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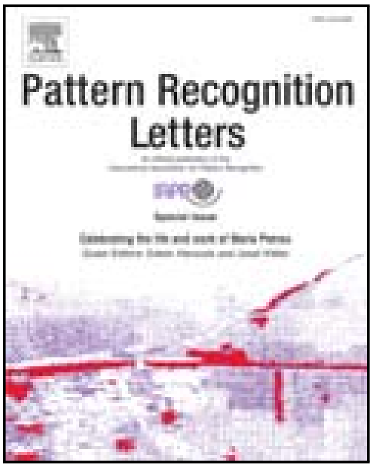

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PII: S0167-8655(22)00351-8
DOI: https://doi.org/10.1016/j.patrec.2022.11.021
Reference: PATREC 8729

To appear in: *Pattern Recognition Letters*

Received date: 12 July 2021
Revised date: 23 October 2022
Accepted date: 18 November 2022

Please cite this article as: Jianing Xue, Zhe Sun, Feng Duan, Cesar F. Caiafa, Jordi Solé-Casals, Underwater sEMG-based Recognition of Hand Gestures using Tensor Decomposition, *Pattern Recognition Letters* (2022), doi: https://doi.org/10.1016/j.patrec.2022.11.021

Highlights

- Acquire sEMG signals underwater based on waterproof the electrode.
- Generate a four-dimensional tensor by wavelet transform.
- Extract features of underwater signals using tensor decomposition.

Underwater sEMG-based Recognition of Hand Gestures using Tensor Decomposition

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Abstract

Amputees have limited ability to complete specific movements because of the loss of hands. Prosthetic hands can help amputees as an effective human-computer interaction system in their daily lives, and some amputees need to use the prosthetic hands for underwater operations. Therefore, it is necessary to solve the problem of using prosthetic hands underwater. There are two main problems in underwater surface Electromyogram (sEMG) signal recognition. The underwater sEMG signals are disturbed by noise, and the traditional sEMG features are easily affected by noise, decreasing the recognition accuracy of underwater sEMG signals. It is difficult for subjects to acquire quantity training data underwater, and satisfactory sEMG recognition accuracy needs to be obtained based on small datasets. Tensor decomposition has the advantage of finding potential features of signals, and it is widely used in many fields. Tucker tensor decomposition was used for feature extraction and recognition of underwater sEMG signals. Seven subjects were selected to complete four hand gestures underwater and two-channel sEMG signals were collected. Wavelet transform was applied to generate a three-dimensional tensor and extracted signal features by tensor decomposition. The recognition accuracy based on K-Nearest Neighbor reaches 96.43%. The results show that the proposed sEMG feature extraction method based on tensor decomposition helps improve the recognition accuracy of underwater sEMG signals, which provides a basis for applying prosthetic hands in a water environment.

Keywords: hand gesture recognition, sEMG signals, tensor decomposition, underwater signal acquisition

1. Introduction

The hand plays an essential role in human interaction with the external environment. The hand can sensitively perceive changes in environmental information, and it can convey human emotions through different gestures. More importantly, the hand can perform many delicate operations, such as grasping, pinching, and pushing. Amputees cannot undertake some daily living activities due to the loss of the hand, which seriously affects their quality of life and has harmful impacts on their lives and work. Amputees can improve their self-care ability with the help of prosthetic hands [1].

The surface Electromyogram (sEMG) signal is the bioelectrical signal that accompanies muscle contraction, and it reflects the level of muscle activity [2]. The sEMG signal can be obtained by attaching non-invasive electrodes to the skin. The sEMG signal is widely used in the clinical and laboratory. The sEMG signal can be used to monitor human activity for the care of elderly persons [3]. It is also important for athletes to improve their performance based on the sEMG. The sEMG signal can be used to evaluate the rehabilitation level of patients [4].

The sEMG signal of the forearm can be used to recognize hand gestures, which is widely used in human-computer interaction. For amputees, the sEMG signal of the forearm can also reflect their hand movement intention. The sEMG signal is ideal control signals for artificial prosthetic hands. Amputees can control prosthetic hands based on the sEMG signal according to their movement intention, and they can use prosthetic hands to replace part of hand functions in daily life [5].

Amputees need to use the prosthetic hands for a long time in their daily life, which requires the prosthetic hands could be used underwater. However, there are currently two problems in the application of prosthetic hands underwater. The traditional feature extraction methods are unsuitable for sEMG signal collected underwater and have adverse effects on recognizing underwater sEMG signal. It is difficult for amputees to collect quantity sEMG signals, which leads to the limitation of the size of the dataset and has an impact on the recognition of hand gestures. It is necessary to propose a novel feature extract method.

Currently, the Ag/AgCl electrode is widely used in laboratory and clinical, and it is considered the gold standard in collecting sEMG signal [6]. The Ag/AgCl electrode is a kind of wet electrode. It has a hydrogel layer at the electrode-skin interface, which reduces the skin-electrode impedance to improve the signal quality [7]. The flexible fabric electrode is also used to collect sEMG signal. For instance, a silver-plated knitted electrode is proposed for the user's comfort in daily life

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[1] Jianing XUE and Zhe SUN contributed equally to the work.

[8]. Traditional sEMG electrodes are not suitable for underwater sEMG signal acquisition. Our existing research proposed a flexible waterproof electrode based on conductive silicone to collect sEMG signals underwater [9]. Our existing research has verified the underwater sEMG signal acquisition performance of the proposed electrode [10].

