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Optimization of EMG-based hand gesture recognition: Supervised vs. unsupervised data preprocessing on healthy subjects and transradial amputees

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ABSTRACT

We propose a methodological study for the optimization of surface EMG (sEMG)-based hand gesture classification, effective to implement a human–computer interaction device for both healthy subjects and transradial amputees. The widely commonly used unsupervised Principal Component Analysis (PCA) approach was compared to the promising supervised common spatial pattern (CSP) methodology to identify the best classification strategy and the related tuning parameters. A low density array of sEMG sensors was built to record the muscular activity of the forearm and classify five different hand gestures. Twenty healthy subjects were recruited to compute optimized parameters for ("*within*" analysis) and to compare between ("*between*" analysis) the two strategies. The system was also tested on a transradial amputee subject, in order to assess the robustness of the optimization in recognizing disabled users' gestures.

Results show that RMS-WA/ANN is the best feature vector/classifier pair for the PCA approach (accuracy 88.81 ± 6.58%), whereas M-RMS-WA/ANN is the best pair for the CSP methodology (accuracy of 89.35 ± 6.16%). Statistical analysis on classification results shows no significant differences between the two strategies. Moreover we found out that the optimization computed for healthy subjects was proven to be sufficiently robust to be used on the amputee subject. This motivates further investigation of the proposed methodology on a larger sample of amputees. Our results are useful to boost EMG-based hand gesture recognition and constitute a step toward the definition of an efficient EMG-controlled system for amputees.

1. Introduction

Surface electromyography (sEMG) is a non-invasive technique for measuring and evaluating the electrical activity of skeletal muscles. By recording EMG signals on forearms' muscles, it is possible to reconstruct different hand gestures [1]. Thanks to its non-invasiveness and ease in acquisition, sEMG signals can be exploited by many human–computer interaction (HCI) devices as input to control a prosthesis [2] or a virtual device [3], either for interactive or clinical/rehabilitative purposes [4,5]. The development of such HCI systems can address the needs of transradial amputees, who could greatly benefit from the resulting augmentation of stump functionalities.

Standard EMG-controlled devices are usually based on the evaluation of thresholds signal amplitude, merely using two sensors. Therefore, they can perform very simple movements (e.g. hand opening and closing) with restricted usability and poor adaptability to different contexts [6]. Multiple/arrays of sensors can be used [7] to avoid this kind of limitations but the increased number of channels leads to an increase in data dimensionality and complexity. To

Abbreviations: sEMG, surface electromyography; EMG, electromyography; EEG, electroencephalography; HCI, human–computer interaction; PCA, principal component analysis; CSP, common spatial patterns; FV, feature vector; ANN, artificial neural network; SVM, support vector machine; LDA, linear discriminant analysis; kNN, k-nearest neighbors; HMM, Hidden Markov Model; HSD, honest significant difference.

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deal with such complexity, more sophisticated EMG signal analysis techniques are needed, and pattern recognition methods [8] can help recognize executed hand gestures within a set of predefined movements.

Several researches have investigated the potentiality of EMG pattern recognition techniques in prosthesis control [9,10], rehabilitation [11] and clinical practice [12], employing high density sEMG configuration. Given the practical constraint of placing a large amount of electrodes onto a small surface [13], in particular for daily/routine applications, studies involving pattern recognition techniques on low density sEMG configurations were proposed [13–15], with the aim to realize an efficient sEMG-controlled device.

In general, a pattern recognition-based system consists of *preprocessing*, *feature extraction* and *classification*. In the preprocessing stage, in addition to the application of simple analog or digital filters, data dimensionality reduction techniques, e.g. Principal Component Analysis (PCA) [16], or signal-to-noise ratio improving techniques, e.g. Common Spatial Patterns (CSP) [14], are implemented. The feature extraction stage consists in the calculation of a vector of signals descriptive characteristics (features), namely *feature vector*; EMG data features are typically computed in time, frequency and/or time-frequency domain (see [17] for a review). Concerning the classification phase, linear/non-linear algorithms (classifiers) assign the extracted features to the class (gesture) they most probably belong to. Different classifiers have been proposed in literature (see [8] for a review), including Euclidean Distance, Logic Regression, k-Nearest Neighbors (kNN), Hidden Markov Model (HMM), artificial neural network (ANN), support vector machine (SVM), linear discriminant analysis (LDA).

