Classifier Performance Evaluation in Wrist and Finger Movement Fitting Task Based on Forearm HD-sEMG

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Research Article

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Abstract

Background: The transmission of human body movements to other devices through wearable smart bracelets have attracted more and more attentions in the field of human-machine interface (HMI) applications. However, due to the limitation of the collection range of wearable bracelets, it is necessary to study the relationship between the superposition of wrist and finger motion and their cooperative motion to simplify the collection system of the device.

Methods: The multi-channel high-density surface electromyogram (HD-sEMG) signal has high spatial resolution and can improve the accuracy of multi-channel fitting. In this study, we quantified the HD-sEMG forearm spatial activation features of 256 channels of hand movement, and performed a linear fitting of the quantified features of fingers and wrist movements to verify the linear superposition relationship between fingers and wrist cooperative movements and their independent movements. The most important thing is to classify and predict the results of the fitting and the actual measured fingers and wrist cooperative actions by four commonly used classifiers: Linear Discriminant Analysis (LDA) ,K-Nearest Neighbor (KNN) ,Support Vector Machine (SVM) and Random Forest (RF), and evaluate the performance of the four classifiers in gesture fitting in detail according to the classification results.

Results: In a total of 12 kinds of synthetic gesture actions, in the three cases where the number of fitting channels was selected as 8, 32 and 64, four classifiers of LDA, SVM, RF and KNN are used for classification prediction. When the number of fitting channels was 8, the prediction accuracy of LDA classifier was 99.70%, the classification accuracy of KNN was 99.40%, the classification accuracy of SVM was 99.20%, and the classification accuracy of RF was 93.75%. When the number of fitting channels was 32, the accuracy of LDA was 98.51%, the classification accuracy of KNN was 97.92%, the accuracy of SVM is 96.73%, and the accuracy of RF was 86.61%. When the number of fitting channels is 64, the accuracy of LDA is 95.83%, the classification accuracy of KNN is 91.67%, the accuracy of SVM is 86.90%, and the accuracy of RF is 83.30%.

Conclusion: It can be seen from the results that when the number of fitting channels is 8, the classification accuracy of the three classifiers of LDA, KNN and SVM is basically the same, but the time-consuming of SVM is very small. When the amount of data is large, the priority should be selected SVM as the classifier. When the number of fitting channels increases, the classification accuracy of the LDA classifier will be higher than the other three classifiers, so the LDA classifier should be more appropriate. The classification accuracy of the RF classifier in this type of problem has always been far lower than the other three classifiers, so it is not recommended to use the RF classifier as a classifier for gesture stacking related work.

Introduction

The transmission of human body movements to other devices through wearable smart bracelets[1] have attracted more and more attentions in the field of human-machine interface (HMI) applications [2].

However, on account of the collection range of the smart bracelet is very limited to the small position of the wrist, so it is necessary to simplify the acquired signal of the hand to expand the collection range of the bracelet to the limb signal and improve the signal processing accuracy. Due to the independent and cooperative movement between fingers and wrist, the human hand is capable of producing complex and high-precision movements [3, 4]. Therefore, the study of independent and coordinated movements between fingers and wrist can further simplify the signals expression, thus greatly improving the input efficiency of bracelet.

Previous studies had focused on independent movements of finger or wrist movements. With the rapid development of flexible electrodes and sensors, the introduction of high-density surface electromyogram (HD-sEMG) [5, 6, 7] technology on human skin surface, study limb movements by acquiring and analyzing EMG signals of human forearm muscles had been proved to be the most effective method [8]. However, previous studies had focused on the classification of gestures as independent of fingers or wrist movements, or on the spatial activation characteristics of forearm muscles based on fingers or wrist movements. Dai et al. [9] classified the spatial activation characteristics of forearm muscles during single-finger movement. In their study, LDA classifier was used to distinguish the types of different fingers, but the correlation between fingers and wrist movements was not mentioned. Jiang et al.[10] studied through the HD-SEMG signal of hand under different finger movements, and their result proved that HD-SEMG signal of hand can be an effective feature of biometric recognition. But there was no study on the correlation between the independent actions of fingers and wrist movements and their coordinated actions. Marco et al.[11] quantified the spatial activation characteristics of human forearm muscles under the condition of fingers and wrist movement, but there was a lack of relevant studies on the coordinated movement of fingers and wrist. Therefore, so far, it was still a vacuum field to study the relationship between the independent actions of fingers and wrist and their coordinated actions, and to represent the coordinated actions of fingers and wrist through their independent actions.

