A STYLE TRANSFER MAPPING AND FINE-TUNING SUBJECT TRANSFER FRAMEWORK USING CONVOLUTIONAL NEURAL NETWORKS FOR SURFACE ELECTROMYOGRAM PATTERN RECOGNITION

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ABSTRACT

Reducing inter-subject variability between new users and the measured source subjects, and effectively using the information of classification models trained by source subject data, is very important for human–machine interfaces. In this study, we propose a style transfer mapping (STM) and fine-tuning (FT) subject transfer framework using convolutional neural networks (CNNs). To evaluate the performance, we used two types of public surface electromyogram datasets named MyoDatasets and NinaPro database 5. Our proposed framework, STM-FT-CNN, showed the best performances in all cases compared with conventional subject transfer frameworks. In the future, we will build an online processing system that includes this subject transfer framework and verify its performance in online experiments.

Index Terms— Transfer learning, style transfer mapping, fine-tuning, convolutional neural network, surface electromyogram

1. INTRODUCTION

Surface electromyogram (sEMG)-based pattern recognition (PR) is a promising technique for human–machine interfaces such as prosthesis control [1] and remote health monitoring [2]. With the development of wearable sensing methods, sEMG data measurement has become easier and easier. This has led to more studies, and machine learning models are known to show well PR performance (e.g., linear discriminant analysis (LDA) [3], support vector machine (SVM) [4], and convolutional neural network (CNN) [5]). Even though sensing methods are becoming easier, it is still a difficult to secure the amount of training data from a user (target); thus, the major idea is to perform generic PR using information from already measured (source) dataset. However, when considering cross-subject classification, interface designers have been plagued by inter-subject variability owing to differences in muscle activity levels and movement sequences performed [6].

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In sEMG-based PR problems, there have been a number of research efforts in the machine learning models to alleviate the above-mentioned problem through transfer learning (TL) by measuring a small amount of calibration data from the target [7, 8, 9]. Vidovic et al. proposed covariate shift adaptation (CSA) for LDA that linearly tunes the balance of both the mean vectors and covariance matrices calculated using calibration and source datasets [7]. Kanoga et al. proposed style transfer mapping (STM) for SVM, which firstly finds destination points from the source dataset and learns an affine transformation matrix using calibration data to convert new data into source-like data [8]. Fan et al. proposed fine-tuning (FT) for CNN to leverage the knowledge of CNNs learned from sEMG signals of different human group [9].

In recent years, TL approaches using FT have been attracting attention with the development of neural networks [10]. However, in CNNs with FT, the intermediate representation obtained from the source dataset is freezed, and the last one or few layers simultaneously correct the bias between the target and source datasets and relearn weights for classification. This is highly complicated. To correct the bias between the target and source datasets and to relearn the weights for classification, we thought it would be better for STM and FT to share their roles independently. Thus, this study proposes an STM and FT subject transfer framework using CNNs for sEMG-based PR. To evaluate the performance of the proposed framework, we used two types of public sEMG datasets named MyoDatasets [11] and NinaPro database (DB) 5 [4].

2. EXISTING SUBJECT TRANSFER APPROACHES

In subject transfer frameworks, a classifier is trained for each subject and stored as a source model. New data will be classified by ensemble processing of class probabilities from multiple source models [12]. Using a small amount of calibration data, subject transfer approaches directly adjust the parameters of the source model to fit the target, or transform the target data to look like the source data.

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2.1. CSA-LDA

The basic idea of CSA-LDA is to transfer information from a calibration dataset $\boldsymbol{X}_{\text{cal}} \in \mathbb{R}^{D\times N_{\text{t}}}$, where D and N_{t} are the feature dimensionality and the size of the calibration dataset, respectively, to the parameters of LDA learned from a source subject's dataset $\boldsymbol{X}_{\text{src}} \in \mathbb{R}^{D\times N_{\text{s}}}$, where N_{s} is the size of the source dataset. Each data contains a class label $c \in \{1, ..., C\}$. LDAs have two kinds of parameters, mean vector $\boldsymbol{\mu}_c \in \mathbb{R}^D$ and covariance matrix $\boldsymbol{\Sigma}_c \in \mathbb{R}^{D\times D}$ that were calculated from the same class of data. Vidovic et al. proposed a subject transfer approach by shrinking parameters $\{\tau, \lambda\} \in [0, 1]$ towards the mean vector and covariance matrix obtained from the calibration and source datasets [7]:

