Towards Robust HD EMG Pattern Recognition: Reducing Electrode Displacement Effect using Structural Similarity

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Abstract— **Even small changes of electrode recording sites after training a classifier heavily influence robustness and usability of traditional pattern recognition-based myoelectric control schemes. This effect occurs during donning and doffing of the prosthesis or when changing the arm position and generally leads to a significant decrease of classification accuracy. On the other hand, image representations taken from high density electromyographic (EMG) signals offer high spatial resolution and only seem to change slightly during electrode shift, preserving most structural information. In this paper, we present a simple one-against-one nearest neighbor classifier based on the Structural Similarity Index (SSIM). SSIM quantifies visual similarity of two images based on decomposition into three components: luminance, contrast and structure. Our experimental results indicate that an SSIM-based classifier can outperform an LDA-based classifier using structural information taken from high density EMG signals during simulated electrode shift.**

I. INTRODUCTION

Pattern recognition-based control schemes are an active research area potentially enabling the amputee to intuitively operate multiple degrees of freedom [1], [2]. A variety of feature extraction methods and classification algorithms have been successfully developed and evaluated for upper-limb prosthesis control in laboratory settings [3], [4]. One challenge in pattern recognition-based control schemes is variation in electrode recording placement. Donning, doffing or using a myoelectric prosthesis over a longer time period can cause the electrodes inside the shaft to change their recording locations which results in a decrease of classification accuracy. The effect has been previously studied but remains an unsolved problem [5], [6]. Hargrove et al. [7] showed that the displacement effect can be alleviated by performing a training in all expected displacement positions, which is unsuitable for real world usage.

Apart from donning and doffing the prosthesis, changes in gravity, muscle length and volume, and other biomechanical effects during limb positioning are another source for the electrode displacement effect. In most literature, EMG signals are acquired in a fixed position and used for both, training and testing of the classifier. This enables the amputee in performing repeatable contractions throughout the experiment and typically results in a high classification accuracy. In clinical testing however, subjects have to perform realistic activities of daily living, causing the limb to move in different positions which leads to accuracy degradation. This effect has also studied [8], [9] but has not yet been satisfactorily solved.

High density EMG recordings offer unprecedented spatial resolution of muscular activity and contain structural information suitable to use as input for pattern recognition of myoelectric control schemes. Analyzing image data extracted from high density EMG recordings it is notable that structural information remain mostly unchanged during electrode shift.

In the field of computer vision, various methods are used to quantify similarity between images based on their structural information. A prominent method is the Structural Similarity Index (SSIM) [10], offering an objective method to quantify the similarity of two images by decomposing them into the components luminance, contrast and structure. The method was successfully used for classifying range-based face recognition [11] and hand writing recognition [12].

Based on this method, we propose a simple one-against-one nearest neighbor classifier to distinguish between 10 hand and wrist movements using image representations from high density EMG recordings. We conduct an experiment to determine the robustness against electrode displacement effect caused by shifting electrodes on the skin and using different limb positions. We then compare the results with LDA, which is commonly used in EMG pattern recognition.

This paper is structured as follows. The experimental setup and structure of the proposed SSIM-based classifier are presented in section II. The experimental results are shown in section III while section IV offers a short discussion.

II. METHODS

A. Data Acquisition and Feature Extraction

For this experiment, EMG data corresponding to 10 hand and wrist motions were acquired from one healthy normally limbed 30 years old male subject. The data were collected from an array of 96 electrodes consisting of 4 rows of 24 electrodes wrapped around the forearm. A TMS International REFA 128 high density EMG system was used for data acquisition.