Accordingly, the objective of this study was to explore the performance of the four kinds of classifiers commonly used in the study of hand movements in the classification and prediction of finger movements or wrist movements and the cooperative movements of these two movements. Specifically, our study makes the following contributions:

1)In the action superposition level in this study, electromyography (EMG) signals of forearm flexor and extensor muscles during hand movement were collected through 256 high-density acquisition channels. After quantifying the high resolution muscle spatial activation features of these high density EMG signals, the quantitative features of fingers and wrist movements were multi-channel linearly fitted to obtain the linear superposition of the two composite signals.

2)In classifier performance evaluation level in this study, the linear superposition composite signal of finger and wrist and the collected cooperative actions of fingers and wrist were put into four kinds of classifiers for classification and prediction. These four kinds of classifiers are commonly used

classification and prediction methods for EMG signal processing. Most importantly, the performance of these four classifiers was compared and evaluated in detail according to the classification results.

As far as we know, this is the first time to study the superposition of finger and wrist through 20 movements of 14 subjects, and also the first time to evaluate the performance of the predictive classifier used in this superposition relationship, which has great guiding significance for the simplification of finger and wrist cooperative signals in the future.

Results

In this paper, as for the number of fitting channels, three cases for comparison were demonstrated, which were 8 channels, 16 channels and 64 channels respectively. In the case of fitting with different number of channels, there was a certain error between the reconstructed signal and the real signal by using the fitting coefficients. The smaller the error result was, the closer the reconstructed signal was to the real one. Experimental data showed that, the data fitting error of the anterior muscle group was relatively large while that of the posterior muscle group was relatively small during hand close, as shown in **Fig.1 (a)**. However, at the time of hand open, the data fitting error of the anterior muscle group was relatively small, while that of the posterior muscle group was relatively large, as shown in **Fig.1 (b)**.

Generally, two-dimensional root-mean-squared (2D RMSE) [12] was often used to calculate the fitting error. However, in this case, the absolute error value was too small, so the relative error relative to the mean value was used in this paper to reflect the fitting error trend under different channels. The RMSE [13] was calculated through **Eq.(1)**. The root mean square error relative to the mean was represented by *mean_err* in our work, and it was calculated through **Eq.(2)**.

$$MSE = \frac{1}{M} \sum_{m=1}^M (y_m - \bar{y}_m)^2$$
$$RMSE = \sqrt{MSE} \quad (1)$$

$$mean_err = \frac{RMSE}{MEAN} * 100\% \quad (2)$$

After *mean_err* was quantified, as shown in **Table 1**, and it was found from the data that in the case of the same gesture, *mean_err* gradually increased with the increase of the number of fitting channels. In the case of the same fitting channel, *mean_err* of hand close will be slightly larger than that of hand open, as shown in **Fig.2**.

Table 1 (%) of different condition

Number Of Channels	Hand Open	Hand Close
8	4.55±0.21	5.41±0.27
32	6.61±0.29	8.08±0.38
64	7.92±0.35	9.82±0.44

The Performance Of Different Classifiers

In order to make a more intuitive comparison from the whole, this paper compared the average accuracy of the whole classification of these three kinds of classifiers together. After averaging the discriminant accuracy of all actions of each person, the whole average accuracy was obtained by averaging the average accuracy of all subjects together, which was presented in **Table 2**. With the increase of the number of fitting channels, the difference between the overall classification accuracy of the four classifiers gradually increases, as shown in **Fig.3**. When the number of fitting channels was 8, the classification accuracy of LDA, KNN and SVM had little difference, maintaining a gesture discrimination accuracy of more than 99%, but the accuracy of RF classifier was about 7% less than that of the other three classifiers. At the time of fitting channels number selected 32, the classification accuracy of the four classifiers became worse, but the accuracy of LDA was still the highest. The accuracy of KNN was slightly worse than that of LDA, but higher than that of SVM, and the accuracy of RF is more than 10% lower than that of the above three classifiers. Compared with the number of fitting channels is 8, under the condition of fitting channels number was 64, the classification accuracy of LDA decreased by 3.87%, but still remained at the level of more than 95%. The classification accuracy of KNN decreased by 7.73% and remained above 91%. The classification accuracy of SVM decreased by 12.3% and remained above 86%. RF's classification accuracy dropped by 10.45%, but accuracy dropped to 83.3%. In the whole classification process, SVM classification accuracy decreased the fastest, LDA classification accuracy decreased the slowest, RF classification accuracy was the worst, the accuracy of LDA classifier was the highest.