It is meaningful to obtain helpful information of raw sEMG through feature extraction [11]. The sEMG features mainly include time-domain, frequency-domain, and time-frequency features [12]. Krasoulis et al. used the time-domain features, which were the Mean Absolute Value (MAV), Waveform Length, 4th-order Auto-Regressive coefficients, and Log-Variance [13]. Zhang obtained four features to characterize the sEMG signals, and the features were MAV, Standard Deviation (SD), SD of the frequency-domain, and Wavelet Transform coefficient [14]. Pizzolato et al. extracted five features for signal recognition: Root Mean Square (RMS), Histogram features, and other features [15].

There are many studies on sEMG signal recognition. Samuel et al. proposed three novel time-domain features. The recognition accuracy of upper-limb motions based on Linear Discriminant Analysis (LDA) reaches 92.00% ± 3.11% [16]. Hu et al. introduced a novel attention-based hybrid Convolutional Neural Network and Recurrent Neural Network model. The sEMG recognition accuracy based on the proposed method is higher than that based on the state-of-the-art method [17]. Shi et al. used K-Nearest Neighbors (KNN) for hand gesture online recognition [18]. Qi et al. used the General Regression Neural Network for nine hand gesture recognition [19].

Tensor decomposition can extract potential features of signals, and it is an important tool for multi-dimensional data analysis. It has been widely used in data mining, signal processing, image recognition, and other fields [20]. Currently, commonly used tensor decomposition methods include CANDECOMP/PARAFAC (CP) decomposition [21]and Tucker decomposition [22].

To improve the recognition accuracy of underwater sEMG signals, this paper proposes a feature extraction method of sEMG signals through Tucker decomposition. The contributions of this paper mainly include the following three aspects:

- Propose the feature extraction method based on tensor decomposition and a method for determining the size of the core tensor;
- Compare the recognition accuracy of hand gestures based on tensor decomposition and that based on the traditional sEMG features in the normal environment;
- Prove that the features based on Tucker decomposition can effectively improve the recognition accuracy of underwater hand gestures.

The structure of this paper is as follows. Section II introduces the process of the sEMG signal acquisition. Section III illustrates the method of feature extraction and recognition. Section IV presents the experimental results. Section V discusses the experimental results. Finally, section VI summarizes the conclusions and future work.

2. Signal Acquisition

The sEMG signals are collected in the normal and water environments. This section presents the basic information for sEMG acquisition experiments.

The Ag/AgCl electrode requires additional waterproofing treatment underwater, which greatly limits signal acquisition and affects the application of sEMG. We have proposed a flexible waterproof electrode for sEMG signal acquisition underwater, and previous works have confirmed that it is feasible to collect sEMG signals in the normal environment and in the water environment.

Two-channel sEMG signals have been collected based on the conductive silicone electrode in our previous study [10]. The same sEMG signal data is also used in this paper.

The signal acquisition equipment was the TeleMyo DTS from Noraxon, and the signal acquisition frequency was 1500 Hz. Seven healthy subjects (23.6 ± 1.4) were selected to collect sEMG signals. All subjects understood the experimental process, and they signed informed consent.

The sEMG waterproof electrodes were fixed in the belly of the flexor carpi radialis and extensor carpi ulnaris [23]. Each subject collected 15 trials sEMG signals in the normal environment and in the water environment. The normal environment was our daily living environment. In the water environment, the water was freshwater without unfiltered, and the subject's forearm was 10 cm below the water's surface.

In a trial of the sEMG acquisition, the subject performed four hand gestures, including hand close (HC), hand open (HO), wrist flexion (WF), and wrist extension (WE), in sequence. Each gesture lasted for 5 seconds, there was a 5 second relaxation time between the two gestures, and the signal acquisition time was 40 seconds in a trial.

3. Method

Signal recognition is important for the application of sEMG signals. This section introduces the method of sEMG signal feature extraction and recognition.

3.1. Framework of sEMG Signal Recognition

In order to realize the recognition of sEMG signals collected underwater, this paper proposes an sEMG signal recognition system based on tensor decomposition, and Fig. 1 is the complete framework. It mainly consists of three parts: signal acquisition, feature extraction, and recognition.

The sEMG signal acquisition is carried out in the normal and the water environments, respectively. The sEMG signals are divided into a training set and a test set according to the order of acquisition. In the application of the sEMG, multiple trials of sEMG signals are collected as the training set for training the recognition model at first, and then the trained model is used to recognize the test set.

Three kinds of methods are selected for feature extraction. The time-domain and the frequency-domain features are commonly used in numerous studies. The tensor decomposition is proposed to extract features. At first, create a tensor based on

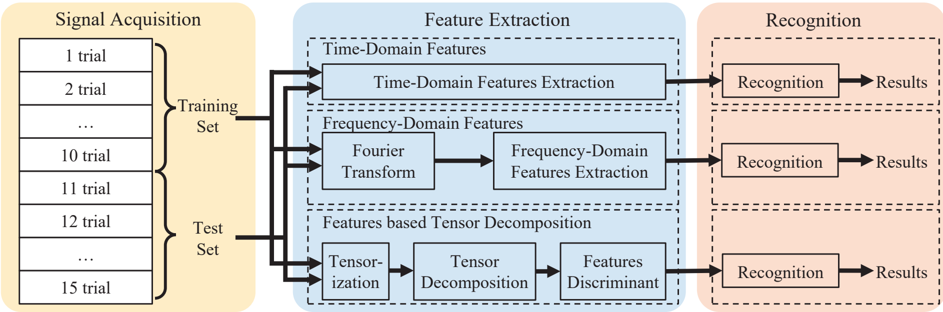


Figure 1: The framework of sEMG signal recognition.

the sEMG signals, and then obtain features by Tucker decomposition. It is noted that the features based on tensor decomposition have high dimensions and are not suitable for direct recognition by machine learning methods. A feature selection method is used to reduce the dimensionality of the features.

