

## Chapter 13

# Classification of Surface Electromyogram Signals Acquired from the Forearm of a Healthy Volunteer

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### ABSTRACT

*Surface EMG (sEMG) signals from the palmaris longus, flexor carpi radialis and flexor carpi ulnaris muscles were recorded using an in-house developed EMG signal acquisition system. The bandwidth of the acquisition system was 1500 Hz. The extracted sEMG signal was processed using Discrete Wavelet Transform (DWT). The features of the extracted and the wavelet processed signals were determined and were used for probable classification using Artificial Neural Network (ANN). A classification efficiency of more than 90% was achieved using ANN classifiers. The results suggested that the sEMG may be successfully used for designing efficient control system.*

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## INTRODUCTION

In recent years, the use of biosignals associated with the residual functional capability of the incapacitated persons has gained much importance for controlling assistive or rehabilitative devices/ aids (Allison, et al., 2012; Barea, Boquete, Mazo, & López, 2002; Chen & Newman, 2004; Moon, Lee, Chu, & Mun, 2005; Tanaka, Matsunaga, & Wang, 2005). This is of utmost importance for such patients because the biosignal controlled devices may provide better independence. Amongst the various biosignals, electromyogram (EMG), electrooculogram (EOG) and electroencephalogram (EEG) signals have been extensively studied (Mukherjee, Dey, Dey, & Dey, 2015; Neto, Celeste, & Martins, 2006; Oskoei & Hu, 2007; Ubeda, Ianez, & Azorín, 2011). Even though EOG and EEG-based control systems are quite efficient, the patient compliance during signal acquisition might be very low. This is due to the fact that the EOG signal acquisition system needs electrodes to be placed around the eyes and hence, might be inconvenient for the patients. But the main advantage of the EOG signals is its stability, even in the severely motor-incapacitated patients. Hence, EOG based control systems have been found useful for the patients suffering from progressive neuro-motor degenerative diseases (Ubeda, et al., 2011; Usakli, Gurkan, Aloise, Vecchiato, & Babiloni, 2010). Similar to the EOG signals, the EEG electrodes are placed on the scalp across the head. Additionally, analysis of the EEG signals is comparatively complex as compared to the EOG and the EMG signals. This is because of the fact that the EEG electrodes acquire the signals from the underlying group of neurons (located within the cortex of the brain) from a specific area of the scalp. The signals, which are represented over the surface of the scalp, are due to addition of the electrical potentials of the groups of neurons present in the underlying area. Proper analysis of the EEG signals can divulge information about the physical and mental state of the persons. The analysis of the EEG signals has found extensive applications in cognitive learning, disorders related to the nervous system of the brain and development of the control systems for neuroprosthetics (Lauer, Peckham, & Kilgore, 1999; Laufs, et al., 2003; Neto, et al., 2006).

EMG signals are the biopotential signals, which are generated due to the activity of the neuro-muscular junctions (Criswell, 2010). The muscles may be excited either voluntarily by the volunteer or by applying an electrical stimulus. The excitation of the muscles induces contraction of the muscles, which is due to the collective contraction of the muscle fibres. These signals are manifested at the surface of the skin. The acquisition of these surface signals, due to the activity of the muscles, is regarded as “surface electromyogram” (sEMG) (Gerdle, Karlsson, Day, & Djupsjöbacka, 1999). The main advantage of acquisition of the sEMG is that the signal may be acquired in a non-invasive manner (Merletti & Parker, 2004). These EMG signals appear as random signals, but the sEMG signals of similar profiles can be generated by activating a specific group of muscles. Similar sEMG profiles are repetitively generated until and unless the muscle becomes fatigued or any physiological changes occur in the muscle. This helps in the analysis of the neural drive, which excites the muscles. Usually, the sEMG signals have amplitude in the range of 0 and 10 mV<sub>p-p</sub> (Reaz, Hussain, & Mohd-Yasin, 2006). The frequency of the sEMG signal lies mainly in the range of 5 and 500 Hz (Merletti & Di Torino, 1999; Van Boxtel, 2001). EMG signals have gained the attention of the researchers as the most preferable physiological signals due to their ability to provide information on both clinical and engineering aspects. These signals have been explored for diagnosing diseased conditions of not only muscles but also of the bones with which the muscles are attached (Drost, Stegeman, van Engelen, & Zwarts, 2006; Hogrel, 2005; Zwarts & Stegeman, 2003). Apart from the clinical investigation, the sEMG signals may be acquired from the limb amputees for extracting information about the voluntary muscular contraction with typical sEMG features. The

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