A Dimension Reduction Technique to Classify Upper Arm Gym-Workouts in Realtime with TinyML

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Abstract. Biopotentials are typically measured by multichannel probes and recorded as time-series data. Accordingly, the measured biopotentials have high dimensionality which impedes to build a fast machine classifier using an affordable system, i.e., TinyML. In this paper, we propose a dimension reduction technique for multichannel surface EMG time series data being measured during various upper arm gym-workouts. The key idea of our approach is to utilize t-stochastic neighbor embedding as a tool for the dimension reduction of a feature space to where data samples belong. Then, the data samples in the reduced feature space are grouped, labeled, and represented as Gaussian distributions according to workout names. Lastly, we train a neural network to functionally approximate the above-mentioned dimension reduction process, which eventually enables us to classify a newly given data sample based on Mahalanobis distance to each workout group. For upper arm gym-workout classification, under the proposed approach, the result shows the accuracy of 85.25 percent in terms of macro-precision.

Keywords: Upper Arm Gym-Workout Classification, Dimensionality Reduction, Surface EMG-based Classification

1 Introduction

Nowadays, time-series data analysis plays essential roles in a broad range of field. By analyzing the time-series data, for example, we can predict a house electricity consumption with quarterly/yearly record, diagnosis a heart difficiency based on ECG, forecast a stock market, and so on. Accordingly, many studies have been undertaken to develop and innovate the time-series data analysis techniques, e.g., parametric time-series identification [1], dynamic time warping-based pattern recognition [2], various data mining approaches [3], etc.

In our previous study presented in [4], we defined a correct workout as "stimulating correct target muscles while performing a timely sequence of correct motion primitives."

We also showed that upper arm gym-workouts could be classified successfully via convolutional neural network by merging surface EMG (sEMG) data with an elbow joint angle data and visualizing it as an image. In this paper, we proposes a dimension reduction technique to solve the same upper arm gym-workouts classification problem. This study has been initiated to investigate a feasibility of building an affordable AI-based home trainer using TinyML. In the proposed technique, t-stochastic neighbor embedding (t-SNE) serves as a tool to reduce a feature space dimensionality. In the reduced feature space, the sample data of each workout group are represented as Gaussian distributions. The outcomes from the t-SNE will be eventually used to train a neural network (NN) to functionally approximate a relationship between a high dimensional input data and a t-SNE output. Consequently, when a new workout data is given, it passes through the trained NN, and the output can be classified based on Mahalanobis distance to each workout group.

The rest of paper is organized as follows. In Section 2, we introduce data measurement, data pre-processing, and a dimensionality reduction technique as well as a corresponding classifier system design. In Section 3, the evaluation results for the proposed approach are presented. Section 4 will be the conclusion of this paper and a future direction will be discussed shortly.

2 Methods

2.1 Data measurement

A professional trainer was recruited to measure upper arm gym-workout data. Four different workouts were demonstrated by the trainer, i.e., dumbbell curl (DC), hammer curl (HC), reverse curl (RC), and triceps kickback (TK). DC, HC, and RC were chosen to stimulate biceps brachii muscles whereas TC targeted triceps brachii muscles. An armband type sEMG sensor (Myo Armband, Thalmic Labs, Brooklyn, NY) was mounted on the trainer's right upper arm. The 8 sEMG channels were deployed as channel 1 through 3 on biceps brachii area and channel 5 through 7 on triceps brachii. Channel 4 and 8 were located on boundaries between biceps and triceps brachii. In addition, an elbow joint angle was measured by a RGB-d camera (Kinect v2 for Windows, Microsoft, Redmond, WA) and a Vitruvius framework (Vitruvius Kinect, LightBuzz Inc., New York, NY).

2.2 Data acquisition and pre-processing

For data acquisition, sampling time was set to 20ms and the trainer was instructed to rhythmically demonstrate one repetition during 1600 ms basis; therefore, 80 data samples were recorded per one repetition. A time stamp was increased rowwise. The data field for one data sample in a row was `[sEMGch(1:8), elbow_joint_angle]` in a form of MATLAB-like notation. To prevent muscle fatigue, one set was limited to 20 repetitions. Three sets were performed for each workout types. Consequently, a total 240 data samples (20 repetitions $\times$ 3 sets $\times$ 4 workout types) were obtained from the trainer's demonstration. The obtained data set was pre-processed by following steps:

1. Take the absolute value for the obtained data set.
2. Apply a moving average filter. A window size was set to 10 time steps.