KNN is a traditional machine learning method that is highly interpretable, easy to understand, and easy to implement. Due to the high degree of aggregation of sEMG features of the same hand gesture, sEMG signals can be recognized by KNN. The recognition accuracy of hand gestures based on the neural network is related to the initial weights of the network, and the recognition results have certain randomness. In contrast, the recognition accuracy by KNN is only related to the data set. Choose KNN to recognize sEMG signals, and compare the recognition accuracy based on traditional sEMG features and that based on the tensor decomposition features to evaluate the performance of the proposed feature extraction method. Some recognition methods are selected to recognize sEMG signals, including Support Vector Machine (SVM), Random Forest(RF), Decision Tree(DT), and LDA.

3.2. Time-Domain Features

Time-domain features are widely used because of their low computational complexity. They are extracted from raw sEMG signals and mainly correspond to the signal amplitude. Four time-domain features are selected. The length of a segment for feature extraction is 200 ms.

RMS reflects the average amplitude of sEMG signals, and it is related to the force of muscle flexion or extension.

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} {x_i}^2} \tag{1}$$

where x_i is a segment of the sEMG signals; and N is the length of a segment.

MAV also reflects the level of muscle activities, and it is the mean absolute value of the sEMG signals.

$$MAV = \frac{1}{N}\sum_{i=1}^{N} |x_i| \tag{2}$$

VAR reflects the variance of the sEMG signals.

$$VAR = \frac{1}{N-1}\sum_{i=1}^{N} (x_i - \bar{x})^2 \tag{3}$$

Zero Crossing (ZC) is the number of changes for the sign of signals [24].

$$ZC = \sum_{i=1}^{N-1} sgn\,(-x_i x_{i+1}) \tag{4}$$

The sEMG time-domain feature normalization is performed through Log Transformation. Features based on Log Transformation have a more symmetrical distribution shape and a smaller range than raw features, which are more helpful for recognition. Furthermore, the Log Transformation reduces the influence of outliers on the recognition results.

3.3. Frequency-Domain Features

Four kinds of features are selected as the frequency-domain features. The length of a segment for calculating frequency features is 200 ms. Log Transformation is used to obtain features based on the raw frequency-domain features.

Median Frequency (MDF) is defined as the frequency for which the following condition is met [25]:

$$\int_0^{MDF} psd\,(f)\,\mathrm{d}f = \int_{MDF}^{M} psd\,(f)\,\mathrm{d}f \tag{5}$$

where $psd(f)$ is the Power Spectral Density (PSD); and M is the maximum frequency. The PSD of the sEMG signals is obtained based on the welch method with the hanning window.

Peak Frequency (PKF) is the frequency corresponding to the peak of the PSD, which reflects the main frequency of the power spectrum of the sEMG [26].

$$PKF = argmax\,(psd\,(f)) \tag{6}$$

Mean Frequency (MNF) refers to the average frequency of the sEMG [27].

$$MNF = \frac{\int_0^M f psd\,(f)\,\mathrm{d}f}{\int_0^M psd\,(f)\,\mathrm{d}f} \tag{7}$$

Mean Power (MNP) refers to the average power of the sEMG based on the frequency [28].

$$MNP = \frac{\int_0^M psd\,(f)\,\mathrm{d}f}{M} \tag{8}$$

3.4. Features based on Tensor Decomposition

Single-dimensional features only in the time or frequency domain are not enough to reflect the information of the sEMG signals collected in different environments. Tensor decomposition is an excellent method for analyzing high-dimensional signals. Tensor decomposition is utilized for multi-domain sEMG feature extraction.

3.4.1. Tensorization

Tensor is a generalization of matrix, and it is regarded as a multi-index array. Tensorization is the process of creating a data tensor [29]. The tensor can be created by rearranging low-dimensional data. A mathematical method can transform data to a tensor, such as Wavelet Transform. Finally, some multi-domain data also can naturally be regarded as a tensor.

The sEMG signal is a two-dimensional signal based on the temporal and spatial domains. The frequency-domain information is the important feature of the sEMG, and the Wavelet Transformation is used to obtain it. Then a third-order tensor based on the frequency domain, the temporal domain, and the spatial domain is obtained. This process is called sEMG signal tensorization.

A tensor based on the two-channel sEMG signals is created. The size of raw sEMG signals is $60000 \times 2 \times 15$ (temporal $\times$ spatial $\times$ trial). The sEMG signals in the middle 3 seconds of each gesture are selected for recognition, and the data size is $18000 \times 2 \times 15$ (temporal $\times$ spatial $\times$ trial). In order to extract features, the sEMG signals are divided into 900 segments, each segment is the sEMG signals of 200 ms, and signals are obtained of which size is $300 \times 2 \times 900$ (temporal $\times$ spatial $\times$ repetitions). The signals are transformed into the time-frequency-domain signals by Morlet Wavelet Transform. The sEMG tensor is obtained with a size of $75 \times 75 \times 2 \times 900$ (spectral $\times$ temporal $\times$ spatial $\times$ repetitions).