Table 2 Overall average accuracy (%)

Channels	LDA	KNN	SVM	Random Forest
8	99.7±0.029	99.4±0.043	99.2±0.071	93.75±0.11
32	98.51±0.074	97.92±0.083	96.73±0.097	86.61±0.27
64	95.83±0.093	91.67±0.14	86.9±0.24	83.3±0.45

In addition, in order to show the performance of different classifiers on different gestures, confusion matrix was employed [14, 15], as shown in **Fig. 4**. For example, in the confusion matrix of LDA classifier in **Fig.4 (a)**, there was a number "3.57" on the left, indicates that the probability that No.7 action ("wrist flexion with hand close") in **Fig.6** was judged by the classifier to be the No.10 action(wrist ulnar with hand close) in **Fig. 6** was "3.57%".

As for the efficiency comparison of the four classifiers[16], in this paper, we calculated the average execution time [17] of the four classifiers on the same platform, which was illustrated in **Table 3**.

Table 3 execution time

	LDA	KNN	SVM	Random Forest
time(millisecond)	980	570	30	4860

The results of the execution time revealed that the running efficiency of RF was far lower than the other three types, LDA was slightly worse than KNN, and SVM had very small running time and high execution efficiency. The data analysis tool used for this processing was: MATLAB 2020A, and the hardware platform was: Intel(R) Core(TM) I5-9400F CPU @ 2.90GHz CPU; 16.0 GB of RAM. Operating system: windows10 professional 21H1 version. The graphics card model was NVIDIA GeForce GTX 1660.

Discussion

In this work, we made a systematic analysis and comparison of the four levels of fitting error, classification accuracy, confusion matrix and time-consuming for the discriminant classification of the fit and superposition results of the finger and the wrist. The results of comparison can provide detailed technical guidance for the research on simplification of gesture signals related to fingers and wrists to select the best classifier.

Error Of Fitting

The difference of *mean_err* was caused by the selection of different fitting channels, because as the number of fitting channels increases, more channels shared a fitting coefficient to express collaborative actions, which caused data distortion. However, the more the number of fitting, the less the fitting coefficient, the less the complexity of finger and wrist motion superimposed into their cooperative action. In order to improve the accuracy of the fitting, we have carried out a more detailed arrangement of the signals before fitting, and interpolated some of the more abnormal data with adjacent mean values. At the same time, in the experiment, we performed a relatively fine control on the force of the subjects to ensure that only the fingers and the wrist are exerting force in the entire arm, and the force is relatively uniform. Our further work will study the influence of the amount of force exerted in hand movements on data fitting.

The Performance Of Different Classifiers

LDA classifier was relatively suitable for multi-type data classification related to finger and wrist data fitting in our work. The data of different types of gestures were maximized by the LDA classifier. In addition, the projection of the intra-class distance of the same type of gestures was the smallest. For gesture data fitting, with the increase of fitting channels, the fitting error kept increasing, and the difference between fitted datasets were much larger than that between acquired datasets and small channels number fitting datasets. In this study, there are many types but the sample size within the class was small, so with the increase of fitting error, the performance of KNN classifier will be worse and worse. Compared with LDA and KNN, SVM classifier had more errors in the performance of this study—it was because that the study was essentially a multi-type classification problem, which has great difficulty in finding a better hyperplane, so the corresponding support vector also have great deviation. For RF classifier, due to the small amount of in-class data in this study, there was not enough in-class data support when forming a decision tree, and there was too little support data outside the node, so many wrong decisions were made. Therefore, RF was not suitable for the processing of this class of problems.

In the choice of the number of fitting channels, three cases of 8, 32, and 64 are selected for illustration in this article. In fact, we had conducted experiments on 4, 8, 16, 32, 64, 128 and 256. In the case of 4 channels, it had the highest spatial resolution of muscle features, and all classifiers can accurately distinguish all actions, which had no test significance for the performance judgment of the classifier. Similarly, because the spatial resolution was too low in the two cases of 128 and 256, the resolution accuracy of all the classifiers was very low, and the ability to distinguish the classifiers was also lost. For 16 channels, there was no significant difference in the classification results compared with 8 channels, so it was also excluded.

