Gait Angle Prediction for Lower Limb Orthotics and Prostheses Using an EMG Signal and Neural Networks

Ju-Won Lee and Gun-Ki Lee*

Abstract: Commercial lower limb prostheses or orthotics help patients achieve a normal life. However, patients who use such aids need prolonged training to achieve a normal gait, and their fatigability increases. To improve patient comfort, this study proposed a method of predicting gait angle using neural networks and EMG signals. Experimental results using our method show that the absolute average error of the estimated gait angles is 0.25°. This performance data used reference input from a controller for the lower limb orthotic or prosthesis controllers while the patients were walking.

Keywords: EMG, prosthesis, gait angle predictor, human computer interaction, neural networks, orthotic.

1. INTRODUCTION

Increasing numbers of patients are being paralyzed or are having lower limbs amputated following industrial and traffic accidents. Many investigators and companies have developed orthotics and prostheses for such patients. Commercial lower limb prostheses or orthotics help give these patients a normal life. However, patients who use such aids need prolonged training to achieve a normal gait. As there is a difference between a normal gait and the gait with an orthotic or prosthesis, a patient's fatigability increases. To solve this problem, optimum control should be achieved based on a patient's gait. Previous research on the optimal control of patient gait posture focused on predicting the exact posture angle of the lower limb with the orthotic or prosthesis. Recently, Chan *et al.* used an electromyographic (EMG) classification for prosthesis control. However, this method cannot predict the posture angles of a prosthesis because it only uses a logical scheme to determine "flexion" and "extension" from the EMG signals [1]. Therefore, we propose a technique for predicting the posture angles of patients' orthotics or prostheses for a single lower limb. We assumed that the gait properties of the normal lower limb equal those of the injured lower limb. The method consists of two steps that predict knee angles in the normal lower limb and the posture angles for the orthotic or prosthesis based on the predicted angle of the knee. First, the knee angle during a patient's gait is predicted using the two-channel surface EMG signals for the one normal lower limb. In the second step, the angles of the orthotic or prosthesis are predicted using the predicted knee angle for the normal lower limb. In this study, the predictor used an artificial neural network. The performance of the predictor was evaluated in simulations and experiments. The experimental results using the proposed method showed that the reference input signal could be used to control the lower limb orthotic and prosthesis to give the patient a smooth gait.

2. FEATURES OF HUMAN GAIT

The human gait involves a cycle in which the lower limb moves though one motion to another while tracing a circular arc [2]. The cycle starts when one leg goes forward and the corresponding heel strikes the ground as the body advances, and ends when the same foot goes forward again and touches the ground. Each cycle can be broken into two phases: stance phase and swing phase. Stance phase is also called support phase and can be subdivided into the heel-strike, loading-response, mid-stance, and terminal stance phases. Swing phase begins when the foot is off the ground and the body advances, and ends when the foot touches the ground. Gait involves the lower limb repeating one motion after another, tracing a circular arc [2]. The human gait involves changes in the angles of each joint in the lower limbs. These angles change with changes in the bioelectrical energy of skeletal muscles [2-4]. Therefore, the posture angle

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of each joint during a patient's gait is related to the EMG signals. However, the human gait includes a simple genetic reflex function learned through activities, as well as personal characteristics of the movement patterns of both legs. This involves various factors, such as the peripheral/central nervous system and heart/lung functions. In addition, the gait angle of each joint depends on the patient's gait habit and physical size, among other things. It is difficult to determine the normal gait pattern of patients with an amputated lower limb [2,3]. In this study, a kinematics model of patient gait was obtained using a neural network. In this method, we assumed that the kinematic properties of the gait posture angles of the orthotic or prosthesis for the injured lower limb equal those of the remaining normal lower limb.

3. PROPOSED METHOD

Human gait depends on walking speed, walking posture, and the type of surface. However, patients using a mechanical encoder sensor in order to measure their gait posture are very uncomfortable. We proposed a gait predictor using a neural network to predict the gait angle from the EMG signals (Fig. 1).

