Human upper limb motion estimation based on electromyography signals

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Abstract

Surface electromyography (EMG) signal contains relevant information about the electrical activity produced by the neuromuscular process of contraction or relaxation [1]. Although, the complexity of the recorded EMG signals makes the movement estimation process a difficult task [2]. It is possible to extract some features, which allow the identification of the produced movement, with respect to the measured electrical activity. In the state of the art, several studies had been proposed, with the aim to identify movements from EMG signals. In [3], the authors focused on the identification of five hand movements in which the obtained accuracy range was 94% to 99%. In the same way, [4] have identified wrist and ring finger movements with an accuracy of 87.3% and [5] put forward the recognition of eight different effective grasping gestures with an accuracy range of 96.9% to 99.65%.

In this work, we propose a novel method to estimate the upper limb motion based on the extraction of features from EMG signals. The selected features are Mean frequency, Entropy, and Mean Absolute values [6]. The features are normalized to describe an n-dimensional feature space, where each dimension corresponds to a feature extracted from EMG signals of superficial upper limb muscles. To estimate the motion in the feature space, we use a supervising learning classifier that creates an hyperplane to separate the different movements. Considering that the distribution of our features is non-linear, we use a non-linear support vector machine (SVM) classifier. To validate our method, we carried out an experiment with four healthy patients, who perform several trials of a combined movement of the upper limb. The motion is achieved with seven 3D VICON cameras with a sampling frequency of 200 Hz, and 30 retro-reflective markers distributed over the upper limb. The EMG signals are captured with wireless sensors at a sampling frequency of 1 kHz.

1 Upper limb kinematic model

To analyse the motion and geometric relationship of the upper limb, we propose a kinematic model, that considers, five degrees of freedom, the limits of each rotation and the geometry of the upper limb. Consequently, we have developed an experiment that measure the position of the upper limb of patients during different movements. The positions are captured with Vicon cameras and retroreflective markers. The movements are computed by linear interpolation of positions.

Then, we process the information and evaluate the rotation angle values in each articulation (i.e. elbow angle, or shoulder angles). Simultaneously, the EMG signals are captured from ten muscles of the upper limb.

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2 Features extraction of EMG signals and Supervised machine learning

Feature extraction is a powerful technique to obtain relevant information from signals. There are several features in the time domain and the frequency domain, but both domains are useful for analyzing EMG signals. In the present analysis, we consider two features in the time domain (Entropy, Mean absolute value) and one in the frequency domain (Mean frequency). Then, the features are normalized to describe an n-dimensional feature space. Then, we use a non-linear support vector machine (SVM) classifier.

3 Conclusion and Perspectives

In this paper, we propose a new method to estimate the human upper limb motion with EMG signals. The validation of our method is carried out through an experiment that allows us to collect EMG signal from ten muscles and to track the upper limb. In future work, we will consider more combination of different movements of the upper limb, the fatigue, and others skin situations.

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