The results of the confusion matrix revealed that the LDA classifier fully recognized 7 kinds of actions, but there were 10 error decisions with probabilities ranging from 1.19% to 5.95% in other actions. The KNN classifier made completely accurate judgment for the two actions, but about the other actions it had 21 mistake judgments with probabilities ranging from 1.19% to 4.76% respectively. SVM classifier had 31 error decisions with probabilities ranging from 1.19% to 4.76%. The Random Forest classifier had 48 incorrect decisions with probabilities ranging from 1.18% to 9.52%. Therefore, in terms of the classification and judgment of actions, the performance of classifiers was ranked according to their performance: LDA performed best, KNN took the second place, SVM was the third, and RF had the lowest performance.

Conclusion

In this work, we systematically studied the relationship between the independent and cooperative motion of human fingers and wrists. This study covered feature extraction and quantification of spatial activation features of HD-sEMG signals of human forearm extensor and flexor muscles in recognition of finger and wrist movements. These features then were fitted according to the corresponding relationship

between independent actions and cooperative actions. The focus of this study was to put the fitted compound action datasets and the actual acquired action datasets into four kinds of classifiers for prediction, and evaluate the performance of the classifiers in detail according to the judgment results. Overall, the collaborative motion data sets of fingers and wrist can be obtained by linear superposition of the independent motion data sets of fingers and wrist. Four kinds of common classifiers were used to predict the compound actions data sets and actual acquired signals of different channels, including LDA, KNN, SVM, RF. If the number of fitting channels was 8 or 32, the classification accuracy of LDA, KNN and SVM was similar, but SVM consumed the least time. However, when the number of fitting channels was 64, accuracy of LDA was the highest, reaching 95.83%, KNN was 91.67%, and accuracy of SVM drops sharply to 86.9%. In all cases, RF had the lowest classification accuracy and consumed the most time. The results of confusion Matrix indicated that for gestures classification prediction, LDA had the least error, KNN was the next, SVM was the third, RF had the most error. Therefore, in the problem of hand gesture fitting classification, when the number of fitting channels was less than 32, the selection of classifier can be considered comprehensively. SVM classifier performed high accuracy and less time consuming. However, when the number of fitting channels was higher than 32, LDA classifier needs to be used, with high classification accuracy and acceptable time consumption. At the end, the results of this study can provide reliable guidance for future studies on the correlation between finger and wrist, and promote the further simplification of human forelimb bionics equipment, which is a very important issue.

Materials And Methods

Materials

Subjects

A total of 14 healthy volunteers (8 males and 6 females, aged 22 to 34 years) with right arm dominance were recruited for this study. All participants provided written informed consent, and none had a history of arm or hand disease. The research protocol was reviewed and approved by the Ethics Committee of Fudan University (Approval number: BE2035).

Experimental setup and protocols

In preparation for the experiment, in order to reduce the electrical impedance of the skin and increase the conductivity between the test electrode and the skin, each subject was required to wash the right forearm from the wrist to the elbow with an exfoliator. After drying, the skin surface was repeatedly wiped with medical alcohol to ensure that there were no residual impurities on the skin surface. The specifications of the acquisition electrode plate used in the experiment were: ELSCH064NM1, made by OT Bioelettronica, Turin, Italy, one matrix electrode with gel. Each gelled electrode sheet contains a matrix array of 8×8 electrode layout, with a center distance of 10-mm (center-to-center) between adjacent electrodes. Each electrode plate in contact with the skin was an elliptical gelled electrode with a long axis of 5mm and a short axis of 2.8mm. Two pieces were attached to the flexor surface and two pieces to the extensor

surface of the right forearm of the subject, as shown in **Fig.5**. A total of 256-channel data acquisition array consisting of four electrodes was used to collect HD-sEMG signals from the forearm.

In order to make the electrode plate stick in a reasonable position, we divided the measurement areas of the electrode plate according to the anatomical marks of the human body. The two ends of the radius and ulna were used as the upper and lower boundaries, and the ulnar and radial sides of the forearm were used as the left and right boundaries, respectively, to draw the fitting area of the skin surface of flexor and extensor muscles.