$$\bar{\boldsymbol{\mu}}_c = (1-\tau)\boldsymbol{\mu}_{\text{src}_c} + \tau\boldsymbol{\mu}_{\text{cal}_c}, \tag{1}$$

$$\bar{\boldsymbol{\Sigma}}_c = (1-\lambda)\boldsymbol{\Sigma}_{\text{src}_c} + \lambda\boldsymbol{\Sigma}_{\text{cal}_c}. \tag{2}$$

When all classes within both datasets share the same covariance matrix $\bar{\boldsymbol{\Sigma}} = 1/C\sum_{c=1}^{C}\bar{\boldsymbol{\Sigma}}_c$, we can obtain a TL-applied linear discriminant of a source subject δ_c for a new sample of the target $\boldsymbol{x}_k \in \mathbb{R}^D$:

$$\delta_c(\boldsymbol{x}_k) := \boldsymbol{x}_k^{\text{T}}\bar{\boldsymbol{\Sigma}}^{-1}\bar{\boldsymbol{\mu}}_c - \frac{1}{2}\bar{\boldsymbol{\mu}}_c^{\text{T}}\bar{\boldsymbol{\Sigma}}^{-1}\bar{\boldsymbol{\mu}}_c - \log 2. \tag{3}$$

2.2. STM-SVM

STM-SVM is based on the concept that a new sample from the target should be similar to the source sample and should be able to be identified by a pre-trained radial-basis-function-kernel-SVM [12]. Assuming that the distributions of the new sample and calibration data are the same, Kanoga et al. proposed a subject transfer approach via an affine transform [8]. The parameters $\boldsymbol{A} \in \mathbb{R}^{D\times D}$ and $\boldsymbol{b} \in \mathbb{R}^D$ are learned by minimizing the weighted squared error:

$$\min_{\boldsymbol{A},\boldsymbol{b}} \sum_{i=1}^{N_t} f_i||\boldsymbol{A}\boldsymbol{x}_{\text{cal}i} + \boldsymbol{b} - \boldsymbol{d}_i||_2^2 + \beta||\boldsymbol{A} - \boldsymbol{I}||_F^2 + \gamma||\boldsymbol{b}||_2^2, \tag{4}$$

where f_i, $\boldsymbol{x}_{\text{cal}i}$, $\boldsymbol{d}_i$, $||\cdot||_F^2$, $||\cdot||_2^2$, and $\boldsymbol{I}$ are the confidence of labelled data, a sample of the calibration dataset, the destination point, the Frobenius norm of matrix, the L_2-norm of vector, and the identity matrix, respectively. In this study, we provided full confidence to the calibration dataset (i.e., $f_i = 1$). The second and third terms prevent the results of this equation from being too far from the original position in the space. In addition, β and γ control the trade-off between non-transfer and over-transfer:

$$\beta = \tilde{\beta}\frac{1}{D}\text{tr}(f_i\boldsymbol{x}_{\text{cal}i}\boldsymbol{x}_{\text{cal}i}^{\text{T}}), \quad \gamma = \tilde{\gamma}\sum_{i=1}^{N_i} f_i, \tag{5}$$

where $\text{tr}(\cdot)$ is the trace of a matrix. Furthermore, $\tilde{\beta}$ and $\tilde{\gamma}$ were selected from 0 to 3 [12]. The search range was set for every 0.2 steps. The computations of $\boldsymbol{A}$ and $\boldsymbol{b}$ can be performed according to Eq.s (7)–(10) in [8]. The definition of the destination point $\boldsymbol{d}_i$ is important. According to a previous study [12], we clustered the source dataset via K-means clustering in each class to derive clustering centers (destination candidates) from these vectors. In this study, we set K to 15. The nearest clustering center of a calibration sample $\boldsymbol{x}_{\text{cal}i}$ from the K cluster centers of class c was defined as the destination point $\boldsymbol{d}_i$ [13].

