Define Model{

In this paper a regression model which relates the multichannel surface EMG signals to human lower limb flexion/extension (FE) joint angles is constructed.

With the raw data, the joint angles of hip, knee and ankle were calculated accurately

a deep belief networks (DBN) that consists of restricted Boltzmann machines (RBM) was built

a back propagation (BP) neural network was used to map the optimal surface EMG features to the FE joint angles

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surface EMG signals have been extensively used to extract human motion information in two ways{

1) researchers use surface EMG signals to recognize different motion modes of human limbs. 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.
   the smoothness of movement of robot and the coordination between human and robot are affected greatly.

2) 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 pro-posed 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.

   … 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.

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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 net-works 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.

2. Experimental and method:

Six able-bodied people

0.8, 1.0, 1.2 m/s

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).

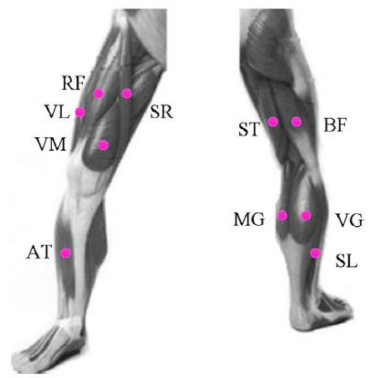


Fig. 1. Locations of electrodes in surface EMG measurement.

The disposable circular electrodes

16 motion capture markers

a10-camera optical motion capture

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:

hip center:

Taking the midpoint of the left and right anterior superior iliac spines (ASIS) as the base point.

(ASI= ستون فقرات)

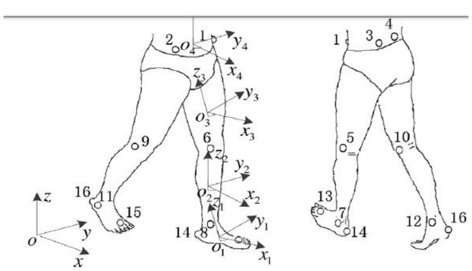


Fig. 2. The motion capture marker placement as well as the reference frames.

$$\begin{cases} x = -0.24\mathrm{P_d} - 9.9 \\ y = -0.30\mathrm{P_W} - 10.9 \\ z = 0.33\mathrm{P_W} + 7.3 \end{cases} \tag{1}$$

where $\mathrm{P_d}$ represents the pelvic depth. It refers to the distance between the midpoint of two ASIS and the midpoint of two posterior superior iliac spines (PSIS); $\mathrm{P_W}$ represents the pelvic width, which refers to the distance between two ASIS (units: mm). After

positions of joint centers

$$P_{\mathrm{Thigh.CG}} = P_{\mathrm{hip}} + 0.39(P_{\mathrm{knee}} - P_{\mathrm{hip}}) \tag{2}$$

$$P_{\mathrm{Calf.CG}} = P_{\mathrm{knee}} + 0.42(P_{\mathrm{ankle}} - P_{\mathrm{knee}}) \tag{3}$$

$$P_{\mathrm{Foot.CG}} = P_{\mathrm{heel}} + 0.44(P_{\mathrm{toe}} - P_{\mathrm{heel}}) \tag{4}$$

where $\boldsymbol{p}_{\mathrm{hip}}$, $\boldsymbol{p}_{\mathrm{knee}}$, and $\boldsymbol{p}_{\mathrm{ankle}}$ indicate the joint center positions of hip, knee, and ankle, respectively. $\boldsymbol{p}_{\mathrm{knee}}$ and $\boldsymbol{p}_{\mathrm{ankle}}$ indicate the positions of metatarsal head and heel, respectively.

centers of gravity locations

second, segment reference frames embedded

reference frame of thigh:

$$k_3 = \frac{p_{\mathrm{hip}} - p_{\mathrm{knee}}}{|p_{\mathrm{hip}} - p_{\mathrm{knee}}|}$$

$$i_3 = \frac{(p_{\mathrm{knee}} - p_{\mathrm{hip}}) \times (p_5 - p_{\mathrm{hip}})}{|(p_{\mathrm{knee}} - p_{\mathrm{hip}}) \times (p_5 - p_{\mathrm{hip}})|}$$

$$j_3 = k_3 \times i_3$$

Third:

the two segments linked by one joint are called proximal segment and distal segment of the distal frame to the proximal one. Make a convention apply to all joints: set $\boldsymbol{j}_{\text{proximal}}$ as the flexion/extension axis and α is the flexion/extension angle, set $\boldsymbol{k}_{\text{distal}}$ as the internal/external rotation axis and $\boldsymbol{\gamma}$ is the internal/external rotation angle, set $\boldsymbol{l}_{\text{joint}}$ as the abduction/adduction axis and is the abduction/adduction angle, of which the vector $\boldsymbol{l}_{\text{joint}}$ is defined as

$$l_{joint} = \frac{j_{\text{proximal}} \times k_{\text{distal}}}{|j_{\text{proximal}} \times k_{\text{distal}}|} \tag{8}$$

$$\alpha_{knee} = \sin^{-1}[l_{\text{knee}} \cdot k_3]$$

$$\beta_{\text{knee}} = -\sin^{-1}[j_3 \cdot k_2]$$

$$\gamma_{\text{knee}} = \sin^{-1}[l_{\text{knee}} \cdot j_2]$$

In this study, the processing of surface EMG signals is divided into two steps. Firstly, the time series of intensity for each surface EMG signal are calculated which constitute 10 dimensional feature vectors. Then, these initial feature vectors are sent into a deep belief network which outputs 3 dimensional vectors.