At the start of the experiment, each subject was seated upright in a chair in front of the experimental apparatus, with the right arm naturally placed horizontally on a table in front of his right body. In order to prevent the electrode plate from shifting due to the arm touching the table by potential mistake in the experiment, the elbow of the right arm and the forearm near the wrist of the subject were placed on the support mat. In the case that the fingers and wrist could move freely, the other forearm parts needed to be suspended. The signals of the hand were related to the force generated by the gesture. Therefore, in order to ensure that every movement in the experiment was at the same force generated level, the experiment required each subject to conduct the force measurement experiment. The five fingers of each subject were fastened to the force sensing device (Interface, SM-100N) to test the maximum voluntary contraction (MVC) of each finger. To test the maximum bending and stretching of the fingers, the subjects were instructed to start pressing the fingers down and lifting them up with maximum force on all five fingers. Each finger force measurement action of the subject asked to maintain the force for 3s, with a total of 3 tests, and a 2-minute rest was required between each test. After a 5-minute rest after the force test, the finger and wrist movement experiment began. The movements used in this experiment are shown in **Fig.6**. [7]

At the beginning of the experiment, a display screen was placed in front of each subject, and the screen was displayed successively from the first action to the 20th action. Each action was played twice for four seconds, with a two-second break between the two movements and a five-second break between the different movements. The action play time sequence is shown in **Fig.7**. Step1: the first holding period of the previous action; Step2: rest between two movements; Step3 maintain the second time for the previous action; Step4 for the rest of different movements and prepare the interval time of the next movement; Step5 for the first time to maintain the latter action.

When a certain action was played on the screen, the subject was asked to make the same gesture according to the action prompt on the screen. In order to make all the actions as a whole have a proper holding degree, the force should be kept at about 60% of the maximum force when doing the action. In order for all movements to have an overall level of hold, the finger strength should be maintained at around 60% of the maximum force when performing the gestures. In addition, in order to ensure that the experimental data were the EMG data of gestures, during the whole action, only the parts suggested by the picture should exert force, and other parts should remain relaxed, especially the arm should be kept in a horizontal posture. The HD-sEMG recording instrument of this experiment was: Quattrocento System

(OT Bioelettronica in Turin, Italy), which was set as to Set to 10-900Hz passband, 1000 gain, 2048Hz sampling rate, and 16-bit resolution.

Methods

Data Preprocessing

According to the frequency characteristics of the sEMG signals, the acquired HD-sEMG signals were first passed through the 8-order Butterworth filter band pass-wave device of 10-500Hz, in order to filter out the clutter and interference signals outside the frequency range of the sEMG signals. A notch filter combination was then employed to eliminate the line interference signal caused by power supply and its harmonic components. The HD-sEMG signals were segmented into different subsections according to different tasks after filtered.

Data Analysis

The following steps involved in the data processing of this study were: 1) signal feature extraction after the pre-processing, 2) data fitting of the feature, 3) gestures discrimination by classifiers. As shown in **Fig.8**, a general framework of HD-sEMG data sets handling for hand gestures.

Feature Extraction

In order to express the overall spatial activation characteristics of forearm flexor and extensor muscles, we calculated the two-dimensional root-mean-squared (2D RMS) of the monopolar sEMG recordings acquired from $4 \times 8 \times 8$ channels (4 electrodes with 8 rows and 8 columns of electrodes). In the calculation of two-dimensional root mean square value, to reduce potential interference, the data selected in this paper included the relatively stable action period in the experiment. In the holding time of 4 seconds, the data of 0.25 seconds before and after were removed, however, the datasets of rest period were not included.

The relatively fixed outliers caused by equipment problems and the random outliers caused by poor contact between electrodes and skin due to excessive hand movements during the experiment were detected and marked, and the outliers were instead of the average values of adjacent channels. This method could avoid the unreasonable problem of fitting coefficient caused by outliers.

Data Fitting

The purpose of data fitting was to analyze the relationship between fingers and wrists [18], so this paper divided the 20 gestures in the experiment into three parts according to the logical relationship between them: 1) Finger movements, including hand close and hand open—refer to No. 19 and No. 20 in **Fig.6**, 2) Wrist movements, including six wrist movements from No. 1 to No. 6 in **Fig.6**, 3) The finger and wrist cooperative movement includes two kinds of movements: hand close and wrist simultaneous cooperative

movement, refer to No. 7 to No. 12 in **Fig.6**, and hand open and wrist simultaneous cooperative movement, refer to No. 13 to No. 18 in **Fig.6**.

