BIOCYBERNETICS AND BIOMEDICAL ENGINEERING 38 (2018) 126–135

Available online at www.sciencedirect.com

ScienceDirect

journal homepage: www.elsevier.com/locate/bbe

Original Research Article

A bionic hand controlled by hand gesture recognition based on surface EMG signals: A preliminary study

Wan-Ting Shi[a], Zong-Jhe Lyu[a], Shih-Tsang Tang[a], Tsorng-Lin Chia[b], Chia-Yen Yang[a,*]

[a] Department of Biomedical Engineering, Ming-Chuan University, Taoyuan, Taiwan
[b] Department of Computer and Communication Engineering, Ming-Chuan University, Taoyuan, Taiwan

ARTICLE INFO

Article history:
Received 1 February 2017
Received in revised form
26 September 2017
Accepted 9 November 2017
Available online 16 November 2017

Keywords:
Hand posture recognition
Surface myoelectric signal
k-nearest neighbors
Hudgins' features
Bionic hand
LabVIEW

ABSTRACT

A bionic hand with fine motor ability could be a favorable option for replacing the human hand when performing various operations. Myoelectric control has been widely used to recognize hand movements in recent years. However, most of the previous studies have focused on whole-hand movements, with only a few investigating subtler motions. The aim of this study was to construct a prototype system for recognizing hand postures with the aim of controlling a bionic hand by analyzing sEMG signals measured at the flexor digitorum superficialis and extensor digitorum muscles. We adopted multiple features commonly used in previous studies—mean absolute value, zero crossing, slope sign change, and waveform length—in the algorithm for extracting hand-posture features, and the *k*-nearest-neighbors (KNN) algorithm as the classifier to perform hand-posture recognition. The bionic hand was controlled by an Arduino microprocessor, which converted the signals received from the classification process that were fed to the servo motors controlling the bionic fingers. We constructed a two-channel sEMG pattern-recognition system that can identify human hand postures and control a homemade bionic hand to perform corresponding hand postures. The KNN approach was able to recognize four different hand postures with a classification accuracy of 94% in the online experiment by using the channel combination. Moreover, the experimental tests show that the bionic hand could faithfully imitate the hand postures of the human hand. This study has bridged the gap between the features of sEMG signals of fingers and the postures of a bionic hand.

* *Corresponding author at*: Department of Biomedical Engineering, Ming-Chuan University, 5 De Ming Rd., Gui Shan District, Taoyuan County 333, Taiwan.
E-mail address: cyyang@mail.mcu.edu.tw (C.-Y. Yang).

https://doi.org/10.1016/j.bbe.2017.11.001

1. Introduction

Operators working in many laboratories, including those involving chemical and biological substances, deal with hazardous reagents while wearing gloves and a laboratory coat, which may not provide sufficient protection for completely avoiding dangers that can appear unexpectedly during an experiment. A bionic hand with a fine motor ability could be a favorable option for replacing the human hand when performing various subtle operations in certain dangerous situations, and a practical and reliable solution might be achievable using motion recognition. That control technology could also be applied in a bio-prosthetic hand with feedback sent by from sensors and achieve high-level functional requirements.

The different methods of motion recognition can be divided into two types: (1) non-vision-based recognition, such as using data gloves and a data coat, and (2) vision-based recognition, such as video image detection [1,2]. Many researchers have used video image detection to recognize body motion. Although this does not require the users to wear any devices, environmental factors (e.g., luminance and color) can adversely affect image recognition. This has prompted researchers to choose surface electromyography (sEMG) to recognize subtle movements in order to obtain more reliable and accurate data, even though this is associated with the need for extra portable devices [3–5]. sEMG is a noninvasive technique of recording the electrical activities of muscles, and the obtained data can be used to determine joint motions [6,7]. Electromyography (EMG) motion-recognition systems have already been widely used in many man–machine interface applications (e.g., multifunction artificial limb, virtual mouse, fingerboard, and electric wheelchairs) [8], and the continuing developments in science and technology mean that portable devices are now compact and highly efficient, and wearing them is no longer deemed a problem—users now consider them to be comfortable, convenient, and even fashionable.