3.4.2. Tensor Decomposition

The three-order tensor is taken as an example, where the raw tensor is approximated by the product of a core tensor and factor matrices. The raw tensor $\mathcal{X} \in \mathbb{R}^{I_1 \times I_2 \times I_3}$ can be expressed as:

$$\mathcal{X} \cong \mathcal{G} \times_1 U^{(1)} \times_2 U^{(2)} \times_3 U^{(3)} \tag{9}$$

where $\mathcal{G} \in \mathbb{R}^{R_1 \times R_2 \times R_3}$ is the core tensor; $U^{(1)} \in \mathbb{R}^{I_1 \times R_1}$, $U^{(2)} \in \mathbb{R}^{I_2 \times R_2}$, and $U^{(3)} \in \mathbb{R}^{I_3 \times R_3}$ are the factor matrices; and $\times_n (n = 1, 2, 3)$ is the mode-n product of tensor and matrix. The core tensor $\mathcal{G}$ has a lower dimension than $\mathcal{X}$. The scalar representation of Tucker decomposition is:

$$x_{i_1 i_2 i_3} = \sum_{r_1=1}^{R_1} \sum_{r_2=1}^{R_2} \sum_{r_3=1}^{R_3} g_{r_1 r_2 r_3} u^{(1)}_{i_1 r_1} u^{(2)}_{i_2 r_2} u^{(3)}_{i_3 r_3} \tag{10}$$

where, $x_{i_1 i_2 i_3}$ is the $\mathcal{X}$ element; $g_{r_1 r_2 r_3}$ is the $\mathcal{G}$ element; and $u^{(1)}_{i_1 r_1}$, $u^{(2)}_{i_2 r_2}$, and $u^{(3)}_{i_3 r_3}$ are the element of the $U^{(1)}$, $U^{(2)}$, and $U^{(3)}$.

The hand gesture recognition based on Tucker decomposition is shown in Fig. 2 [30]. Three-order Tucker decomposition is applied to the first three dimensions of the four-order sEMG tensor that is equivalent to 900 third-order sEMG tensors. Each third-order sEMG tensor in the training set $\mathcal{X}_{tr}$ approximates the product of the core tensor and factor matrix by Tucker decomposition, ensuring that 600 sEMG tensors in the training set obtain the same factor matrix through tensor decomposition, and the factor matrix is the basic factor matrix $U^{(n)} (n = 1, 2, 3)$. According to the basic factor matrix, the corresponding core tensors $\mathcal{G}_{tr}$ can be obtained. The test features $\mathcal{G}_{te}$ can be extracted based on the test set $\mathcal{X}_{te}$ and the basic factor matrix. Tucker factors matrix must be fixed for all repetitions, and only the core tensor is computed for each sEMG tensor [31].

The size of the core tensor has an important influence on the recognition results. The appropriate size of the core tensor is different based on different signals and different classifiers. To determine the size of the core tensor, the 5-fold cross-validation method is used to obtain the recognition accuracy of the training set based on the different sizes of the core tensor.

3.4.3. Feature Discriminant

The features obtained by the Tucker decomposition are redundant, and the Fisher discriminant analysis is used for the dimensionality reduction.

The method of Fisher discriminant analysis is used to obtain the score of features [32], and a high score of a feature means that the feature provides more information for recognition. Preserve the top n features with the highest scores and propose a method to determine a suitable n. The score of the n^{th} feature is significantly lower than that of the $(n-1)^{th}$ feature, but its score is not significantly higher than the score of the $(n+1)^{th}$ feature. The information contained in the $(n+1)^{th}$ feature is thought to be redundant. The top n features are selected as the final features. The method is expressed as follows:

$$s(n-1) - s(n) \geq Thre \tag{11}$$

$$s(n) - s(n+1) < Thre \tag{12}$$

where $s(n)$ is the score of the n^{th} feature; $Thre$ is the threshold for judging whether the scores of two features are significantly different. If the score of the n^{th} feature satisfies equation 11 and equation 12, the top n features are reserved as the features of the sEMG signals. To determine the appropriate threshold, the 5-fold cross-validation method is used to obtain the recognition accuracy of the training set based on different thresholds.

4. Results

The sEMG signals were collected in a normal environment and a water environment. Three kinds of features were extracted based on time-domain, frequency-domain, and tensor decomposition. The machine learning methods were used to perform hand gesture recognition.

4.1. Recognition in a Normal Environment

The recognition model is trained based on the training set and the recognition accuracy is obtained based on the test set. The

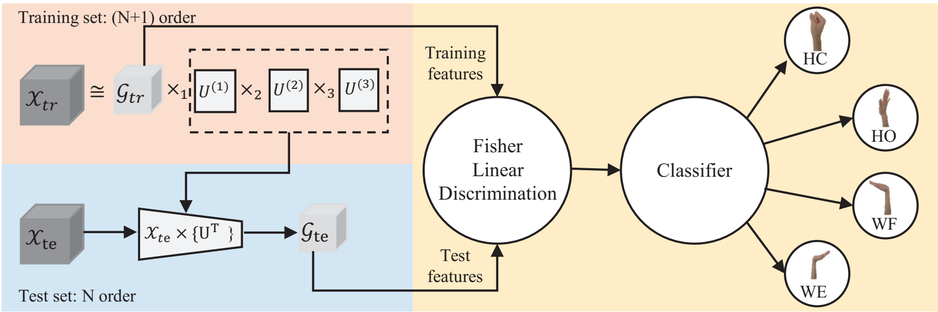


Figure 2: Hand gestures recognition based on Tucker decomposition.