We first assumed that each coordinated movement of the fingers and wrist could be seen as a superposition of the corresponding independent fingers and wrist movements. In order to verify this superposition relation, the linear fitting of the three kinds of actions was employed to get the fitting coefficient. Then, the combination coefficient and discrete actions were used to regression into the corresponding composite actions under the condition of different fitting channels. Finally, the compound action and the original real action were put into classifiers for judgment. If the compound action can be correctly classified through the network of real action training, it shows that the compound action can be replaced by the real action. The selection of the number of fitting channels was divided into three cases, namely 8 channels, 32 channels and 64 channels. The different number of fitting channels means that different areas of the skin sEMG signals were selected as a superimposed whole. More fitting channels mean the superposition of large area sEMG signals, so that the superposition of finger and wrist movements could replace more fingers and wrist cooperative signals. The fitting relation of different actions is shown in **Table 4**.

Table 4 Fitting relationship between actions

wristmovement (serialnumber in Fig.2)	fingermovement(serialnumber in Fig.2)	coordinationaction(serialnumber in Fig.2)
wrist flexion1	Hand close (19)	Hand close with wrist flexion (7)
wrist flexion1	Hand open(20)	Hand open with wrist flexion (13)
wrist extension (2)	Hand close (19)	Hand close with wrist extension (8)
wrist extension (2)	Hand open (20)	Hand open with wrist extension (14)
wrist radial (3)	Hand close (19)	Hand close with wrist radial (9)
wrist radial (3)	Hand open (20)	Hand open with wrist radial (15)
wrist ulnar (4)	Hand close (19)	Hand close with wrist ulnar (10)
wrist ulnar (4)	Hand open (20)	Hand open with wrist ulnar (16)
wrist pronation (5)	Hand close (19)	Hand close with wrist pronation (11)
wrist pronation (5)	Hand open (20)	Hand open with wrist pronation (17)
wrist supination (6)	Hand close (19)	Hand close with wrist supination (12)
wrist supination (6)	Hand open (20)	Hand open with wrist supination (18)

Classification

After the completion of data fitting, the composite data after fitting and the original acquired real cooperative action data were put into classifiers for prediction and decision, in order to verify whether the composite action after fitting can restore the corresponding real cooperative action—including 1) Linear Discriminant Analysis (LDA) [9, 19, 20], 2) K-Nearest Neighbor (KNN)[21], 3) Support Vector Machine (SVM) [22, 23, 24], 4) Random Forest (RF) [25, 26].

In the design of parameters and kernel functions involved in the classifier, we compared with different parameters or kernel functions, and finally select the parameters and kernel functions with the best performance. For examples, For the KNN classifier, we tried different k values. According to the classification accuracy of the classifier, we finally set K=1 [27], which achieved the highest classification accuracy.

For the SVM classifier, we tried linear kernel, RBF kernel and quadratic kernel respectively, and finally chose RBF kernel. For Random Forest, we tried the number of different trees, and finally selected 64 as the highest precision in the number of trees.

The training sets of classifier adopted the real collected cooperative action datasets, which contained 12 kinds of actions (the 7th to 18th as shown in **Fig. 6**). Each action was performed twice, so there were 24 datasets in total. The data of the test sets were the composite action datasets after fitting. There were also 12 corresponding actions, and each action was done twice, so there were 24 datasets in total. Under the selection of different number of fitting channels and classifier types, the classification results of 14 subjects were finally averaged to express the classification performance of the classifier on the whole model. At the same time, in order to reduce the deviation of the experimental results, a five-fold cross validation was provided.

Abbreviations

HD-sEMG: high-density surface electromyogram

LDA : Discriminant Analysis

KNN : K-Nearest Neighbor

SVM : Support Vector Machine

RF : Random Forest

Et al.: et alii

HMI: Human-machine interface

MVC: maximum voluntary contraction

Fig.: Figure

Eq.: Equation

No.: Number

2D RMSE: two-dimensional root-mean-squared

Declarations

Data Availability Statement

The data used to support the findings of this study are available from the corresponding author upon request.

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Ethics approval and consent to participate

The study was approved by the Ethics Committee of Fudan University (Approval number: BE2035).

Consent for publication

Applicable.

Competing interests

All authors declare that there are no conflicts of interest.

Authors' contributions

Haiqiang Duan: project development, data analysis, and validation, and manuscript writing.

Chenyun Dai: experimental equipment, method guidance.

Wei Chen: guide project structure, the article review.

All authors read and approved the final manuscript.