The experiment consisted of three runs, each performed in a different limb position: during the first run, the test subjects arm was hanging straight down at the side. In the second run, the arm was straight reaching forward. In the last run, the arm was reaching up in an angle of 45°. During each experiment run, the test subject was prompted to perform 10 contractions: extension, flexion, pronation, supination, ulnar deviation, radial deviation, hand open, power grip, pincer grip and key grip. Each contraction was held for 5

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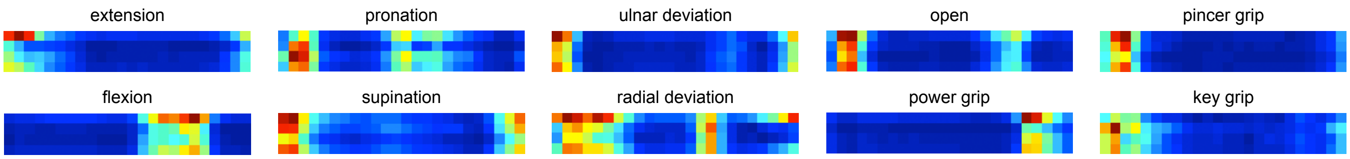

Fig. 1. Grid representation of EMG movement data in arm low position, each pixel representing an EMG channel. Each channel was RMS-smoothed using a 100 ms sliding window. High RMS activity channels are colored red, low RMS activity channels are colored blue.

seconds, followed by a 2 seconds rest period. For each limb position, 10 different trials were recorded, each consisting of 12 repetitions of the same contraction. After each trial, a one-minute rest period was included to avoid muscle fatigue effects. From each contraction, 4 seconds of data from the steady state phase were extracted. In total 12 × 4 sec = 48 seconds of data were recorded for each movement class and limb position. The first 24 seconds were used for training the classifier; the remaining 24 seconds were used for classification. Fig. 1 shows a grid representation of the EMG data during the acquired movements.

B. The Structural Similarity (SSIM) Index

In order to calculate the SSIM index [10] of two images represented by the non-negative signals x and y, the images are decomposed into three components: luminance, contrast and structure. The components are then compared separately. Finally a value between -1 and 1 is calculated as an index of similarity between the input images. First, the luminance μ of both signals is estimated as the mean intensity:

$$\mu_x = \frac{1}{N}\sum_{i=0}^{N-1} x_i. \tag{1}$$

The luminance comparison function $l(x,y)$ is a function of μ_x and μ_y:

$$l(x,y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1}. \tag{2}$$

C_1 and C_2 are constants included to avoid instability when $\mu_x^2 + \mu_y^2$ is very close to zero. The mean intensity is then removed from the signal and the standard deviation (square root of variance) is estimated as the signal contrast σ:

$$\sigma_x = \left(\frac{1}{N-1}\sum_{i=0}^{N-1}(x_i - \mu_x)^2\right)^{\frac{1}{2}}. \tag{3}$$

The contrast comparison function $c(x,y)$ is a function of σ_x and σ_y:

$$c(x,y) = \frac{\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2}. \tag{4}$$

Furthermore, structure comparison $s(x,y)$ is conducted:

$$s(x,y) = \frac{\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3} \tag{5}$$

with $C_3 = C_2/2$ and σ_{xy} estimated as the covariance of the signals:

$$\sigma_{xy} = \frac{1}{N-1}\sum_{i=0}^{N-1}(x_i - \mu_x)(y_i - \mu_y). \tag{6}$$

Finally, the three comparisons (2), (4) and (5) are combined in the SSIM index between signals x and y:

$$SSIM(x,y) = [l(x,y)]^{\alpha} \cdot [c(x,y)]^{\beta} \cdot [s(x,y)]^{\gamma} \tag{7}$$

where non-negative α, β and γ are used to adjust the relevance of the three components. In this paper, we use $\alpha = \beta = \gamma = 1$. For two given images, the SSIM index is first locally calculated using an 11-pixel Gaussian sliding window filter and then averaged into one value ranging between -1 and 1, with 1 being the index value for two identical images.

For illustration purposes, Figs. 2 and 3 depict image decomposition and SSIM index calculation of high density EMG data used in the experiments. Fig. 2 shows the comparison between two similar but not identical signals representing the same movement class. The difference in luminance and contrast between the input signals are almost zero, while there are minor differences in image structure due to the slightly differently performed movement. In this example, his results in a relatively high SSIM index of 0.931.