Table 1: Recognition in a Normal Environment Based Time-Domain Features (%)

Method	KNN	SVM	RF	DT	LDA
Subject 1	86.00	85.33	89.00	85.67	84.67
Subject 2	97.33	97.67	96.00	95.33	99.33
Subject 3	99.33	99.33	96.67	94.33	99.33
Subject 4	96.67	97.00	97.67	98.00	97.33
Subject 5	96.00	95.33	95.67	95.00	96.33
Subject 6	91.00	92.00	91.67	88.33	92.33
Subject 7	99.33	99.33	99.67	97.67	99.00
Average	95.09	95.14	95.19	93.48	95.47

Table 2: Recognition in a Normal Environment Based Frequency-Domain Features (%)

Method	KNN	SVM	RF	DT	LDA
Subject 1	83.00	85.00	88.67	78.67	85.00
Subject 2	95.67	97.67	98.33	94.00	96.00
Subject 3	96.33	96.67	96.33	96.33	96.67
Subject 4	97.00	97.33	95.67	94.67	97.00
Subject 5	93.33	95.33	94.67	95.00	96.33
Subject 6	88.00	90.67	89.00	88.00	92.67
Subject 7	98.67	99.67	96.33	97.33	98.67
Average	93.14	94.62	94.14	92.00	94.62

results determine whether the tensor decomposition is suitable for recognizing sEMG collected in a normal environment.

Based on the time-domain features, the average recognition test accuracy of KNN is 95.09%. It can be found that the hand gesture recognition accuracy based on different machine learning methods is similar except based on DT.

Based on the frequency-domain features, the recognition accuracy by KNN is 93.14%, and the results of recognizing hand gestures by other classifiers are shown in Table 2. The recognition accuracy based on SVM and that based on LDA are the highest, and the recognition accuracy based on DT is the lowest.

According to the recognition accuracy of the training set, for the sEMG collected in the normal environment, the size of the core tensor and the threshold based on different classifiers are shown in Table 3. As shown in Table 4, the recognition accuracy based on tensor decomposition features by KNN is

Table 3: The Size of the Core Tensor and the Threshold in the Normal Environment

Method	Core size	Threshold
KNN	$14 \times 13 \times 2$	0.0012
SVM	$13 \times 16 \times 2$	0.0001
RF	$20 \times 19 \times 2$	0.0013
DT	$9 \times 18 \times 2$	0.0017
LDA	$10 \times 13 \times 2$	0.001

Table 4: Recognition in a Normal Environment Based Tensor Decomposition Features (%)

Method	KNN	SVM	RF	DT	LDA
Subject 1	89.33	91.00	90.33	88.33	91.00
Subject 2	98.67	98.67	97.67	95.67	96.33
Subject 3	97.33	96.67	97.00	94.67	94.00
Subject 4	98.00	98.00	91.67	95.67	91.33
Subject 5	99.67	99.67	98.67	98.33	98.33
Subject 6	94.67	94.33	90.33	87.33	93.00
Subject 7	99.33	99.00	98.33	97.33	97.67
Average	96.71	96.76	94.86	93.90	94.52

96.71%. A satisfactory hand gesture recognition results can be obtained based on KNN and SVM.

Using KNN and SVM to recognize hand gestures, the features based on tensor decomposition are significantly better than traditional sEMG features. Using RF, DT, and LDA to recognize hand gestures, the recognition accuracy based on tensor decomposition features is similar to that based on traditional features. The tensor decomposition features combined with SVM or KNN can get the highest recognition accuracy.

4.2. Recognition in a Water Environment

The recognition accuracy in a water environment is obtained, proving that the tensor decomposition improves the recognition accuracy for the underwater sEMG signals.

Based on time-domain features, the recognition accuracy by KNN is 91.86%. The recognition accuracy based on LDA is highest, and the recognition accuracy based on DT is the lowest.

Based on the frequency-domain features, the recognition accuracy by KNN reaches 91.43%. Table 6 shows the recognition

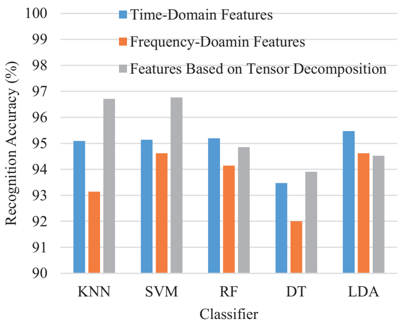


Figure 3: Hand gesture recognition in the normal environment.

Table 5: Recognition in a Water Environment Based Time-Domain Features (%)

Method	KNN	SVM	RF	DT	LDA
Subject 1	90.67	91.00	92.00	91.67	94.33
Subject 2	87.67	84.00	76.33	73.00	89.67
Subject 3	97.00	94.67	96.67	94.00	98.00
Subject 4	97.33	97.67	97.67	97.00	99.00
Subject 5	83.33	89.00	86.67	84.33	91.00
Subject 6	87.00	88.00	86.00	89.00	91.67
Subject 7	100.00	100.00	99.67	99.67	100.00
Average	91.86	92.05	90.72	89.81	94.81

Table 6: Recognition in a Water Environment Based Frequency-Domain Features (%)

Method	KNN	SVM	RF	DT	LDA
Subject 1	91.00	91.67	91.67	90.00	90.33
Subject 2	84.67	92.00	81.33	77.00	90.33
Subject 3	95.33	97.33	93.00	94.33	99.33
Subject 4	98.00	97.67	98.33	97.67	98.33
Subject 5	84.67	89.33	90.00	83.33	88.67
Subject 6	86.33	89.67	86.67	83.33	91.33
Subject 7	100.00	99.67	99.67	98.33	99.33
Average	91.43	93.91	91.52	89.14	93.95

Table 7: The Size of the Core Tensor and the Threshold in the Water Environment

Method	Core size	Threshold
KNN	$17 \times 10 \times 2$	0.0002
SVM	$15 \times 10 \times 2$	0.0002
RF	$18 \times 18 \times 2$	0.001
DT	$10 \times 15 \times 2$	0.0019
LDA	$19 \times 18 \times 2$	0.0007

results for each subject. As same as based on the time-domain features, it is challenging to recognize HO based on KNN.