In this approach, the new sample can be transformed as if it were a source sample, and it will not interfere with the source models (i.e., SVMs). However, they have two hyperparameters $\{C, \sigma\}$. We optimized these parameters by a grid search ($\{C, \sigma\} \in [10^{-3}, 10^{-2}, 10^{-1}, \ldots, 10^{3}]$) and 5-fold cross validation of source dataset.

3. PROPOSED SUBJECT-TRANSFER APPROACH

In this study, we propose an STM and FT subject transfer framework using CNNs (STM-FT-CNN). The processing scripts were implemented by MATLAB R2020a and can be downloaded from `https://github.com/Suguru55/STM-FT-CNN_for_sEMG_PR`. The subject transfer approach of one source subject is presented in Fig. 1. Normalized probabilities obtained in the output layer are ensemble processed to determine the estimated class. The concept of STM-FT-CNN is to directly translate target sample into source sample (to remove subject bias) by STM and to modify the decision boundary of respective source CNN by FT and the source-like target samples. We hypothesize that this would allow for conservative TL, in which the parameters of the trained network of the source subject are respectively fine-tuned by providing samples that are similar to the source data.

The window length was 50 samples (i.e., 250 ms), unlike the previous approaches, the shift width was set to 1 sample (i.e., 5 ms). Thus, the input dimensionality was $50\times D$. Since STM is a linear projection approach using a $D\times D$ transformation matrix $\boldsymbol{A}$ and a D-dimensional vector $\boldsymbol{b}$, it can be used even if the input is a map. The CNN architecture was proposed by Fan et al. [9] and was inspired by NinaPro study [5] and LeNet [14] (see Fig. 1 B). It consists of five convolutional layers and two average pooling layers with a fully connected layer. Before the first pooling layer, convolutional layers have 32 3×3 filters with a stride of 1×1. Third and fourth convolutional layers have 64 5×5 filters with a stride of 1×1. The last convolutional layer has 32 1×1 filters. Both pooling layers are with a pooling size of 3×3 and a stride of 1×1. The nonlinear activation functions of respective convolutional layers are ReLU. Before applying activation functions, batch normalization is applied. After the fully connected (FC) layer, dropout is set to be 0.5. In the end, the output layer has a softmax layer to calculate normalized class probabilities.

For training CNNs, we used stochastic gradient descent with momentum (SGDM) optimizer where momentum was

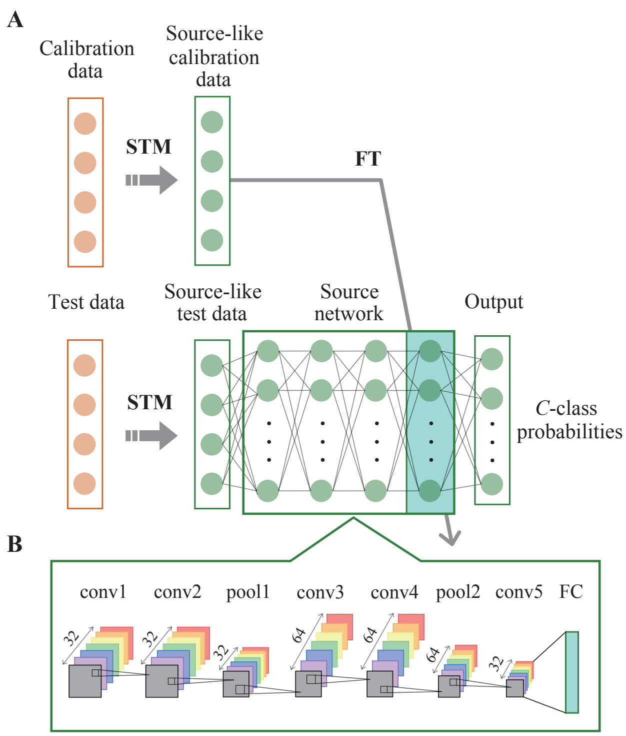

Fig. 1. Proposed subject transfer approach of one source. The CNN architecture is modified from reference [9].

0.9, learning rate was 0.0001, batch size was 64, and the number of epochs was 50. The weights of FC layer in the trained CNN were fine-tuned where the quintuplet (optimizer, momentum, learning rate, batch size, and the number of epochs) was SGDM, 0.9, 0.0001, 64, and 10, respectively.

