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Review

Current state of digital signal processing in myoelectric interfaces and related applications



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ABSTRACT

This review discusses the critical issues and recommended practices from the perspective of myoelectric interfaces. The major benefits and challenges of myoelectric interfaces are evaluated. The article aims to fill gaps left by previous reviews and identify avenues for future research. Recommendations are given, for example, for electrode placement, sampling rate, segmentation, and classifiers. Four groups of applications where myoelectric interfaces have been adopted are identified: assistive technology, rehabilitation technology, input devices, and silent speech interfaces. The state-of-the-art applications in each of these groups are presented.

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1. Introduction

The wearable and mobile technology market has demonstrated significant growth and adoption in various end-user market segments, in particular telecommunication, fitness, wellness, healthcare, and medical monitoring. However, the technology lacks an effective method to communicate with devices. Currently popular input methods such as touch screens, small keyboards, and portable controllers are impractical in situations where hands cannot easily be used to directly manipulate an input device. Portable input devices are also difficult to carry around. Additionally, for people with severe physical disabilities such as spinal cord injury, quadriplegia, hemiplegia, Parkinson's disease, or muscular dystrophy, the traditional user interfaces currently available are inadequate. Fehr et al. [1] surveyed 200 practicing clinicians, asking them to provide information about their patients with power wheelchairs relying on conventional controllers. Of respondents, 85% reported evaluating some number of patients annually for whom a power wheelchair is not an option because they cannot control it. Of the patients, 40% with power wheelchairs had difficulties with steering tasks and 5-9% needed assistance with such tasks. Such examples indicate the need for new controller interfaces accommodating the abilities of the patients. Attempts have been made to overcome these problems by using voice commands [2], as well as camera-[3], electroencephalography (EEG)-[4], electrooculography (EOC)- [5] or electromyography (EMG)-based control [6].

EMG interface classifies the voluntary-contraction-related muscle activity and associates it to the desired function of the given device. The EMG interface could offer an intuitive and easy way of communication that relieves the user from portable control devices and direct eye contact to the device. The only requirement is that the user is able to activate some of his or her voluntary skeletal muscles. EMG interfaces generate control commands for a given device relying on information content of EMG signals. The methods used to measure these signals include surface EMG (sEMG) where electrodes are placed on the skin over the measured muscle, intramuscular EMG (iEMG) where the electrodes are inserted through the skin into the muscle tissue and percutaneous EMG (pEMG) where a needle or wire is inserted under the skin and subcutaneous

tissue over the aponeurosis of the muscle. According to our best knowledge, pEMG measurements have not been used in the EMG interfaces. Comparative studies have found that, at least in laboratory conditions, intramuscular and surface recordings yield similar accuracy in classifying hand and forearm movements [7,8]. Surface electrodes are advantageous because they are inexpensive and noninvasive. In contrast to relatively selective intramuscular electrodes, surface electrodes detect activity from many muscles on one channel, which makes it possible to acquire sufficient information for the EMG interface with smaller number of electrodes [8]. However, intramuscular recordings may be beneficial because of their potential ability to overcome some of the major problems of surface recordings, such as electrode shifts and skin impedance changes. Because iEMG [7–13] and have seldom been investigated in the context of EMG interfaces, this study deals only with sEMG recordings.

The sEMG signal is a superposition of individual motor unit action potentials (MUAPs) within the pick-up range of the surface electrodes. As sEMG amplitude and frequency content changes with contraction-force level [14,15], it is possible to associate the muscle contractions of the user to control the device concerned. The concept of sEMG interface was introduced in the 1940s [16], and the first sEMG application, a myoelectric prosthetic arm, was developed in 1960 [17]. In the recent years, the interest has grown toward sEMG interfaces. It has been noted that myoelectric interfaces have a huge potential in applications designed not only for people with disabilities [18–24] but also in applications for healthy people [25–30]. The numerous benefits of the sEMG interface over traditional input devices have inspired patents [31,32], especially in the field of mobile technology.

The sEMG interface is suggested to offer many benefits over other man-machine control methods. The sEMG control may require less attention from the user than EEG based controls or the control with eye movements. In contrast to visual-based control, myoelectric control allows the user to look around while controlling the device. Compared to many other biosignals, such as EEG, sEMG signals have relatively high signal-to-noise ratio. Unlike voice control, sEMG control has only a minimal delay, is not sensitive to ambient sound perturbations, does not cause embarrassment to the user, or disrupt the environment. The sEMG interfaces can

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