For the sEMG signals in a water environment, the size of the core tensor and the threshold are shown in Table 7. The recognition accuracy by KNN based on tensor decomposition features is 96.43%. sEMG signals collected underwater can be accurately recognized by KNN.

Using machine learning methods to recognize hand gestures, except LDA, the recognition results based on tensor decomposition features are significantly better than traditional sEMG features. The recognition accuracy by LDA based on tensor decomposition features is similar to that based on traditional features. The tensor decomposition features combined with KNN obtain the highest recognition accuracy.

5. Discussion

The results demonstrate that the tensor decomposition is reliable for feature extraction. Especially in a water environment, signal feature can be extracted by the tensor decomposition to improve the recognition accuracy.

5.1. Principal Findings

The recognition accuracy decreases underwater compared with that in a normal environment. The paper speculates on the reasons for the decline in recognition accuracy. Water fluctuation decreases the signal quality and signal-to-noise ratio during the underwater signal acquisition process, which leads to a decrease in recognition accuracy. The traditional sEMG features are based on raw sEMG signals, and they will be affected if raw signals contain noise. Traditional feature extraction methods are susceptible to noise, such as RMS is easily affected by noise. The underwater recognition accuracy based on tensor decomposition features is highest. Since tensor decomposition can extract the potential features of the sEMG signals, it can remove some components produced by noise and preserve the components produced by the sEMG signals. The features extracted by Tucker decomposition are not easily affected by noise, and it is helpful to improve the underwater sEMG signal recognition accuracy.

It can be found that HO is easily mistaken based Fig. 5. The paper speculates the reason for the low recognition accuracy of HO. The sEMG of HO has a small amplitude and a low signal power. The sEMG of HO is easily interfered with by noise, and the proportion of noise and movement artifacts in the sEMG increases, resulting in a low recognition accuracy of HO.

The recognition accuracy of underwater sEMG signals is effectively improved based on tensor decomposition features by machine learning methods except for LDA. There is no significant difference between the recognition accuracy based on tensor decomposition features and traditional features when selecting LDA as the classifier. Features extraction by tensor decomposition includes tensor decomposition and feature selection. It is speculated that because the feature selection method has similarities with LDA, the advantages of tensor decomposition cannot be reflected when selecting LDA as the classifier. The specific reasons deserve further research.

5.2. Ablation Experiment

The paper further studies the method of extracting sEMG features by tensor decomposition. The feature extraction by tensor decomposition includes two steps: Tucker decomposition and

Table 8: Recognition in a Water Environment Based Tensor Decomposition Features(%)

Method	KNN	SVM	RF	DT	LDA
Subject 1	95.33	94.33	94.00	93.00	93.33
Subject 2	95.00	91.33	88.33	85.00	92.33
Subject 3	97.67	96.33	91.67	94.33	98.33
Subject 4	99.67	98.33	98.67	96.33	94.67
Subject 5	91.00	90.67	89.67	83.33	91.00
Subject 6	96.67	95.67	90.33	92.33	95.00
Subject 7	99.67	100.00	98.67	98.33	98.67
Average	96.43	95.24	93.05	91.81	94.76

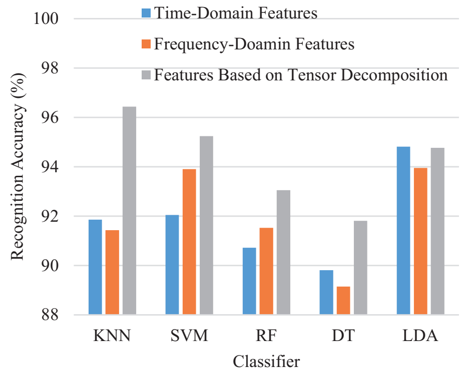


Figure 4: Hand gesture recognition in the water environment.

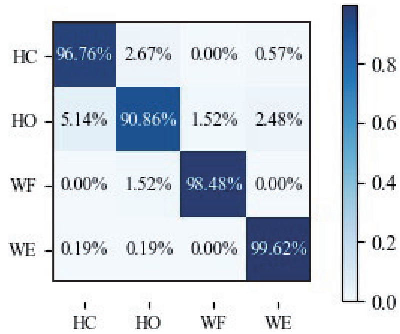
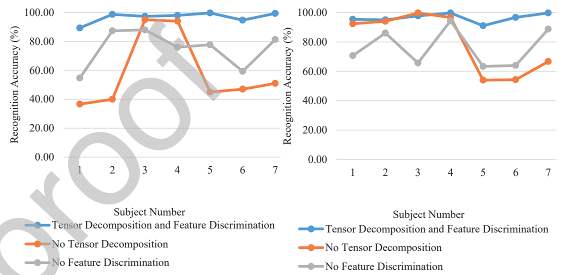


Figure 5: Recognition confusion matrix based tensor decomposition in the water environment by KNN.



(a) In the normal environment (b) In the water environment

Figure 6: Recognition results based tensor decomposition by KNN

feature discrimination. In order to explore the influence of these two components on the recognition results, an ablation experiment is designed. The recognition accuracy based on KNN without tensor decomposition or feature discrimination is calculated. Fig. 6(a) and Fig. 6(b) are the experimental results in the different environments. The experimental results show that satisfactory results cannot be obtained without tensor decomposition or feature discrimination. Valuable features cannot be extracted only based on feature discrimination method without tensor decomposition, and the dimension of the core tensor base on Tucker decomposition is too large without feature discrimination, resulting in a decrease in recognition accuracy.