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References

- 1 Jayun Patel, Ragib Hasan, and Ieee, 'Smart Bracelets: Towards Automating Personal Safety Using Wearable Smart Jewelry', *2018 15TH IEEE ANNUAL CONSUMER COMMUNICATIONS & NETWORKING CONFERENCE (CCNC)* 2018.
- 2 P. Bach-y-Rita, and S. W. Kercel, 'Sensory Substitution and the Human-Machine Interface', *TRENDS IN COGNITIVE SCIENCES*, 7 2003, 541-46.
- 3 S. L. Kilbreath, and S. C. Gandevia, 'Limited Independent Flexion of the Thumb and Fingers in Human-Subjects', *JOURNAL OF PHYSIOLOGY-LONDON*, 479 1994, 487-97.
- 4 V. M. Zatsiorsky, Z. M. Li, and M. L. Latash, 'Coordinated Force Production in Multi-Finger Tasks: Finger Interaction and Neural Network Modeling', *BIOLOGICAL CYBERNETICS*, 79 1998, 139-50.
- 5 F. Nougrou, A. Campeau-Lecours, Md R. Islam, D. Massicotte, B. Gosselin, and Ieee, 'Muscle Activity Distribution Features Extracted from Hd Semg to Perform Forearm Pattern Recognition', in *2018 IEEE LIFE*

SCIENCES CONFERENCE (LSC) (2018), pp. 275-78.

6 Mariam Al Harrach, Vincent Carriou, Sofiane Boudaoud, Jeremy Laforet, and Frederic Marin, 'Analysis of the Semg/Force Relationship Using Hd-Semg Technique and Data Fusion: A Simulation Study', *COMPUTERS IN BIOLOGY AND MEDICINE*, 83 2017, 34-47.

7 A. Holobar, D. Farina, M. Gazzoni, R. Merletti, and D. Zazula, 'Estimating Motor Unit Discharge Patterns from High-Density Surface Electromyogram', *CLINICAL NEUROPHYSIOLOGY*, 120 2009, 551-62.

8 Nebojsa Malesevic, Alexander Olsson, Paulina Sager, Elin Andersson, Christian Cipriani, Marco Controzzi, Anders Bjoerkman, and Christian Antfolk, 'A Database of High-Density Surface Electromyogram Signals Comprising 65 Isometric Hand Gestures', *SCIENTIFIC DATA*, 8 2021.

9 Chenyun Dai, and Xiaogang Hu, 'Extracting and Classifying Spatial Muscle Activation Patterns in Forearm Flexor Muscles Using High-Density Electromyogram Recordings', *INTERNATIONAL JOURNAL OF NEURAL SYSTEMS*, 29 2019.

10 Xinyu Jiang, Ke Xu, Xiangyu Liu, Da Liu, Chenyun Dai, Wei Chen, and leee, 'High-Density Surface Electromyogram-Based Biometrics for Personal Identification', in *42ND ANNUAL INTERNATIONAL CONFERENCES OF THE IEEE ENGINEERING IN MEDICINE AND BIOLOGY SOCIETY: ENABLING INNOVATIVE TECHNOLOGIES FOR GLOBAL HEALTHCARE EMBC'20* (2020), pp. 728-31.

11 Marco Gazzoni, Nicolo Celadon, Davide Mastrapasqua, Marco Paleari, Valentina Margaria, and Paolo Ariano, 'Quantifying Forearm Muscle Activity During Wrist and Finger Movements by Means of Multi-Channel Electromyography', *PLOS ONE*, 9 2014.

12 Antonio Fratini, Antonio La Gatta, Paolo Bifulco, Maria Romano, and Mario Cesarelli, 'Muscle Motion and Emg Activity in Vibration Treatment', *MEDICAL ENGINEERING & PHYSICS*, 31 2009, 1166-72.

13 C. J. Willmott, and K. Matsuura, 'Advantages of the Mean Absolute Error (Mae) over the Root Mean Square Error (Rmse) in Assessing Average Model Performance', *CLIMATE RESEARCH*, 30 2005, 79-82.

14 Xiong YunBo, L. I. RongLu, and H. U. YunFa, 'Comparison of Constructions for Hierarchical Structure Based on Confusion Matrix', *Pattern recognition and artificial intelligence*, 20 2007, 205-10.

15 Xinyang Deng, Qi Liu, Yong Deng, and Sankaran Mahadevan, 'An Improved Method to Construct Basic Probability Assignment Based on the Confusion Matrix for Classification Problem', *INFORMATION SCIENCES*, 340 2016, 250-61.

16 Chongsheng Zhang, Changchang Liu, Xiangliang Zhang, and George Almpanidis, 'An up-to-Date Comparison of State-of-the-Art Classification Algorithms', *EXPERT SYSTEMS WITH APPLICATIONS*, 82 2017, 128-50.

