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Research Paper

Surface EMG based continuous estimation of human lower limb joint angles by using deep belief networks

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ABSTRACT

Surface electromyography (EMG) signals have been widely used in locomotion studies and human-machine interface applications. In this paper, a regression model which relates the multichannel surface EMG signals to human lower limb flexion/extension (FE) joint angles is constructed. In the experimental paradigm, three dimensional trajectories of 16 external markers on the human lower limbs were recorded by optical motion capture system and surface EMG signals from 10 muscles directly concerned with the lower limb motion were recorded synchronously. With the raw data, the joint angles of hip, knee and ankle were calculated accurately and the time series of intensity for surface EMG signals were extracted. Then, a deep belief networks (DBN) that consists of restricted Boltzmann machines (RBM) was built, by which the multi-channel processed surface EMG signals were encoded in low dimensional space and the optimal features were extracted. Finally, a back propagation (BP) neural network was used to map the optimal surface EMG features to the FE joint angles. The results show that, the features extracted from multichannel surface EMG signals using DBN method proposed in this paper outperform principal components analysis (PCA), and the root mean square error (RMSE) between the estimated joint angles and calculated ones during human walking is reduced by about 50%. The proposed model is expected to develop human-machine interaction interface to achieve continuous bioelectric control and to improve motion stability between human and machine, especially for lower limb wearable intelligent equipment.

1. Introduction

The new-class of intelligent equipment, such as rehabilitation robots, power-assisted robots, and intelligent prosthetics, require human-machine interaction and collaboration is the focus of research in the field of robotics [1–3]. With the development of bio-information technology, EEG, EMG, and other biological signals have been widely used to develop interface for man-machine systems. Surface EMG signal is the recording of muscle electrical activity and is much stronger than EEG signal. By performing a signal processing procedure on the raw surface EMG signals, muscle activity and body movement information can be acquired. Therefore, engineers use surface EMG to develop feasible interface for man-machine systems. The most notably application is as a souse of control for the Human Assisted Limb (HAL) exoskeleton [4].

In recent years, surface EMG signals have been extensively used to extract human motion information in two ways. For the first way, researchers use surface EMG signals to recognize different motion modes of human limbs. In this way, higher recognition rate and more motion modes are the two goals and feature extraction methods and classification algorithms are the research focus [5–9]. However, only a limited number of motion modes can be identified from surface EMG signals and the recognition results are only used as a switch signal for the robot. As a result, the smoothness of movement of robot and the coordination between human and robot are affected greatly. By contrast, the second way in which surface EMG signals are used to continue estimate the motion variables can achieve smooth motion control. Many methods have been proposed to build the relationship between the surface EMG signals and movement variables. For example, a forward biomechanical model is constructed and calibrated to calculate the joint torques by using surface EMG signals [10]. Artificial neural networks [11–13] and polynomial fitting [14] are also used to map the surface EMG signals to joint angles or joint torques. Although these methods have been applied to specific applications successfully, they still suffer some problems. For example, the forward biomechanical

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model includes many physiological parameters which have a vast difference between individuals and a calibration is required for a specific subject. Comparing with the biomechanical model method, the regression methods, such as artificial neural network, show the merits of simple and quick. Moreover, the estimation accuracy can be improved if more available channels of surface EMG signal are used as the input.

For the regression methods, feature extraction and selection contributes significantly to the learning efficiency and estimation accuracy of the regression model. How to extract the optimal features which is continuous, robust and non-redundant from multichannel surface EMG signals has become the key issue. In the previous work, principal component analysis (PCA) is often used to obtain an optimal feature vector from multichannel surface EMG signals [6,15,16]. However, PCA is a linear dimensionality reduction algorithm and cannot extract the nonlinear structure components which hide in high dimensional dataset. So PCA has limitations for the surface EMG signals which have high and strong nonlinear characteristics. In order to automatically learn the complex structure components from high dimensional dataset and achieve a dimension reduction, Hinton et al. [17] proposed an efficient and fast learning algorithm for the deep neural networks which has many hidden layers and uses the trained network to convert high dimensional data to lower dimensional codes. For such a multilayer network, the output of each layer contains all the information of the input data and can be seen as a new code of the input data in a new space. The dimensionality of input vectors can be reduced by using a multilayer network with a small central layer to reconstruct them. Most importantly, it has been proved that this network can reveal the nonlinear structure hide in high dimensional data because of multiple levels of non-linear operations.