5.3. Limitations and Future Work

Although our proposed method can effectively improve the recognition accuracy of underwater hand gestures, it also has shortcomings. The sEMG feature extraction based on tensor decomposition take more time than traditional sEMG feature extraction. The computation complexity of extracting time-domain features is the lowest. Extracting frequency-domain features requires Fourier transformation first, which increases the computational cost. The proposed feature extraction method requires Wavelet Transformation. The time it costs mainly includes Wavelet Transformation and mode-n product of tensor and matrix. It is also necessary to spend time obtaining the factor matrix during the training process. In future research, the sEMG tensor with a smaller dimension by Wavelet Transformation will be obtained, which can reduce the computation complexity of Wavelet Transformation and the mode-n product of tensor and matrix.

In future work, the real-time sEMG signals will be collected in the water environment. The hand gestures based on sEMG signals will be recognized in real-time using tensor decomposition, and it will be used to control the sEMG prosthesis hands.

6. Conclusion

Underwater sEMG signal acquisition and recognition are widely needed in numerous fields. In order to solve the problem of underwater sEMG signal recognition, this paper proposes an sEMG signal recognition system based on tensor decomposition. The waterproof electrode was used to collect two-channel sEMG signals in a water environment. Furthermore, tensor decomposition was used to extract features and machine learning methods were chose to recognize hand gestures. The recognition accuracy of four hand gestures based on KNN and tensor decomposition features is 96.43%. Thus, The proposed method can achieve underwater sEMG signal recognition. In the future, more gestures will be recognized.

Acknowledgments

This work was supported by the National Key R&D Program of China [No. 2017YFE0129700], the National Natural Science Foundation of China (Key Program) [No. 11932013], the Tianjin Natural Science Foundation for Distinguished Young Scholars [No. 18JCJQJC46100], and Tianjin Research Innovation Project for Postgraduate Students under Grant [No. 2020YJSB003].

Conflict of Interest

The authors declare that there is no conflict of interest.

References

[1] H. Zhou, A. Mohamtnadi, D. Oetomo, G. Alici, A novel monolithic soft robotic thumb for an anthropomorphic prosthetic hand, IEEE Robotics and Automation Letters 4 (2) (2019) 602–609. doi:10.1109/lra.2019.2892203.

[2] Y. Zhou, J. B. Liu, J. Zeng, K. R. Li, H. H. Liu, Bio-signal based elbow angle and torque simultaneous prediction during isokinetic contraction, Science China-Technological Sciences 62 (1) (2019) 21–30. doi:10.1007/s11431-018-9354-5.

[3] P. Kumari, L. Mathew, P. Syal, Increasing trend of wearables and multimodal interface for human activity monitoring: A review, Biosensors and Bioelectronics 90 (2017) 298–307. doi:10.1016/j.bios.2016.12.001.

[4] D. Volpe, F. Spolaor, Z. Sawacha, A. Guiotto, D. Pavan, L. Bakdounes, V. Urbani, G. Frazzitta, R. Iansek, Muscular activation changes in lower limbs after underwater gait training in parkinson's disease: A surface EMG pilot study, Gait and Posture 80 (2020) 185–191. doi:10.1016/j.gaitpost.2020.03.017.

[5] M. Tavakoli, C. Benussi, J. L. Lourenco, Single channel surface EMG control of advanced prosthetic hands: A simple, low cost and efficient approach, Expert Systems with Applications 79 (2017) 322–332. doi:10.1016/j.eswa.2017.03.012.

[6] L. Guo, L. Sandsjo, M. Ortiz-Catalan, M. Skrifvars, Systematic review of textile-based electrodes for long-term and continuous surface electromyography recording, Textile Research Journal 90 (2) (2020) 227–244. doi:10.1177/0040517519858768.

[7] H. F. Posada-Quintero, R. T. Rood, K. Burnham, J. Pennace, K. H. Chon, Assessment of carbon/salt/adhesive electrodes for surface electromyography measurements, IEEE Journal of Translational Engineering in Health and Medicine-Jtehm 4. doi:10.1109/jtehm.2016.2567420.

[8] S. Lee, M. O. Kim, T. Kang, J. Park, Y. Choi, Knit band sensor for myoelectric control of surface EMG-based prosthetic hand, IEEE Sensors Journal 18 (20) (2018) 8578–8586. doi:10.1109/jsen.2018.2865623.

[9] J. Xue, Y. Yang, J. Chen, Y. Jiang, C. Zhu, H. Yokoi, F. Duan, The development of an underwater sEMG signal recognition system based on conductive silicon, in: 2019 IEEE International Conference on Advanced Robotics and Its Social Impacts (ARSO), 2019, pp. 387–392.

[10] F. Duan, J. Xue, Z. Sun, X. Chen, Y. Liu, H. Yokoi, A novel waterproof sEMG electrode based on conductive silicone for underwater signal recognition, IEEE Sensors Journal.

[11] A. Phinyomark, R. N. Khushaba, E. Ibanez-Marcelo, A. Patania, E. Scheme, G. Petri, Navigating features: a topologically informed chart of electromyographic features space, Journal of the Royal Society Interface 14 (137) (2017) 12. doi:10.1098/rsif.2017.0734.

[12] Y. K. Gu, D. P. Yang, Q. Huang, W. Yang, H. Liu, Robust EMG pattern recognition in the presence of confounding factors: features, classifiers and adaptive learning, Expert Systems with Applications 96 (2018) 208–217. doi:10.1016/j.eswa.2017.11.049.

[13] A. Krasoulis, I. Kyranou, M. S. Erden, K. Nazarpour, S. Vijayakumar, Improved prosthetic hand control with concurrent use of myoelectric and inertial measurements, Journal of Neuroengineering and Rehabilitation 14 (2017) 14. doi:10.1186/s12984-017-0284-4.

