Chapter 98
The Relationship Between Anthropometric Variables and Features of Electromyography Signal for Human-Computer Interface

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ABSTRACT

Muscle-computer interfaces (MCIs) based on surface electromyography (EMG) pattern recognition have been developed based on two consecutive components: feature extraction and classification algorithms. Many features and classifiers are proposed and evaluated, which yield the high classification accuracy and the high number of discriminated motions under a single-session experimental condition. However, there are many limitations to use MCIs in the real-world contexts, such as the robustness over time, noise, or low-level EMG activities. Although the selection of the suitable robust features can solve such problems, EMG pattern recognition has to design and train for a particular individual user to reach high accuracy. Due to different body compositions across users, a feasibility to use anthropometric variables to calibrate EMG recognition system automatically/semi-automatically is proposed. This chapter presents the relationships between robust features extracted from actions associated with surface EMG signals and twelve related anthropometric variables. The strong and significant associations presented in this chapter could benefit a further design of the MCIs based on EMG pattern recognition.

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INTRODUCTION

Surface electromyography (EMG) signals are measured by surface electrodes that are placed on the target muscles. During muscle contractions, a compound of the whole motor unit action potentials (MUAPs) occurred in the muscles. These MUAPs are the useful information for numerous fields, e.g. rehabilitation engineering, biomechanics, ergonomics, and human-computer interfaces (HCIs) (Merletti & Parker, 2004). Surface EMG signals can also be used in a medical decision support system, e.g. the diagnosis of neuromuscular disorders (Subasi, 2012, 2013). In this chapter, we focus on the development of the HCIs based on surface EMG signals, as called “muscle-computer interfaces or MCIs” (Saponas, Tan, Morris, & Balakrishnan, 2008). These interfaces can widely use in controlling many external devices, e.g. prosthetic limbs, electric-power wheelchairs, interactive surfaces, a virtual computer mouse or keyboard, a portable music player, and in-car electronic equipment (e.g. Barreto, Scargle, & Adjouadi, 2000; Benko, Saponas, Morris, & Tan, 2009; Khushaba, Kodagoda, Liu, & Dissanayake, 2013; Saponas et al., 2009; Shenoy, Miller, Crawford, & Rao, 2008; Wei, Hu, & Zhang, 2011; Yang, Lin, Lin, & Lee, 2013).

MCIs generally consist of three main modules, as shown in Figure. 1. The first module composes of two sub-modules: surface EMG signal acquisition (hardware) and data pre-processing (software). In the data acquisition sub-module, surface EMG signals are firstly amplified with an amplifier due to small EMG amplitude, and may be filtered by hardware filters, i.e., notch, high pass and/or low pass filters. Then, continuous surface EMG signals are sampled using an analog-to-digital converter. In case of no hardware filters, the raw EMG data can be filtered by software filters, before the EMG data go to the next module, the pattern recognition module. Different patterns of surface EMG signals are classified and matched to the control commands in this module. The second module can be divided into three sub-modules: feature extraction, dimensionality reduction, and classification algorithms. All sub-modules are in the software part. The pre-processed surface EMG data from the first module are segmented into small time slot length using an adjacent or an overlapped windowing technique, and then some features are extracted in order to emphasize the relevant structures in the EMG signals and remove noises/irrelevant parts. A feature vector is formed and can be sent directly to a classifier, or the dimension of a feature vector is reduced by the dimensionality reduction technique before sending it to the classifier. The classifier maps the extracted features (the representative of the actions associated with surface EMG signals) to the target classes (the control commands for an external device). After the control commands were generated based on the mathematical functions in the second module, the third module is a control system, which serves as an interface between the software and hardware. In other words, an output command is converted from a digital code to an analog signal for controlling an external device. In this chapter, we focus on the second module, particularly the extraction of EMG features.

Nearly all previous studies on MCIs based on EMG pattern recognition concentrate on improving recognition rate together with increasing the number of discriminated motions. Currently, the recognition rate is more than 90% in discriminating 4-12 finger, wrist, hand, and forearm motions. It should be noted that the recognition rate or the classification accuracy is calculated as a ratio of the number of correct classifications to the total number of classifications. More details about many previous studies on MCIs based on EMG pattern recognition concentrate on improving recognition rate can be found in additional readings in the Additional Reading Section. However, the high recognition rates reported are usually based in single-session experiments conducted in research laboratories (Tkach, Huang, & Kuiken, 2010). On the other hand, in clinics when the context of the real-world requirements have been given attention, there are many issues that have to find the solutions, e.g. the robustness against a variety of