The proposed method consisted of two steps. First, the knee angle of the patient's gait was predicted using two-channel surface EMG signals for the normal lower limb and a radial basis function neural network (RBFNN). In the second step, the angles of the orthotic or prosthesis were based on the predicted knee angles of the normal lower limb, and a multilayer neural network (MLNN) was used. The EMG signal [$S_e(n)$] used was that of the rectus femoris muscle. This muscle was used because it is involved in the change in the knee angle of the normal lower limb. The two neural networks were used in this study to allow real-time processing, because the convergence speed is slow when many numbers are input to the neural network or when the training signals are nonlinear [7,8]. The following section presents the detailed structures and algorithm of the proposed method.

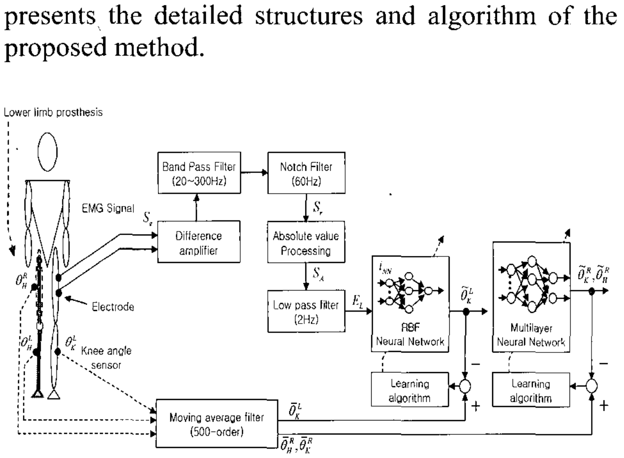


Fig. 1. The proposed gait angles predictor for a prosthesis.

3.1. Knee angle prediction

Usually, the amplitude of an EMG signal is 20~300 mV and the frequency band is 20~300 Hz [4-6]. In this study, the electrode for measuring the EMG was attached to the rectus femoris (Fig. 1). To remove the noise included in the amplified EMG signal, a 2nd-order 20~300-Hz Butterworth band-pass filter and a 60-Hz notched filter were designed. The RBFNN was used to learn the kinematics of the knee angles and the rectus EMG. The desired signal and input signal of the RBFNN were the filtered output signal $\bar{\theta}_k^L(t)$ of a tilt sensor attached to the center of the shin and the absolute value vector of the EMG signals, i_{NN}.

$$\bar{\theta}_K^L(n) = \sum_{p=0}^{P-1} \theta_K^L(n-p)\alpha_p, \tag{1}$$

$$S_A(n) = | S_r(n) |, \tag{2}$$

$$E_L(n) = \sum_{m=0}^{M-1} S_A(n-m)\beta_m, \tag{3}$$

$$i_{NN} = \left[E_L(n) ,\dots , E_L(n-I-1)\right], \tag{4}$$

where n is the sampling number, P and M are filter orders, and a_p and β_m are the coefficients of the moving average filter and FIR low-pass filters, respectively. The extracted feature signal was input to the RBFNN (Fig. 2). Table 1 shows the structure of the neural network used for learning.

The desired angle of the knee joint of the normal leg was set to $\bar{\theta}_k^L(n)$, minimizing the error in estimating the knee joint angle. After completing the neural network learning, the knee joint angle was extracted from a forward operation as shown:

$$\tilde{\theta}_K^L = \sum_{q=1}^{Q} w_q(n)\exp\left[-\sum_{i=1}^{I} \frac{\left(i_{NN}(i)-m_{qi}(n)\right)^2}{\sigma_{qi}^2(n)}\right] j=1,2\cdots,J, \tag{5}$$

where $m_{qi}(n)$ is the center value of the q-th RBF function for the i-th input, $\sigma_{qi}^2(n)$ is the distribution of the q-th RBF function for the i-th input, and $\tilde{\theta}_K^L(n)$