Fig. 3 shows comparison between images representing slightly different movement classes, resulting in a relatively low SSIM index of 0.221. While the difference in luminance is only minor, there are significant differences in contrast and structure.

Due to a minimum amount of pixels necessary for calculating the SSIM index, input signals (4 × 24 pixels) are linearly interpolated with factor 3 when used as input for SSIM index calculation.

C. Training Phase

As previously indicated, the first 24 seconds of data representing each contraction class are used to train the pattern recognition system while the remaining 24 seconds are used for classification. For each movement class, n frames of 4 × 24 pixels are extracted from the high density EMG raw data using a 100 ms wide, 50 ms overlapping RMS filter window. These 10 × n × 4 × 24 = n × 960 values will be used as feature vectors for training of a traditional LDA classifier that we use as a reference for comparing against the SSIM-based classifier in the Results section.

The extracted n frames are then averaged into 1 frame for each movement class. The resulting 10 frames of 4 × 24 pixels form the training model for the SSIM-based classifier.

D. Test Phase

In this phase, we use SSIM as a simple one-against-one nearest neighbor classifier. For this purpose, we extract n test frames from the test data in the same manner as the frames

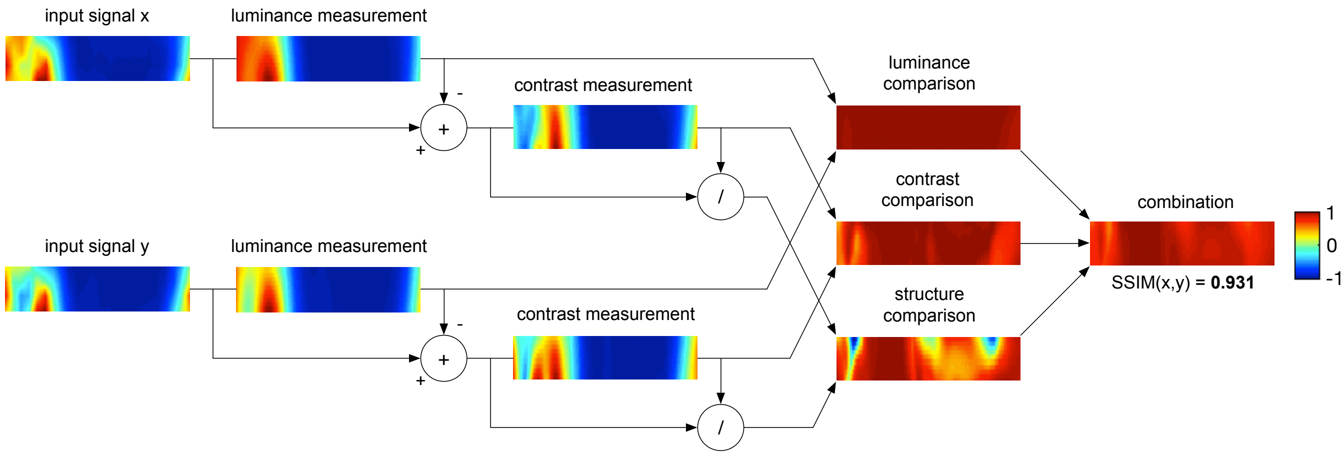

Fig. 2. Decomposition and SSIM comparison of two similar signals representing the same movement class (extension), resulting in a relatively high SSIM index value. The input signals were linearly interpolated with factor 3.