4. MATERIALS

4.1. MyoDatasets

This DB can be downloaded from `https://github.com/Suguru55/SS-STM_for_MyoDatasets`. Twenty-five healthy subjects aged 20 to 31 years (including eight females and five left-handed subjects) participated in the experiments. They were asked to stand in front of a laptop PC with a relaxed posture and to enact eight types of simple forearm motions. In addition, each motion was repeated five times, resulting in 40 trials. Each trial lasted for 6 s.

Eight-channel sEMG data with a sampling rate of 200 Hz were recorded from the right forearm using a banded device with evenly arranged sensors based on the fourth channel was placed 1 cm distal to the belly of the brachioradialis muscle. The signals were high-pass filtered at 15 Hz through a fifth-order Butterworth filter.

We extracted 1.5 s active segments from the 6 s data by applying a sample entropy-based thresholding onset detection approach (Fig. 3 in [15]). Each 1.5 s eight-channel segment was further divided into analysis windows of 250 ms with 4/5 overlaps (50 ms shifts), because the length of the analysis windows should be less than 300 ms for the permissible range, considering the time lag of the human interfaces [16].

For each analysis window, 11 dimensional features were determined: (1) mean absolute value, (2) zero crossing, (3) slope sign changes, (4) waveform length, (5) root mean square, and (6-11) sixth-order auto-regressive coefficients [17]. This feature set is the gold-standard in sEMG-based motion recognition. We collected eight-channel data; therefore, a 250-ms analysis window was translated into 88-dimensional features ($D = 88$).

4.2. NinaPro DB5

This DB can be downloaded from `https://zenodo.org/record/1000116`. Ten healthy subjects aged 22 to 34 years (including two female and zero left-handed subjects) participated in the experiments. They were asked to perform three types of exercises (exercise A, B, and C [18]) represented by movies shown on the screen of a loptop PC. We considered each exercise as a separate DB and defined them as DB5-A, DB5-B, and DB5-C. The participants enacted 12, 17, and 23 types of motions for exercise A, B, and C, respectively. In addition, each motion was repeated six times, resulting in 72, 102, and 138 trials for each DB. Each trial lasted for 5 s.

Sixteen-channel sEMG data with a sampling rate of 200 Hz were recorded from the right forearm using two banded devices. The upper device was placed closed to the elbow with the first channel on the radio-humeral joint. The lower device was placed just below the first, closer to the hand, and tilted by 22.5° to fill the gap left by the sensors of the other device. The signals were high-pass filtered at 15 Hz through a fifth-order Butterworth filter.

We extracted active segments from the 5 s data based on the `restimulus` variable given by the provider of NinaPro DB5. The segment was further divided into analysis window with the same setting to MyoDatasets. Then, the same 11-dimensional features were determined; a 250-ms analysis window was translated into 176-dimensional features ($D = 176$).

5. EVALUATION

All the data from a source subject were used for training a source model. To evaluate the subject transfer frameworks, we divided the five-trial/six-trial target data of MyoDatasets and NinaPro DB5 into three different datasets: (1) the calibration dataset (1st trial/1st and 2nd trials), (2) the validation dataset (2nd trial/3rd and 4th trials), and (3) the testing dataset (3rd–5th trials/5th and 6th trials). The calibration datasets were used to train the TL approaches. The validation datasets were used to optimize the hyperparameters of TL approaches. Then, we

Table 1. Motion recognition performances (Mean ± S.D.%) for MyoDatasets and NinaPro DB5. Written in parentheses is the best hyperparameter set for TL approaches. The best performance in the DB is written in bold.