Identifying the best choice and the related tuning parameters for the three above-mentioned stages still remains the main challenge: here we present a methodological offline study that compares a supervised CSP with an unsupervised PCA data preprocessing technique to optimize sEMG-based hand gestures classification. Out of the wide variety of preprocessing EMG classification techniques being investigated [18–20], we chose to analyze PCA, the widely commonly used technique, and CSP, which has shown interesting potentialities in EMG pattern recognition [14]. We investigated the performances of the two approaches by using 32 combinations of features (feature vectors) and 3 different classifiers: linear discriminant analysis (LDA, linear classifier), support vector machines (SVM, non-linear kernel classifier) and artificial neural networks (ANN, non-linear classifier). EMG signals were acquired by means of a low-density sEMG-based device designed for the recognition of hand gestures [21]. Twenty able-bodied (healthy) subjects were recruited to identify ("*within*" analysis) and compare ("*between*" analysis) the optimal PCA and CSP pattern recognition parameters (best feature vector/classifier pair). Non-parametric statistical tests, i.e. Friedman and Wilcoxon signed-rank tests, were used to detect any statistically significant differences in the performances.

Furthermore, intended hand gestures from a transradial amputee subject have been classified to evaluate the robustness of the optimization algorithm toward amputees' anatomy modifications. As a matter of fact, during surgical intervention, amputees' residual muscles and tendons are directly sutured to the bone with a procedure called myodesis [22], causing changes in muscle shape and length.

This study provides information on the optimization of system performances for the online implementation of EMG-controlled devices based on pattern recognition, such as HCI devices, for both healthy subjects and transradial amputees. Our results can be also exploited by different EMG signal classification studies for medical and engineering applications, where it is crucial to identify the best parameters for the tuning of preprocessing, feature extraction and classification stages.

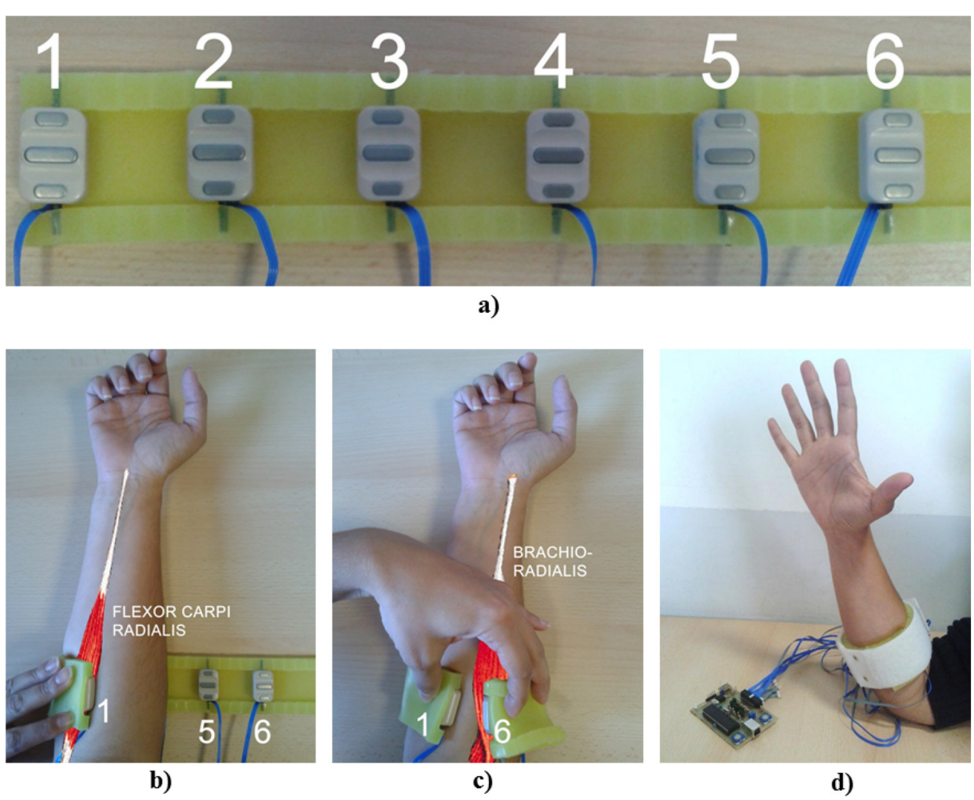

Fig. 1. Silicone support bracelet with six sEMG sensors (a) and its placing around the forearm (b–d).