The building block of the DBN is called restricted Boltzmann machines (RBM). An RBM is a two-layer, undirected, and energy based model in which the visible units in the first layer represent observations, and the visible units are connected to the hidden units which represent the features in the second layer.

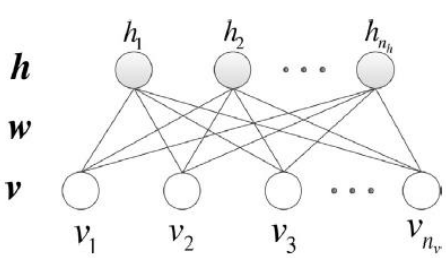


Fig. 3. Schematic diagram of RBM architecture.

v, **w**, and **h** represent the visible unit data, the weight parameters, and the hidden unit data respectively.

$$E_\delta(v,h) = -\sum_{i=1}^{n_v}\sum_{j=1}^{n_h} w_{ij} v_i h_j - \sum_{i=1}^{n_v} b_i v_i - \sum_{j=1}^{n_h} a_j h_j$$

a_i and b_i are the constant offsets,

Through the energy function of (12), the RBM model assigns a probability to every possible visible-hidden vector pairs(v, **h**) and can be calculated as

$$P_\delta(v,h) = e^{-E_\delta(v,h)} / \sum_{v,h} e^{-E_\delta(v,h)}$$

the conditional distribution P_(**h** |**v**) and P_(**v** |**h**) can be given by

$$P_\delta(h_j = 1|v) = f\left(b_j + \sum_{i=1}^{n_v} w_{j,i} v_i\right)$$

$$P_\delta(v_i = 1|h) = f\left(a_i + \sum_{j=1}^{n_h} w_{j,i} v_j\right)$$

$$P_\delta(v) = \sum_h e^{-E_\delta(v,h)} / \sum_{v,h} e^{-E_\delta(v,h)}$$

the task of training the RBM is to maximize the marginal probability by adjusting the model parameters

$$\frac{\partial \log(P_\delta(v))}{\partial w_{ij}} = \langle v_i h_j \rangle_{\text{data}} - < v_i h_j >_{\text{model}}$$

$$\frac{\partial \log(P_\delta(v))}{\partial a_i} = \langle v_i \rangle_{\text{data}} - < v_i >_{\text{model}}$$

$$\frac{\partial \log(P_\delta(v))}{\partial b_j} = \langle h_j \rangle_{\text{data}} - < h_j >_{\text{model}}$$

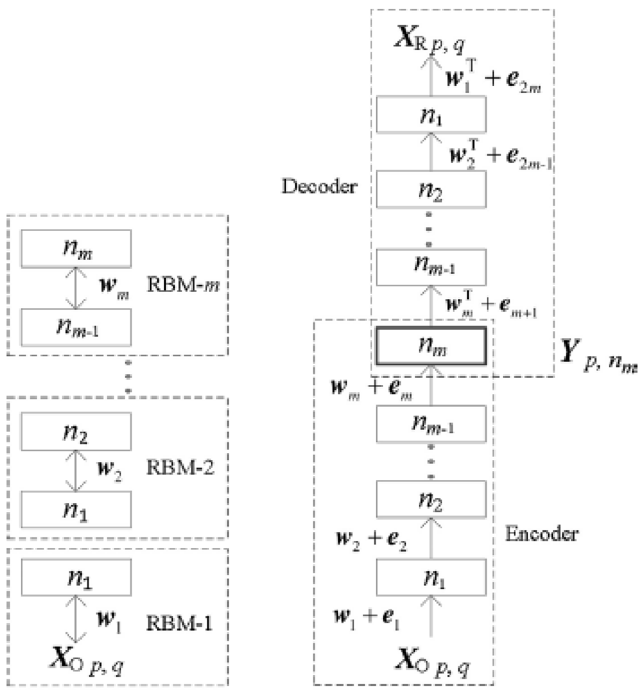
The training of the stacked RBMs is as follows: the training data XO(initialfeature vectors of surface EMG) are fed into RBM-1 to update itsweights and offsets until the number of epochs is reached

Then, the parameters of RBM-1 are fixed and the outputs are treated as the input data for training the upper-level RBM,

After training the stacked RBMs, the RBMs are unfolded to produce the DBN with the same model parameters,

So the fine-tuning step whose goal is to minimize the discrepancy between the input data X_O and the output data $X_R$of the network is carried out. Because a set of good initial values for the DBN parameters have been learned during the unsupervised pretraining step, back propagation algorithm can be used efficiently to fine-tune the parameters for optimal reconstruction.

in order to reduce the dimensionality of initial feature matrix of surface EMG, a DBN which has 9 layers was constructed and the numbers of units for each layer were 10, 18, 12, 6,3, 6, 12, 18, and 10 respectively.