3. Integrate the filtered data. An interval size was set to 5 time steps.
4. Perform inter-channel normalization. By completing upto this step, we obtain a matrix whose size is 9 by 16.
5. Flatten the above matrix; hence, a data sample for one repetition was converted into a vector in $\mathbb{R}^{144\times 1}$.

For more details, please refer to our previous study disseminated in [4].

2.3 Dimension reduction and workout group representation

Recall that we converted total 240 data samples into the flattened vector which consisted of 144 features. The high dimensionality of the resulting flattened vector indeed impeded to design an affordable AI-based home trainer or exercise monitoring system. To address this issue, we utilized t-SNE to reduce a feature space dimensionality with the following purposes:

- We wanted to stochastically project all data samples onto a visible dimension.
- We wanted to investigate whether data samples are separable according to their workout groups(types).
- If separable, we wanted to find a way to represent workout groups, e.g., separating hyperplanes, mean and covariance, etc.

Figure 1 illustrates all data samples projected onto two dimensional feature space and workout groups represented by Gaussian distributions. From Fig. 1(left), we could observe that data samples could be separable according to their workout groups. Also, without a loss of generality, we could conclude that it would be better way to represent workout groups as Gaussian distributions as shown in Fig. 1(right) than linearly separating hyperplanes. Of course, kernel estimation-based approaches, for instance, support vector machine, could yield outperforming nonlinear decision boundaries; however, we note that the simpler method was preferred by considering affordability. The mean μ_i and covariance matrix Σ_i were calculated from the samples belong to each workout group.

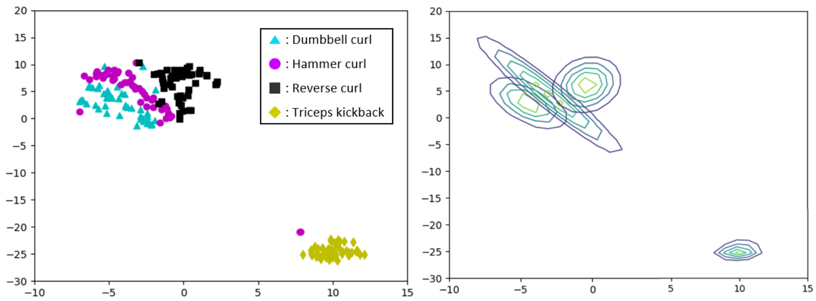

Fig. 1. All data samples projected onto two dimensional feature space (left) and workout groups represented by Gaussian distributions (right).

2.4 Training a neural network and classifying a new workout data

If the t-SNE is needed to be performed for every newly given data sample, then the entire workout classification process would be severely down-speeded. Therefore, given the flattened input vectors and the t-SNE outputs, we trained a NN to functionally approximate the t-SNE, which in turn serves as a surrogate system for the t-SNE. After training the NN, workout classification could be processed for an upcoming flattened input vectors as follows:

1. Pass the flattened input vector of $\mathbb{R}^{144\times 1}$ through the trained NN and obtain the corresponding output of $\mathbb{R}^{2\times 1}$.
2. (optional) Plot the output in the reduced feature space.
3. Calculate a Mahalanobis distances to each workout group.
4. The new data belong to the workout group which returns the minimum Mahalanobis distance.

A total 240 data samples was divided into 192:24:24 samples as training:validation:test sets. To evaluate proposed classification approach, we performed upper arm gym-workout classification twenty-five times by pseudo-randomizing the test set, which corresponded to 150 classification test for each workout group.

3 Results and Discussion

Table 1 presents a confusion matrix of upper arm gym-workout classification results. As it could be expected by observing Fig. 1, the correct prediction for TK outperformed all biceps brachii workouts. The largest Type I error occurred when ground truth was DC but prediction was HC. Among biceps brachii workouts, RC showed the most correct prediction. The resulting workout classification accuracy was 85.25 percent in terms of macro-precision.

Table 1. A confusion matrix of upper arm gym-workout classification results

		Prediction			
		DC(▲)	HC(●)	RC(■)	TK(◆)
Ground truth	DC(▲)	104	46	0	0
	HC(●)	13	118	17	2
	RC(■)	0	18	132	0
	TK(◆)	0	0	0	150

4 Conclusion

Throughout this paper, we proposed the dimension reduction technique to classify upper arm gym-workouts. The proposed approach first projected the high dimensional features onto two dimensional feature space by utilizing the t-SNE. After reducing the dimensionality of the feature space, data samples were represented by Gaussian distributions in two dimensional feature space. The functionality of the t-SNE was approximated by a neural network, which in turn allowed us to classify a newly given data sample based on the Mahalanobis distance from each group. As future works, this study will be culminated to the development of an affordable AI-based home training system.

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