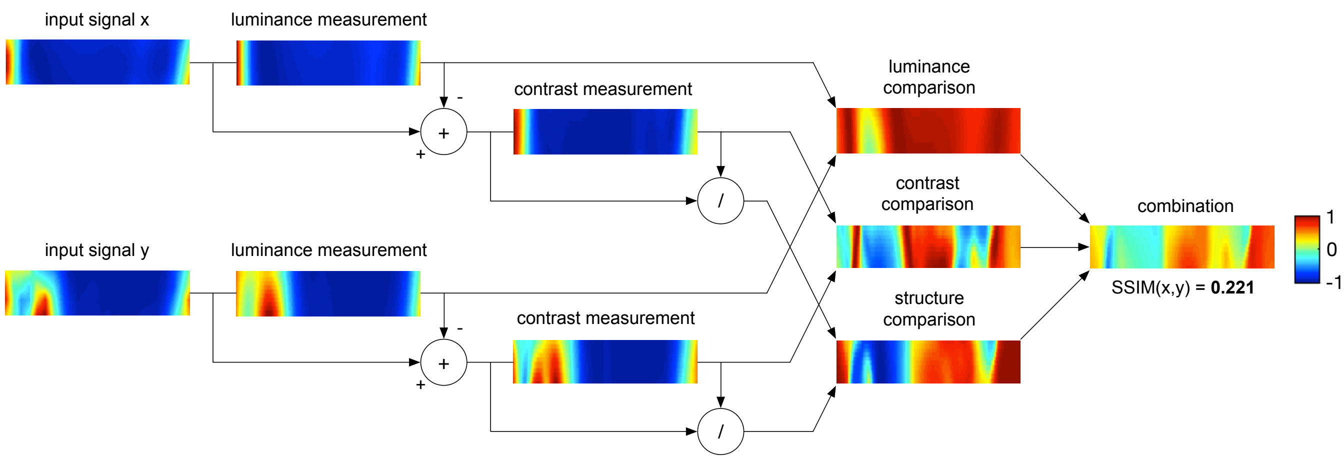

Fig. 3. Decomposition and SSIM comparison of two dissimilar signals representing different movement classes (ulnar deviation and extension), resulting in a relatively low SSIM index value.

for the training model. A frame representing EMG data of an unknown movement class is interpolated and SSIM-compared with each of the 10 interpolated frames from the training model. The highest resulting SSIM index decides the class.

To simulate electrode displacement due to gravity and biomechanical reasons, three different limb positions were used for training and testing the classifiers. To simulate the electrode displacement effect caused by shifting electrodes on the skin surface, the representation of the electrode array in the test data was horizontally shifted by 1 cm in the software simulation. This is equivalent to the amount of electrode displacement that is likely to occur during everyday prosthesis wear.

III. Results

We have performed the experiment to answer two specific questions: First, can a computer vision-based classifier that treats high density EMG data as images and classifies them based on structural information outperform a traditional pattern recognition-based classifier? Second, since electrode shift has minor influence on image representation of EMG data, is a computer vision-based classifier more robust to it?

To evaluate the performance of the SSIM-based and LDA classifier when classifying unshifted and 1 cm shifted EMG data, we have trained and tested both classifiers in all 3 arm positions and 24 possible electrode array positions successively. Then, we have averaged the performance in terms of classification accuracy. The results are depicted in Fig. 4. It can be seen that both classifiers perform best when arm position is not changed while testing (Fig. 4 (a), (e), and (i)). The average intra-class accuracy rate is 95.3% for unshifted and 90.2% for 1 cm shifted data using SSIM and 79.3% (unshifted) and 43.8% (shifted) using LDA. When taking changes of limb position into account (Fig. 4 (b), (c), (d), (f), (g), and (h)) one can observe a accuracy degradation in both classifiers. The average inter-class accuracy of SSIM is 71.3% for unshifted and 65.5% for 1 cm shifted data while LDA's average accuracy drops to 46.8% (unshifted) and 39.8% (shifted).

While both, the SSIM-based and LDA classifier suffer from electrode displacement due to limb positioning and