- 17 Jing Liu, Mengxue Wei, Wei Hu, Xin Xu, and Aijia Ouyang, 'Task Scheduling with Fault-Tolerance in Real-Time Heterogeneous Systems', *JOURNAL OF SYSTEMS ARCHITECTURE*, 90 2018, 23-33.
- 18 E. Vieth, 'Fitting Piecewise Linear-Regression Functions to Biological Responses', *JOURNAL OF APPLIED PHYSIOLOGY*, 67 1989, 390-96.
- 19 Daohui Zhang, Xingang Zhao, Jianda Han, Yiwen Zhao, and Ieee, 'A Comparative Study on Pca and Lda Based Emg Pattern Recognition for Anthropomorphic Robotic Hand', in *2014 IEEE INTERNATIONAL CONFERENCE ON ROBOTICS AND AUTOMATION (ICRA)* (2014), pp. 4850-55.
- 20 Bushra Saeed, Muhammad Zia-ur-Rehman, Syed Omer Gilani, Faisal Amin, Asim Waris, Mohsin Jamil, and Muhammad Shafique, 'Leveraging Ann and Lda Classifiers for Characterizing Different Hand Movements Using Emg Signals', *ARABIAN JOURNAL FOR SCIENCE AND ENGINEERING*, 46 2021, 1761-69.
- 21 Shangchun Liao, Gongfa Li, Jiahan Li, Du Jiang, Guozhang Jiang, Ying Sun, Bo Tao, Haoyi Zhao, and Disi Chen, 'Multi-Object Intergroup Gesture Recognition Combined with Fusion Feature and Knn Algorithm', *JOURNAL OF INTELLIGENT & FUZZY SYSTEMS*, 38 2020, 2725-35.
- 22 Abdulhamit Subasi, 'Classification of Emg Signals Using Pso Optimized Svm for Diagnosis of Neuromuscular Disorders', *COMPUTERS IN BIOLOGY AND MEDICINE*, 43 2013, 576-86.
- 23 Chengcheng Li, Gongfa Li, Guozhang Jiang, Disi Chen, and Honghai Liu, 'Surface Emg Data Aggregation Processing for Intelligent Prosthetic Action Recognition', *NEURAL COMPUTING & APPLICATIONS*, 32 2020, 16795-806.
- 24 Mohammadreza Asghari Oskoei, and Huosheng Hu, 'Support Vector Machine-Based Classification Scheme for Myoelectric Control Applied to Upper Limb', *IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING*, 55 2008, 1956-65.
- 25 Zhong Li, Xiaorong Guan, Kaifan Zou, and Cheng Xu, 'Estimation of Knee Movement from Surface Emg Using Random Forest with Principal Component Analysis', *ELECTRONICS*, 9 2020.
- 26 Ercan Gokgoz, and Abdulhamit Subasi, 'Comparison of Decision Tree Algorithms for Emg Signal Classification Using Dwt', *BIOMEDICAL SIGNAL PROCESSING AND CONTROL*, 18 2015, 138-44.
- 27 Shichao Zhang, Xuelong Li, Ming Zong, Xiaofeng Zhu, and Ruili Wang, 'Efficient Knn Classification with Different Numbers of Nearest Neighbors', *IEEE TRANSACTIONS ON NEURAL NETWORKS AND LEARNING SYSTEMS*, 29 2018, 1774-85.

Figures

(a) Hand close and wrist

(b) Hand open and wrist

Figure 1

Exemplar fitting channels as 8, the curve was fitted when hand open and hand close. 1) The red line in the figure represents the sequence of characteristic curves of wrist movements. 2) The green line represents the sequence of characteristic curves of finger movements (Hand open or Hand close). 3) The blue curve represents actual acquired of finger - wrist coordination. 4) The black curve represents the composite action data after fitting.

Figure 2

mean_err (%) of different condition

Figure 3

Overall average accuracy comparison

(a)LDA

(b)KNN

(c)SVM

(d)RF

Figure 4

Confusion Matrix (The serial numbers at the bottom represent the number of the real acquired coordinated actions in Fig. 6, and the numbers on the left represent the actions that is compounded by fingers and wrist actions after fitting corresponding to the numbered actions in Fig. 6.)

Figure 5

placement of electrode sheet

Figure 6

The involved gestures

Figure 7

Schematic diagram of action playing

Figure 8

The general framework of HD-sEMG