The aim of this work is to build the regression model which relates the multichannel surface EMG signals to human lower limb joint angles in order to develop a more natural human-machine interface. Specifically, in this research, a deep belief networks is built to extract the optimal feature vectors that has low dimensionality from multichannel surface EMG signals and a back propagation network is used to map the optimal feature vectors to the lower limb joint angles. To validate the effectiveness of the methods proposed in this paper, experiments have been conducted and the results showed that higher estimation accuracy was obtained comparing to the traditional methods.

This paper includes four sections in total and these sections are arranged as follows: Section 2 talks about the proposed method, to be more specific, it introduces about the acquisition of gait kinematics data and surface EMG data as well as the joint angles calculation, surface EMG data processing, and back propagation network construction. Section 3 presents the experimental results followed by a discussion. Finally, Section 4 concludes the paper.

2. Experimental and method

2.1. Data acquisition

Gait is a basic movement for human lower limbs and estimating the joint angles of lower limbs under human walking is the main goal of this work. The dataset used in this paper were collected in the scenarios of human walking. Six able-bodied people were selected in this study, with age ranging from 24 to 30 (mean ± S.D.: 26 ± 2.2 years). Body weight ranges from 57 to 74 kg (62.6 ± 3.7 kg), and body height ranges from 166 to 180 cm (170.6 ± 3.6 cm). All subjects were required to complete walking on flat ground with speeds of 0.8, 1.0, 1.2 m/s and transition speed from 0.8 to 1.2 m/s, separately. Each trial was repeated 3 times. During each trial, the surface EMG signals from ten muscles which relate to the movements of right leg were collected with a wireless surface EMG collection device (MyoMove–EOW, Shanghai Ncc Electronic Company Limited, P.R. China). The sample rate is 1200 Hz and the muscles selected were biceps femoris (BF), semitendinosus (ST), vastus medialis (VM), vastus lateralis (VL), rectus femoris (RF), sartorius (SR), medial gastrocnemius (MG), lateral gastrocnemius (LG), anterior tibialis (AT), and soleus (SL). The disposable circular electrodes with a diameter 10 mm were placed according to the guideline of SENIAM [18] and the locations of electrodes are shown in Fig. 1. Meanwhile, the kinematics data of 16 motion capture markers placed on the surface of lower limbs were collected using a 10-camera optical motion capture system (VICON, Oxford Metrics Limited, UK); the sample rate is 100 Hz and the position numbers and names of external marker positions are described in Table 1. The motion capture system, VICON, mainly consists of MX-cameras, MX-Giganet, and host PC with NEXUS software. The MX-Giganet, which connects the host PC and MX-cameras, provides interface between VICON and EMG system and allows the kinematics and EMG data to be recorded synchronously.

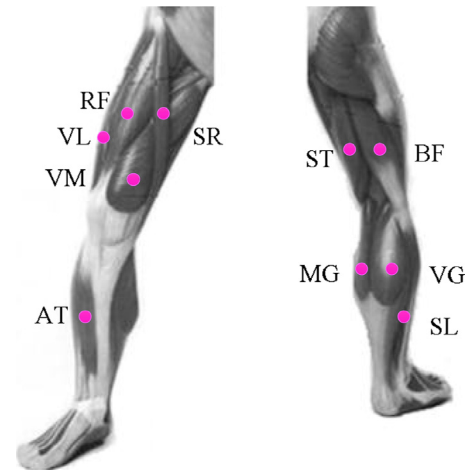

Fig. 1. Locations of electrodes in surface EMG measurement.

Table 1
Position numbers and the corresponding names of external marker positions for motion capture.

No.	name	No.	name
1	Left anterior superior iliac spines	9	Right lateral knee
2	Right anterior superior iliac spines	10	Right medial knee
3	Left posterior superior iliac spine	11	Right lateral ankle
4	Right posterior superior iliac spine	12	Right medial ankle
5	Left lateral knee	13	Left metatarsal head
6	Left medial knee	14	Left heel
7	Left lateral ankle	15	Right metatarsal head
8	Left medial ankle	16	Right heel

2.2. Markers data processing

Correct calculation of joint angles is a prerequisite for building their relationship to the surface EMG signals. The joint angles can be computed by using the trajectories of markers in this work and the calculation procedure is as follows:

The first step is to determine the positions of the joint centers and segment centers of gravity by using the data of makers. The knee and ankle centers can be approximated by the midpoints of the two external markers attached beside the corresponding joint. For the hip center determination, the method proposed by Camomilla et al. [19] could be used. Taking the midpoint of the left and right anterior superior iliac spines (ASIS) as the base point, the local reference frame of the pelvis is set up, as shown in Fig. 2. Then