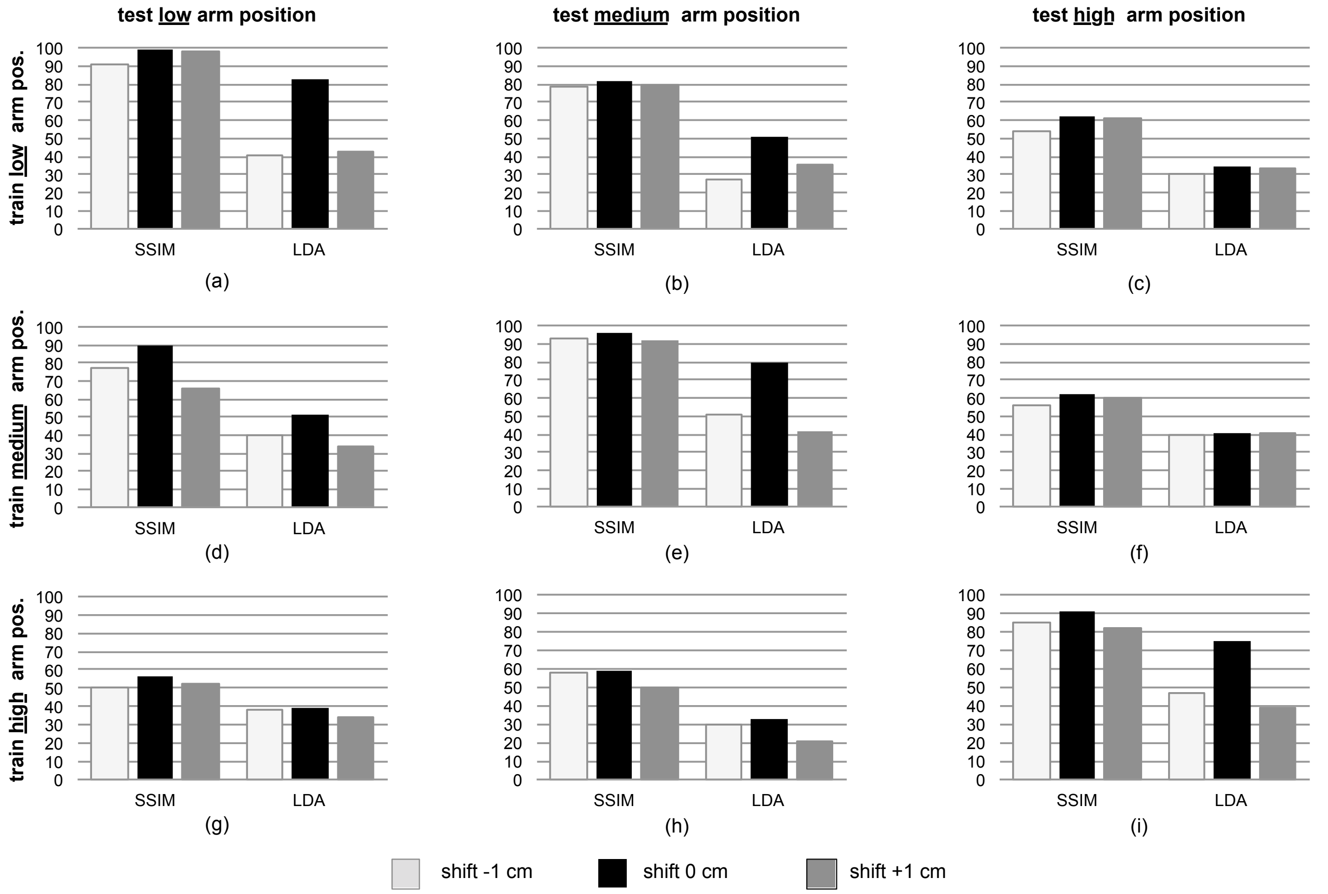

Fig. 4. Average classification accuracies of SSIM and LDA are compared. In (a), (e), and (i), the arm position remained the same during training and test phase while in all other cases the arm position was changed. For each case, there was either no simulated shift of test data (black bar), a simulated shift of 1 cm to the left (light grey bar) or 1 cm to the right (dark grey bar).

simulated electrode shifting, the SSIM-based classifier seems more robust against both effects.

IV. Discussion

The Structural Similarity Index quantifies the visual similarity between two images as the product of three components: luminance, contrast and structure. Our results indicate that a simple one-against-one classifier based on SSIM seems to outperform a traditional pattern recognition-based classifier like LDA using structural information from images of high density EMG data in terms of absolute classification accuracy and robustness to electrode shift.

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