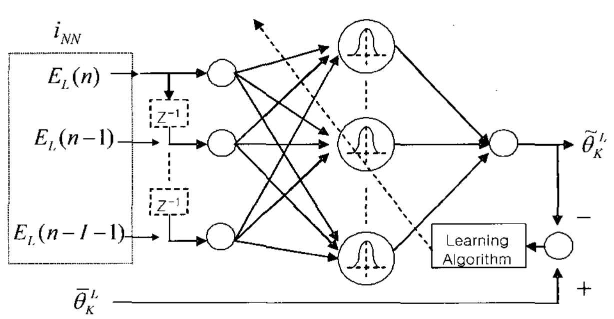


Fig. 2. Knee angle predictor using RBFNN.

is the output (estimated knee angle) of the neuron in the output layer. To obtain the optimal $m_{qi}(n)$, $\sigma_{qi}(n)$, and $w_q(n)$ for minimizing the learning error $E(n)$ between $\bar{\theta}_K^L(n)$ and $\tilde{\theta}_K^L(n)$, the adaptive learning algorithm of the neural network was used as follows:

$$E(n) = \frac{1}{2}\left(\bar{\theta}_k^L(n) - \tilde{\theta}_k^L(n)\right)^2, \tag{6}$$

$$w_q(n+1) = w_q(n) + \Delta w_q, \tag{7}$$

$$m_{qi}(n+1) = m_{qi}(n) + \Delta\ m_{qi}, \tag{8}$$

$$\sigma_{qi}(n+1) = \sigma_{qi}(n) + \Delta\sigma_{qi}, \tag{9}$$

$$\Delta w_q = \eta_q\left(\bar{\theta}_k^L(n) - \tilde{\theta}_k^L(n)\right) \cdot \exp\left[-\sum_{i=1}^{I} \frac{\left(i_{NN}(i) - m_{qi}(n)\right)^2}{\sigma_{qi}^2(n)}\right], \tag{10}$$

$$\Delta m_{qi} = \eta_m \cdot 2 \cdot \exp\left[-\sum_{i=1}^{I} \frac{\left(i_{NN}(i) - m_{qi}(n)\right)^2}{\sigma_{qi}^2(n)}\right] \cdot \frac{\left(i_{NN}(i) - m_{qi}(n)\right)}{\sigma_{qi}^2(n)} \cdot \left(\bar{\theta}_k^L(n) - \tilde{\theta}_k^L(n)\right) \cdot w_q(n), \tag{11}$$

$$\Delta\sigma_{qi} = \eta_\sigma \cdot 2 \cdot \exp\left[-\sum_{i=1}^{I} \frac{\left(i_{NN}(i) - m_{qi}(n)\right)^2}{\sigma_{qi}^2(n)}\right] \cdot \frac{\left(i_{NN}(i) - m_{qi}(n)\right)^2}{\sigma_{qi}^3(n)} \cdot \left(\bar{\theta}_k^L(n) - \tilde{\theta}_k^L(n)\right) \cdot w_q(n), \tag{12}$$

where η_q, η_σ, and η_m are learning constants.

3.2. Posture angle prediction for lower limb orthotics and prostheses

We used a multilayer neural network (MLNN) [7] to predict the gait angles of orthotics or prosthesis. The structure of the MLNN is shown in Fig. 3. The MLNN was used to predict the coxa and knee joint angles of the artificial leg during walking based on the predicted knee joint angle of the normal leg. This proposes an identification method for the patient's gait kinematics. To estimate the coxa and knee joint angles of the orthotic or prosthesis of a patient with one amputated leg, this method obtained gait patterns of a physically similar person. The pattern data were then used to obtain the gait angle. The learning algorithm used the Error Back Propagation Algorithm (EBPA) [7] of the multi-layer.