[14] L. Zhang, An upper limb movement estimation from electromyography by using BP neural network, Biomedical Signal Processing and Control 49 (2019) 434–439. doi:10.1016/j.bspc.2018.12.020.

[15] S. Pizzolato, L. Tagliapietra, M. Cognolato, M. Reggiani, H. Muller, M. Atzori, Comparison of six electromyography acquisition setups on hand movement classification tasks, Plos One 12 (10) (2017) 17. doi:10.1371/journal.pone.0186132.

[16] O. W. Samuel, H. Zhou, X. X. Li, H. Wang, H. S. Zhang, A. K. Sangaiah, G. L. Li, Pattern recognition of electromyography signals based on novel time domain features for amputees' limb motion classification, Computers and Electrical Engineering 67 (2018) 646–655. doi:10.1016/j.compeleceng.2017.04.003.

[17] Y. Hu, Y. K. Wong, W. T. Wei, Y. Du, M. Kankanhalli, W. D. Geng, A novel attention-based hybrid CNN-RNN architecture for sEMG-based gesture recognition, Plos One 13 (10) (2018) 18. doi:10.1371/journal.pone.0206049.

[18] W. T. Shi, Z. J. Lyu, S. T. Tang, T. L. Chia, C. Y. Yang, A bionic hand controlled by hand gesture recognition based on surface EMG signals: A preliminary study, Biocybernetics and Biomedical Engineering 38 (1) (2018) 126–135. doi:10.1016/j.bbe.2017.11.001.

[19] J. X. Qi, G. Z. Jiang, G. F. Li, Y. Sun, B. Tao, Surface EMG hand gesture recognition system based on PCA and GRNN, Neural Computing and Applications 32 (10) (2020) 6343–6351. doi:10.1007/s00521-019-04142-8.

[20] Z. Zhang, S. Aeron, Exact tensor completion using t-SVD, IEEE Transactions on Signal Processing 65 (6) (2017) 1511–1526. doi:10.1109/tsp.2016.2639466.

[21] Q. B. Zhao, L. Q. Zhang, A. Cichocki, Bayesian CP factorization of incomplete tensors with automatic rank determination, IEEE Transactions on Pattern Analysis and Machine Intelligence 37 (9) (2015) 1751–1763. doi:10.1109/tpami.2015.2392756.

[22] N. D. Sidiropoulos, L. De Lathauwer, X. Fu, K. Huang, E. E. Papalexakis, C. Faloutsos, Tensor decomposition for signal processing and machine learning, IEEE Transactions on Signal Processing 65 (13) (2017) 3551–3582. doi:10.1109/tsp.2017.2690524.

[23] F. Duan, L. L. Dai, W. N. Chang, Z. Q. Chen, C. Zhu, W. Li, sEMG-based identification of hand motion commands using wavelet neural network combined with discrete wavelet transform, IEEE Transactions on Industrial Electronics 63 (3) (2016) 1923–1934. doi:10.1109/tie.2015.2497212.

[24] Y. F. Fang, D. L. Zhou, K. R. Li, H. H. Liu, Interface prostheses with classifier-feedback-based user training, IEEE Transactions on Biomedical Engineering 64 (11) (2017) 2575–2583. doi:10.1109/tbme.2016.2641584.

[25] E. F. Shair, S. A. Ahmad, M. H. Marhaban, S. B. M. Tamrin, A. R. Abdullah, EMG processing based measures of fatigue assessment during manual lifting, Biomed Research International 2017. doi:10.1155/2017/3937254.

[26] S. Pancholi, A. M. Joshi, Portable EMG data acquisition module for upper limb prosthesis application, IEEE Sensors Journal 18 (8) (2018) 3436–3443. doi:10.1109/jsen.2018.2809458.

[27] P. A. Karthick, D. M. Ghosh, S. Ramakrishnan, Surface electromyography based muscle fatigue detection using high-resolution time-frequency methods and machine learning algorithms, Computer Methods and Programs in Biomedicine 154 (2018) 45–56. doi:10.1016/j.cmpb.2017.10.024.

[28] R. H. Chowdhury, M. B. I. Reaz, M. A. B. Ali, A. A. A. Bakar, K. Chellappan, T. G. Chang, Surface electromyography signal processing and classification techniques, Sensors 13 (9) (2013) 12431–12466. doi:10.3390/s130912431.

[29] A. Cichocki, D. P. Mandic, A. H. Phan, C. F. Caiafa, G. X. Zhou, Q. B. Zhao, L. De Lathauwer, Tensor decompositions for signal processing applications, IEEE Signal Processing Magazine 32 (2) (2015) 145–163. doi:10.1109/msp.2013.2297439.

[30] P. Xie, Y. Song, Multi-domain feature extraction from surface EMG signals using nonnegative tensor factorization, in: IEEE International Conference on Bioinformatics and Biomedicine (IEEE BIBM), 2013.

[31] A. Cichocki, N. Lee, I. Oseledets, A. H. Phan, Q. B. Zhao, D. P. Mandic, Tensor Networks for Dimensionality Reduction and Large-Scale Optimization Part 1 Low-Rank Tensor Decompositions, Vol. 9, 2017.

[32] A. H. Phan, A. Cichocki, Tensor decompositions for feature extraction and classification of high dimensional datasets, Nonlinear Theory and Its Applications, IEICE 1 (1) (2010) 37–68. doi:10.1587/nolta.1.37.

Decla

The authors have no conflicts of interest directly relevant to the content of this article.