The process of sEMG-based motion recognition can be divided into several parts. The first part is recording the raw signals. We need to decide the number and positions of electrodes according to the type of motion being performed in the experiment. Most studies of motion recognition for whole-hand movement have recorded from four or more channels on the whole arm, since each motion depends on several muscles [9,10]. However, in studies of hand postures the used muscles are mainly in the forearm, and so the number of channels can be reduced. Although this may reduce the accuracy, this can be ameliorated by appropriately combining features in different channels. Ensuring the effectiveness while minimizing the cost are important practical considerations when establishing a system, such as decreasing the computation burden by reducing the dimensionality of the data [11,12]. The second part is signal preprocessing. The raw signals are separated into data segments using either adjacent or overlapping windowing [6,13]. Khushaba et al. [14] found that the window size needs to be less than 300 ms for real-time control to be possible, with the optimal size being from 150 ms to 250 ms [11]. Some studies found that the overlapping windowing technique can improve the accuracy of processing [14,15], but this also requires more calculations of the feature values and classification properties [12]. The third part is feature extraction. Many studies have used a combination of different EMG features to identify different movements [8,13,16]. However, this increases the classification overhead when combining many features are involved [11,12]. Hence, the users need to choose the effective EMG feature values to classify the movements. There are several common types of features: time domain (e.g., mean absolute value [MAV] and zero crossing [ZC]), frequency domain (e.g., mean frequency and median frequency), and time–frequency domain (e.g., wavelet transform and short-time Fourier transform); among which time-domain features are rapid and simple to implement because they are extracted directly from raw data in a time series, and thereby also avoid high computational complexity [5,12,13,16,17]. Hudgins' features or Du's features are typically used, with Hudgins' features being by far the most popular [4,5,12,13,16,17]. Besides, the elimination of redundant features should be considered to optimize the learning parameters of the pattern classifier, and the convergence of learning error. Among various feature dimensionality reduction techniques in myoelectric pattern recognition, one of the most widely used techniques is principal component analysis (PCA). It captures the orthogonal directions in the input data space where the variance is maximal and increases the efficiency of classification by well-described features from high-dimensional feature spaces (i.e., selection and reduction of features) before engaging the classifier [18]. The last part is the classification method. Many classification methods can be used to analyze whether the selected features, such as the support vector machine (SVM), linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), and k-nearest neighbors (KNN). A SVM can solve high-dimensional and nonlinear problems, but it does not provide a general solution to a nonlinear problem [19]. LDA factor analyses look for linear combinations of variables that best fit the data. Comparing with PCA, LDA is computational easier and is better for identifying differences between samples [8], while both of these techniques are usually used to reduce the data dimensionality [9,11,20]. QDA is closely related to LDA, as indicated by their names: quadratic and linear analyses, respectively. However, QDA only applies to the situation of nonsingular scatter matrix within the class, which may result in problems with small samples in practical applications. KNN is simple to understand, easy to implement, and inexpensive in retraining, but may lead to inaccurate results when entering a new sample with an imbalanced data set (i.e., unequal sample sizes between classes). Among these classifier, LDA and KNN are computationally efficient and hence are relatively easy to implement in real-time applications [21].

Myoelectric control has been widely used in recent years, with hand-posture recognition based on EMG technology predominating. Most previous studies have focused on the larger and more complex motions of the hand, wrist, and arm, such as forearm pronation, forearm supination, wrist extension, wrist flexion, wrist radial deviation, wrist ulnar deviation, and wrist internal rotation and external rotation [14–17,22,23]. Those whole-hand motion studies have produced quite accurate results. However, further studies which have considered the subtler finger postures could have more diverse