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# Time series modeling of surface EMG based hand manipulation identification via expectation maximization algorithm

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ABSTRACT

In this paper, we focus on the method of employing the expectation maximization (EM) algorithm to the modeling of surface electromyography (sEMG) signals based on hand manipulations via available time series of the measured data. The model for the sEMG is developed as a hidden Markov model (HMM) framework. In order to represent dynamical characteristics of sEMG when multichannel observation sequence are given, a stochastic dynamic process is included in it based on the maximum likelihood estimation (MLE) principle. By using the EM algorithm, the hidden model parameters and the feature of the signal can be identified easily. Ten people of different time series data sets of different hand grasps and in-hand manipulations captured from different subjects are collected. The two different classifiers were used to recognize these hand manipulation signal. Compared with time and time–frequency domains and their combination feature, the proposed algorithm of the inferred model gains better performance and demonstrates the effectiveness. The average identification accuracy rate is 93% and the maximum classification ratio is 100%.



## 1. Introduction

It is well known that there are existing strong relationship between hand manipulation and the movement of articulatory forearm muscles. Also, sEMG signal contains information sent from the human neural system to control the activation of muscles and the power of sEMG signal reflects the property of hand manipulation [5,13,31]. Because the sEMG signal is easy accessed and recorded from the remnant muscles of the stump, and in practical utilizing of multifunction upper limb prostheses is considered to be actual control signal, it has been under special investigations in the past decade [17]. Although a lot of effort is being spent on improving these weaknesses, the efficient and effective method has yet to be developed.

Recently, a major concern in constructing a mathematical model of sEMG signal continues to improve the precision of the dynamical characteristics [2,6,15,25]. sEMG signal is indeed extensively used for human–machine interfacing, for example for the control of prosthetic devices [4,27], by extracting significant feature of the signal for control. In [1,2], a novel recurrent neural network based on the hidden Markov model is used to establish the model of time series data in sEMG signal. In [10–12,24], similar techniques are used, but a hidden Markov model is derived from the physiological generation of the sEMG signal. In [6], fuzzy entropy is applied to measure the characterization of sEMG signal. In [25], nonlinear measures based on recurrence plot is exploited for evaluating the hidden dynamical characteristics of sEMG signal. In [21], an adaptive neuro-fuzzy inference system is proposed to identify hand motion commands and a hybrid algorithm is used to train and the average classification ratio is 92%. In [14], the association of autoregressive models and a neural network is used for EMG pattern discrimination and the rates of success of control the movements of a virtual prosthesis is 100%. In [8,9], a novel multiscale model and the iterated Hilbert transform is used for simulating the sEMG of an antagonistic pair of muscles during pathological tremor. In [22], the EMG signal processing of hand motion is represented by a linear multiple regression model. Advanced signal processing of the sEMG signal will inevitably promote the development of advanced multifunction upper limb prostheses, often called as "the mind-controlled artificial hands" [16].

This paper presents a new method to construct a model of time series data in sEMG signal. It differs from the existing research method in that we concentrate more on gaining deep insight into the

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relationship between the sEMG signal intensities and the hand manipulation movement control. In order to gain better control performance, the primary thing to do is to extract the main feature of the test sEMG signal. At the same time, a sEMG signal is assumed to be the output of a stochastic dynamic process driven by the physiological properties of the muscle and the form of the contraction [7,19]. Also, a hidden Markov model (HMM) is a representation of a type of random process, it can describe time-varying processes in signal processing. Accordingly, HMM can be applied for representing the dynamic and stochastic character of sEMG signals. Therefore, the model output captures the sEMG signal's statistical properties according to some goodness measure.

In essence, in order to improve the accuracy for hand motions classification, the measured sEMG signal intensities can be described as a stochastic dynamic model, so the HMM stochastic dynamic process inevitably is contained into it. There are three main reasons why we select this model. Firstly in terms of the measured signal intensities, there is certain input–output causality. Secondly, in the course of observing measurement outputs of the model, there unavoidably exists noises owing to measurement accuracy. Finally since time series data that we got from digital computation is discrete, it is easy to analyze using the discrete-time stochastic dynamic model. Unfortunately, in previous research about sEMG model, few people pay attention on the issue of processing available time-series sEMG signals with certain noise.

In [35], the sEMG signal model identification (parameter estimation) is rather straightforward as it boils down to solving a system of linear equations. Different from this method, the focus of this paper is going to find a new way to jointly estimate the model parameters and the actual signal intensities simultaneously. The expectation maximization (EM) algorithm, firstly proposed by Shumway and Stoffer [32], is fit for dealing with the estimation problem via time series data depending on the above addressing features of the sEMG signal model. It can efficiently find maximum likelihood estimates of parameters in statistical model by using an iterative method. As we can see from [20,28–30,34,36–39], the EM algorithm has been widely used in all kinds of signal processing problems and gained computationally efficient estimations. The main motivation of studying the modeling method for time series data in sEMG signal is mainly twofold. (1) Up to now, it is still a challenge and is becoming the main focus of the on-going research in hand manipulation identification, in order to achieve a satisfactory rate for the sEMG signal recognition, the method of time-series modeling in sEMG signal is applied in this paper. (2) Based on the feature difference between sEMG signal of different hand manipulations, for continuous hand manipulation, HMM framework is used to extract and recognize sEMG signal feature.