(a) Stack of RBMs **(b) Deep belief network**

Fig. 4. The typical topological structure of deep belief networks.

$$\dot{\theta} = \boldsymbol{W}_{\text{out}} \left[\frac{2}{1 + e^{-2(\boldsymbol{W}_{\text{in}} \boldsymbol{y} + \boldsymbol{b}_{\text{in}})}} - 1 \right] + \boldsymbol{b}_{\text{out}} \tag{22}$$

where $\boldsymbol{W}_{\text{in}}$ is the matrix consists of weights of the hidden layer, $\boldsymbol{W}_{\text{out}}$ is the matrix consists of weights of the output layer, and $\boldsymbol{b}_{\text{in}}$ and $\boldsymbol{b}_{\text{out}}$ are the threshold vectors.

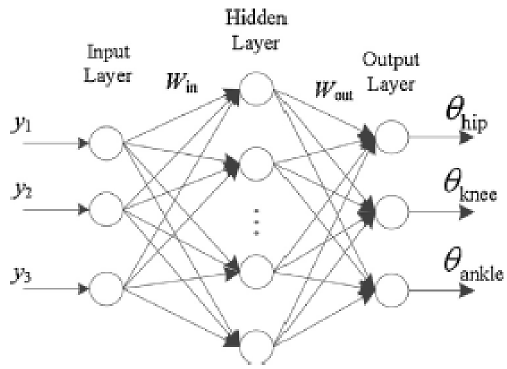
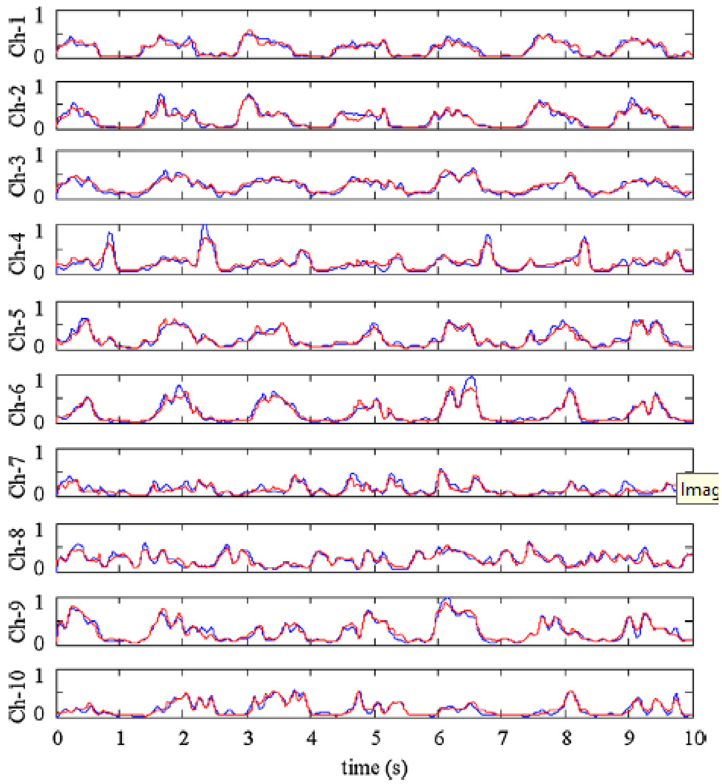


Fig. 5. The topological structure of the BP network.

2.4. BP network for angle estimation

In general, the relationships between each muscle activity and joint angles are highly nonlinear and difficult to be described with conventional approach [11–13]. Therefore, after obtaining the optimal feature vectors of surface EMG, a three layer BP neural network can be constructed and used to map the feature vectors to the FE joint angles and the topological structure is shown in Fig. 5. The input layer of the BP neural network consists of three nodes which represent three optimal feature vectors of surface EMG that generated by DBN. The input vector is represented by $\boldsymbol{Y} = [y_1, y_2, y_3]$. The output layer of the BP neural network consists of three nodes which predict the angles of lower limb joints rotation. The output vector is represented by $\tilde{\boldsymbol{\theta}} = [\tilde{\theta}_{hip}, \tilde{\theta}_{knee}, \tilde{\theta}_{ankle}]$ and they are FE angles.

Results and discussion



From six healthy subjects, 72 groups of raw data for different speed walking trials were collected in total. The joint angles were calculated across 12 trails for each subject .

Each subject provides 5 groups of data (one group from each uniform speed and two groups from transition speed) for the training data. Therefore, the training data cover all subjects and all walking speeds.

In the figure, the blue lines indicate the input data (initial feature data) while the red lines indicate the output data (reconstruction data).