The input of the gait angle predictor neural network

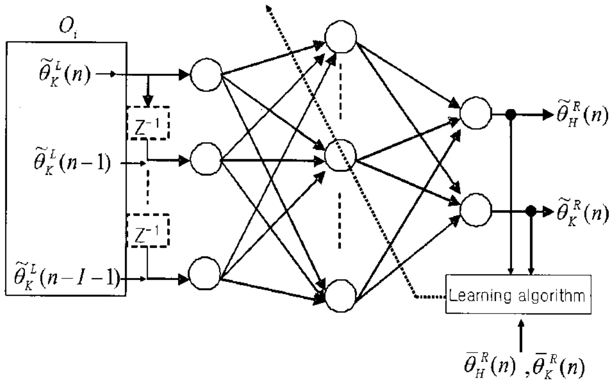


Fig. 3. The MLNN structure used to predict gait angles.

was the knee joint angle predicted from the EMG. The output was the predicted posture angle of each joint of the orthotic or prosthesis during walking. The following shows the learning method of the neural network used to predict the patient's gait patterns. The respective outputs $O_i(n)$, $O_p(n)$, and $O_q(n)$ of neurons in the input, hidden, and output layers of the gait prediction neural network are:

$$O_i(n) = [\tilde{\theta}_k^L(n), \tilde{\theta}_k^L(n-1), \ldots, \tilde{\theta}_k^L(n-I-1)], \tag{13}$$

$$O_p(n) = \lambda_h f_h\Big(\sum_{i=0}^{I-1} w_{pi}(n) O_i(n)\Big)\ P=0,1,2,\cdots,P-1, \tag{14}$$

$$O_q(n) = \begin{bmatrix} \tilde{\theta}_H^R \\ \tilde{\theta}_K^R \end{bmatrix} = \begin{bmatrix} \lambda_o \cdot f_o\left(\sum_{p=0}^{P-1} w_{0p}(n)\ O_p(n)\right) \\ \lambda_o \cdot f_o\left(\sum_{p=0}^{P-1} w_{1p}(n)\ O_p\ (n)\right) \end{bmatrix}, \tag{15}$$

where I and P are the numbers of neurons in the input and hidden layers, respectively; the filter orders f_h and f_o are the activate functions of each neuron; and λ_h and λ_o are the slopes of the respective activation functions. In neural network learning, the error from the desired value of the neural network, $d_q(n) = [\bar{\theta}_H^R(n)\ , \bar{\theta}_K^R(n)]^T$, was obtained as shown in the following equations:

$$\bar{\theta}_H^R(n) = \sum_{l=0}^{L-1} \theta_H^R(n)\gamma(n-l), \tag{16}$$

$$\bar{\theta}_K^R(n) = \sum_{l=0}^{L-1} \theta_K^R(n)\gamma(n-l), \tag{17}$$

$$E(n) = \frac{1}{2}\sum_{q=1}^{Q} (d_q(n) - O_q(n))^2, \tag{18}$$

where L and γ are the filter order and coefficients of the moving average filter with an FIR structure, respectively. The weights adjusting the weight to minimize $E(n)$ should change in the negative gradient direction. Therefore, the weight variation could be obtained by partially differentiating the direction vector of the weight for the error. The variation of the weight in each layer is:

$$w_{pi}(n+1) = w_{pi}(n) - \eta \frac{\partial E(n)}{\partial w_{pi}}, \quad (19)$$

$$w_{qp}(n+1) = w_{qp}(n) - \eta \frac{\partial E(n)}{\partial w_{qp}}, \quad (20)$$

where η is the learning constant. The initial weight ranged from –0.5 to 0.5. The gait posture angle of each joint of the artificial leg was estimated using the knee joint angle obtained during walking with forward operation of the neural network. This was based on the weight data of the neural network that learned the normal gait data.