Approaches	Conventional or Proposed	sEMG DBs MyoDatasets	DB5-A	DB5-B	DB5-C
CSA-LDA [7]	Conventional	85.63 ± 12.48 ($\tau = 0.6, \lambda = 0.4$)	52.45 ± 11.84 ($\tau = 0.6, \lambda = 0.3$)	45.25 ± 6.55 ($\tau = 0.7, \lambda = 0.4$)	33.72 ± 4.36 ($\tau = 0.5, \lambda = 0.3$)
STM-SVM [8]	Conventional	90.04 ± 6.00 ($\beta = 0.2, \gamma = 0.2, C = 10, \sigma = 10^{-3}$)	55.71 ± 6.90 ($\beta = 0, \gamma = 0, C = 10, \sigma = 10^{-3}$)	45.82 ± 5.01 ($\beta = 0, \gamma = 0, C = 10, \sigma = 10^{-3}$)	32.32 ± 2.59 ($\beta = 0, \gamma = 0, C = 10, \sigma = 10^{-3}$)
STM-CNN	Proposed	90.74 ± 6.66 ($\beta = 0, \gamma = 1.0$)	54.57 ± 8.93 ($\beta = 0, \gamma = 0$)	40.67 ± 7.77 ($\beta = 0, \gamma = 0$)	28.49 ± 2.66 ($\beta = 0, \gamma = 0$)
FT-CNN [9]	Conventional	87.90 ± 7.04	59.85 ± 6.94	56.97 ± 6.94	49.90 ± 4.35
STM-FT-CNN	Proposed	$\mathbf{91.31 \pm 6.33}$ ($\beta = 0.2, \gamma = 2.8$)	$\mathbf{62.12 \pm 7.25}$ ($\beta = 0.2, \gamma = 0$)	$\mathbf{58.44 \pm 5.39}$ ($\beta = 0.2, \gamma = 0$)	$\mathbf{50.22 \pm 4.31}$ ($\beta = 0, \gamma = 1.8$)

calculated the recognition accuracies of the 8-, 12-, 17-, and 23-class data in the testing datasets.

6. RESULTS AND DISCUSSION

Our proposed framework, STM-FT-CNN, showed the best performances in all cases (see Table 1). STM-SVM showed higher average performance and smaller variance than CSA-LDA, which is consistent to the previous study [8]. In the case of choosing CNN as the source model, STM-CNN and FT-CNN showed higher performance than CSA-LDA and STM-SVM, but STM-CNN and FT-CNN showed different trends depending on the dataset.

By separating the roles of STM and FT, our proposed framework can perform stable subject transfer for both simple and complex data structures. When the dataset deals with simple motions, measured data are easy to classify (i.e., MyoDatasets) and STM improved performance by combining with a powerful classifier. However, the dataset deals with complex and delicate motions, measured data are difficult to classify (i.e., NinaPro DB5) and the decision boundaries are inherently tight and samples may cross the boundaries after mapping. On the other hand, FT was robust even when the dataset deals with a complex and delicate motions. This may suggest that as long as the complex data structure can be represented, there is a high degree of similarity in the intermediate representations when the source and target subjects are performing the same task, and that simply adjusting the parameters of the final layer while using the same intermediate representation will work. STM-FT-CNN is able to have the best of STM and FT together. For a simple data structure, the source model learns an efficient decision boundary, which is mapped by STM to the space of each class with low risk. If the data structure is complex, there is a possibility that the destination mapped by the STM crosses the boundary, but the boundary can be corrected by FT.

Whereas direct comparisons cannot be made due to the different experimental settings such as feature set, analysis window length, and classifiers, STM-FT-CNN presented a performance higher or close to that of the experimental setting where the target subject's data can be used for training the source model (MyoDatasets: 88.20% [19], DB5-A: 69.62% [20], DB5-B: 67.42% [20] and 60.12% [21], and DB5-C: 61.63% [20]). It is important to note that in this study, the source model was trained only with data from the source subject. In other words, the new user (i.e., target) only needs to measure one trial or two trials of data for each class, and the source model can perform as closed as if it were trained on the training data obtained from long-time data measurement of the target. An interface that can be driven by a short measurement time from new users is very beneficial for daily use.

7. CONCLUSIONS

This study proposed a subject transfer framework with double TL approaches, STM-FT-CNN, for sEMG pattern recognition. The performance of this framework was evaluated by using two types of public sEMG datasets named MyoDatasets and NinaPro DB5. STM-FT-CNN showed the best performances in all cases. The proposed framework is able to have benefit of STM and FT together, resulting in providing robustness to both simple and complex data structures. We believe that this framework can be applied to user-friendly interfaces for various applications. However, when using CNNs and other deep learning source models, we should consider accelerating the computation using GPUs. While using devices such as smartphones as the core of the human–machine interface, it is important to configure the system to work with hardware that has GPUs to take over the computation. Our future work is to build an online system that includes this subject transfer framework and verify its performance in online experiments.

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