Chapter 49
Using Myoelectric Signals to Manipulate Assisting Robots and Rehabilitation Devices

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ABSTRACT

Myoelectric signal is known as an alternative human-machine interface (HMI) for people with motor disability in dealing with assisting robots and rehabilitation devices. This chapter examines a myoelectric HMI in real-time application and compares its performance with traditional tools. It also studies the manifestation of fatigue in long-term muscular activities and its impact on ultimate performance. The core of applied HMI is built on the support vector machine as a classifier. The experiments confirm that the myoelectric HMI is a reliable alternative to traditional HMI. Meanwhile, they show a significant decline in the dominant frequency of myoelectric signals during long-term applications.

INTRODUCTION

Since most disabled people have problems manipulating current assistive robots and rehabilitation devices that employ traditional user interfaces, such as a joystick and/or keyboard, they need more advanced hands-free human-machine interfaces (HMIs). Surface myoelectric signal (MES) is a biological signal collected non-invasively from surface of the skin covering the muscles, and contains rich information to identify neuromuscular activities. A myoelectric HMI uses MES as an input signal to recognize various patterns of muscular activities and employs them to produce the effect of user's intention on its output. It eases the interaction with electric devices, assisting robots, or rehabilitating devices to the minimum level of movements for the disabled.

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A pattern recognition-based myoelectric HMI recognizes input patterns by classifying the signal features, and outputs their corresponding commands, hence, the selection of effective features and a classifier that provide accurate as well as fast reactions are crucial issue (Asghari-Oskoei & Hu, 2007). The application of pattern recognition to myoelectric HMI was first introduced in the 1960-70s (Englehart et al., 2001b); however, due to limited acquisition instruments and computing capacity at that time, real time control was not feasible. (Hudgins et al., 1993) were pioneers in developing a real time pattern-recognition-based myoelectric HMI. Using time domain (TD) features and a multilayer perceptron (MLP) neural network, they succeeded in classifying four types of upper limb motion, with an accuracy of approximately 90%. This work was continued over the last fifteen years, by employing various classifiers, such as LDA, MLP/RBF neural networks, time-delayed ANN, Fuzzy, NEURO-Fuzzy, Fuzzy ARTMAP networks, Fuzzy-MINMAX networks, Gaussian mixture models (GMM), and hidden Markov models (HMM). (Vuskovic & Du, 2002) introduced a modified version of a fuzzy ARTMAP network to classify prehensile myoelectric signals. (Englehart et al., 2001a) showed that linear discriminant analysis (LDA) outperforms MLP on time-scale features which are dimensionally reduced by PCA.

In addition, significant results were achieved using probabilistic approaches. (Chan & Englehart, 2005) applied a hidden Markov model (HMM) to discriminate six classes of limb movement based on a four-channel MES. It resulted in an average accuracy of 94.63%, which exceeded an MLP based classifier used in (Englehart et al., 2003) (93.27%). Furthermore, (Huang et al., 2005) and (Fukuda et al., 2003) developed a Gaussian mixture model (GMM) as a classifier; the former showed an accuracy of approximately 97%. (Englehart et al., 2003) introduced a continuous classification scheme that provided more robust results for a shortened segment length of signal, and high speed controllers.

In (Asghari-Oskoei & Hu, 2008), the authors have conducted a research to deploy support vector machine (SVM) as a classifier for myoelectric HMI. It proposes and evaluates the application of SVM to classify upper limb muscle activities using surface myoelectric signals. The optimum configuration for a SVM-based myoelectric HMI is explored by suggesting an advantageous data segmentation technique, feature set, model selection approach for SVM, and post-processing method. Meanwhile, it presents a method to adjust SVM parameters before classification. It is shown that SVM offers classification performance that matches or exceeds other classifiers (i.e. LDA and MLP). A TD multi-feature set consisting mean absolute value (MAV), waveform length (WL), and zero-crossing (ZC), outperforms other features, because of its relatively high rate of accuracy, stability against changes in segment (window) length, low discrepancy over several sessions, and computational simplicity. WL outperforms single-features, because of its high rate of accuracy and stability to changes in segmentation methods. A disjoint segmentation with a length of 200 ms provides high performance during MES classification, and a reasonable response time to allow real-time application. Overlapped segmentation with a length of 200ms and an increment of 50 ms shortens the response time without a noticeable degradation in accuracy. Majority voting (MV), as a post-processing method, provides stable output. It is also shown that the entropies of correct and non-correct outputs are significantly distinct.

However, the performance of myoelectric HMI in real-time applications is still an open question. This Book Chapter makes an effort to examine myoelectric HMI in real applications and evaluate its performance in dynamic aspects. This study employs the HMI developed in (Asghari-Oskoei & Hu, 2008) and applies it to an assisting robot and a rehabilitation device. In real-time applications, visual feedback provides interactive interface that improves the quality of control. Users can adjust the level of muscles contraction using visual feed-

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