (SR) was used for dimension reduction of the extracted features, and the TD-PSD with SR and LDA yielded average accuracy of 82.58%. Before supervised learner, the semi-supervised subspace learner, SR has positive biasing effect on classification performance. However, it required more processing time for each sample (i.e., each testing vector should be processed within training at a time, or all testing and training data should be processed together at once, but it is not suitable for control strategies of a prosthetic hand). For

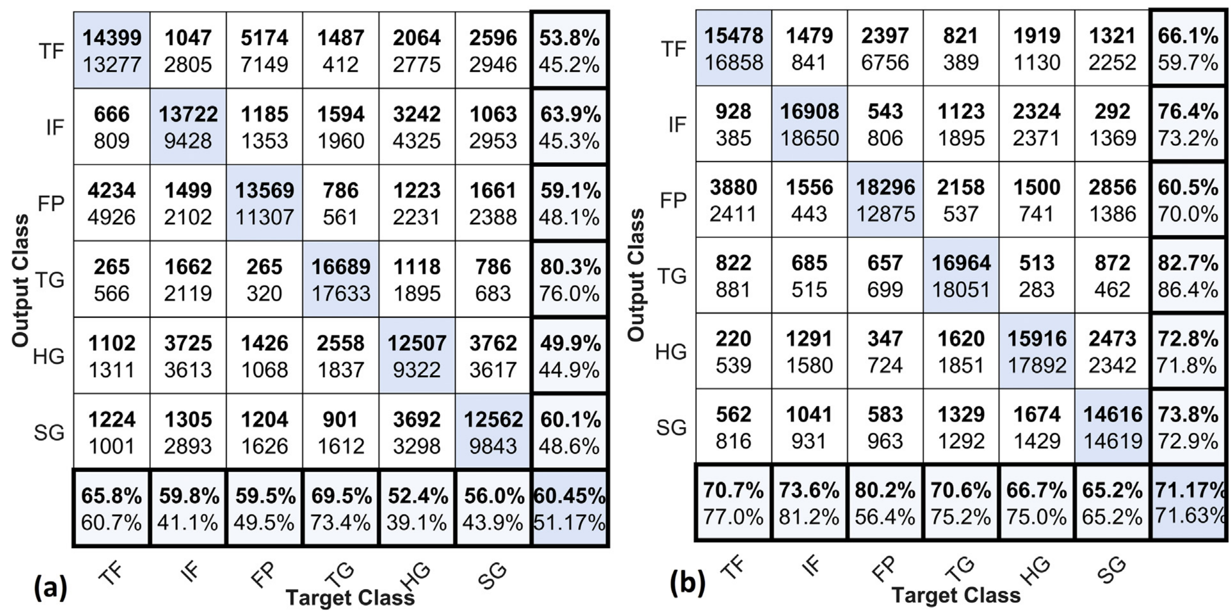

Fig. 7. Confusion matrices of LDA (a), and QDA (b) classifiers for scheme 3. The PRE, and TD-PSD results are presented in bold, and normal font, respectively.

this reason, we apply the same procedure of the TD-PSD without SR to compare with our results. Authors also performed recent EMG feature extraction methods without reduction namely DFT-Norm-1 and DFT-Norm-2 on the dataset [10]. These yielded 70.84%, and 74.14%, respectively. Considering the results of the previous studies on the dataset in terms of accuracy and processing time, the proposed phasor represented form of the EMG signal techniques is effective approach for prosthetic hand control of transradial amputees.

5. Conclusion

The novel electromyography (EMG) feature extraction is proposed for transradial amputees considering prosthetic hand control strategies. The phasor representation of the features for EMG (PRE) is introduced in this paper. Instead of using the well-known EMG methods, namely root mean square (RMS), and waveform length (WL) as feature vector, we construct it depending on phasor diagram inspired by electrode placement on the residual limp. RMS and WL of the 8-channel signals from the transradial amputees are computed, and turned into phasor form according to their electrode angles. After adding logarithmically scaled results of phasor Euclidean distances to them, improved feature extraction is obtained for force level variations. Linear (LDA) and quadratic (QDA) discriminant analysis, and k-nearest neighbor (k-NN) algorithms are used to classify six hand movements with three force levels. Experimental scheme 1 (disregarding the effect of force variations), 2 (tested with unseen force levels), and 3 (tested a single force, trained with all) [2] are simulated to evaluate the performance of the proposed PRE. For scheme 1, LDA with PRE outperforms, but time domain power descriptor (TD-PSD) is more successful than PRE for QDA and k-NN. PRE yields the highest accuracy rates, when unseen force classification. For scheme 3, the most general application of the prosthesis control, our proposed PRE reaches to the accuracy levels of the TD-PSD method (up to 71.17%, and 71.63% with QDA, respectively), but the PRE decreases processing time by 81.83% (from 732.83 s to 133.13 s). k-NN has the highest rate for all schemes, but the delay rate due to processing time makes it impossible for prosthetic control.

Authors' contributions

Fatih Onay: Signal pre-processing, Software.
Ahmet Mert: Methodology, Writing – Reviewing.

Declaration of Competing Interest

The authors declare no conflicts of interest.

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