As we all know, the sEMG signals recorded from natural behaviors are time-varying and nonstationary. For modeling these properties of the sEMG time series data, HMM framework has many advantages for some reasons. First, HMM framework is available for better representation of the dependent relationships of multivariate sEMG signals comes from different channels. Furthermore, HMM framework gives a probabilistically tractable and robust method of modeling the non-stationary and dynamic changes of state. On the basis of an analysis of the feature and parameters of HMM, the HMM framework can be applied to represent the feature of sEMG signal and related parameters. The main contribution of this paper is mainly twofold. (1) A HMM framework technique for modeling the sEMG signals is proposed to the issue of the hand manipulation recognition. Note that the proposed model can correctly and effectively recognize the hand manipulation. (2) Experiment results have shown that the EM algorithm that used for solving this model parameters can not only improve the convergence speed, but also obtain a higher recognition accuracy than other classical model such as AR, ARIMA, WAMP, RMS, MUAP and GMM.

The remaining of this paper is organized as follows. Section 2 describes a hidden Markov model for the sEMG signal. The EM algorithm is introduced in Section 3 for handling the parameter identification problem. Section 4 applies EM algorithm to classify the collected data sets of sEMG and discussed the results. Section 5 gives related concluding remarks.

## 2. Hidden Markov model framework for the sEMG signal

A sEMG signal represents an electrical signature of muscle activity [24]. It can be described by the stochastic dynamic model. Let $y_i(k)k \in [0,m]$ be a Markov chain taking values in a finite state space, in fact it is a sequence of observed signal, $S=\{1,2,\dots,s\}$, $m$ is the measurement time points, $x_i(k)k \in [0,m]$ is actual value of the test sEMG signal, and $v_i(k)k \in [0,m]$ is an embedded measurement noise, suppose it is zero mean Gaussian white noise with covariance $V_i > 0$. Thus, the sEMG signal model is in the following form:

$$y_i(k) = Hx_i(k) + v_i(k), \quad i=1,2,\dots,n, \quad k=1,2,\dots,m, \tag{1}$$

where $H = \begin{bmatrix} x_1^1 & \cdots & x_1^n \\ \cdots & \ddots & \vdots \\ x_p^1 & \cdots & x_p^n \end{bmatrix}$ is the design matrix with the time-series of a set of $p$ voxels. The shapes of the impulse $H$ represent the motor unit action potential shapes (MUAP) and are assumed time-variant. In this model, we do not consider of the effect of variable neuromuscular junction transmission and variable conduction velocities, it is a simplified representation of the actual sEMG signal.

Furthermore, we consider the following class of stochastic discrete-time system to model the sEMG signal containing $n$ states:

$$x_i(k+1) = \sum_{j=1}^{n} Ha_{i,j}x_j(k) + w_i(k), \quad i=1,2,\dots,n, \quad k=1,2,\dots,m, \tag{2}$$

where $a_{i,j}$ represents the relationship and degree amongst the value of test signal. $a_{i,j} > 0$ means the $j$th state positive stimulating the $i$th state and, similarly, $a_{i,j} < 0$ stands for the $j$th state negative repressing the $i$th state, while a value of zero indicates that $j$th state does not influence the transcription of $i$th state. $w_i(k)$ is the system noise. We also assume that $w_i(k)$ is a zero mean Gaussian white noise sequence with covariance $W_i > 0$, and $w_i(k)$ and $v_i(k)$ are mutually independent. Suppose

$$x(k) = [x_1(k)\, x_2(k) \cdots x_n(k)]^T, \quad k=1,2,\dots,m$$

and

$$\alpha_i = [\alpha_{i,1}\, \alpha_{i,2} \cdots \alpha_{i,n}], \quad i=1,2,\dots,n$$

It can be rewrite simplified as

$$x_i(k+1) = Hx(k) + w_i(k), \quad i=1,2,\dots,n. \tag{3}$$

In this paper, our aim is to establish the model (1) and (3) from the observed data

$$Y := \{y_1(1), y_1(2), \dots, y_1(m), y_2(1), y_2(2), \dots, y_2(m), \dots, y_n(1), y_n(2), \dots, y_n(m)\}. \tag{4}$$

Suppose that above sequence of observed data $y_1(1), y_2(2), \dots, y_n(m)$, each of which is associated with a hidden state $q_1(1), q_2(2), \dots, q_n(m)$, as shown in Fig. 1. In terms of Ref. [26], we assume that the points are generated from an underlying density $p(x)$. Also, we further assume that $p(x)$ is defined as a finite hidden Markov model with $K$ components containing $n$ states:

$$p(x|\Theta) = \sum_{k=1}^{n} \alpha_k p_k(x|z_k, \theta_k) \tag{5}$$