4. EXPERMENT AND RESULTS

4.1. Sensor interface design and filtering

The EMG sensor and gait angle sensor interfaces were designed to verify the efficiency of the proposed gait posture prediction. The Ag/AgCl electrode and TILT SA1 (DAS Co.) tilt sensor for measuring the EMG and each joint angle were attached to the rectus femoris and center of the shin, respectively (Fig. 4). The tilt sensor had a ±60° range. In the sensor interface, the EMG signal was amplified 200 times and the tilt sensor was amplified one time.

The analog filters used to remove the noise included in the amplified EMG signals were designed as a 2nd-order Butterworth band-pass filter with 20~300 Hz and a 60-Hz notched filter. The implemented analog interface is shown in Fig. 5.

The filtered EMG signal and each joint angle signal were acquired using an MP100 (Biopac Co.) after setting the sampling frequency to 1 kHz. The acquired

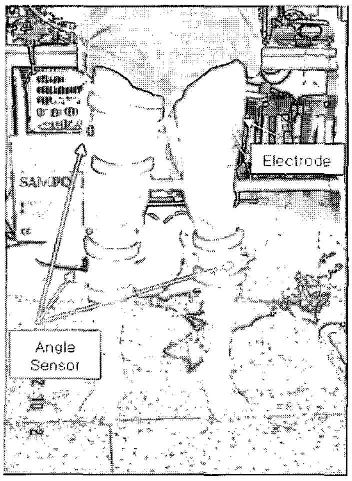


Fig. 4. Positions of the sensors for measuring the angles and EMG signals.

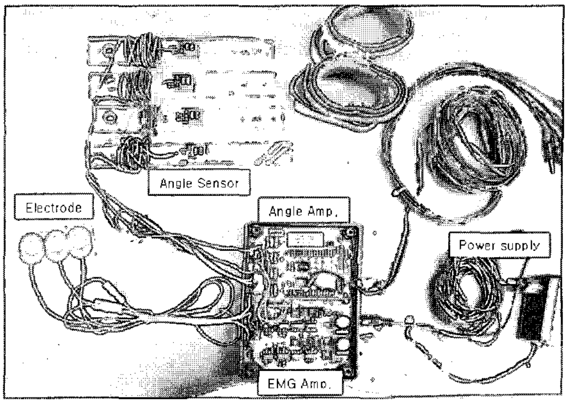


Fig. 5. The implemented interface system.

Table 1. The RFBNN and MLNN structures used in the experiment.

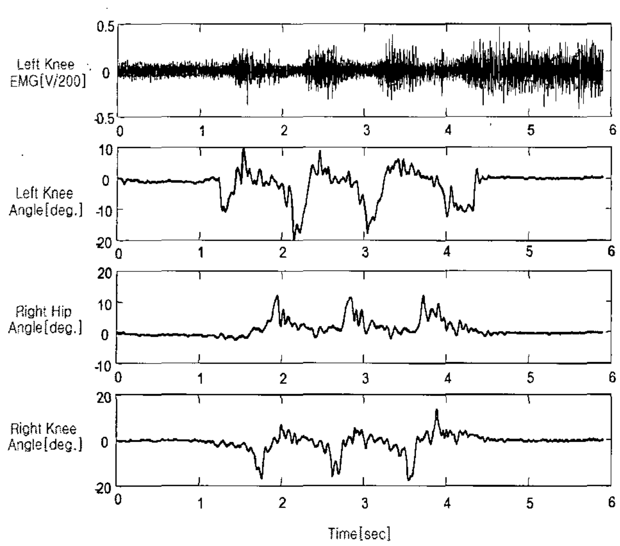
		Neural Networks	
		RBF	MLNN
Input Neurons		20	100
Hidden Neurons		10	20
Output Neurons		1	2
Activation function		Gaussian	bipolar sigmoid
Learning rate, η		0.1	0.1
Initial weights	σ	$\sigma = (\lvert -60[\text{deg.}]\rvert + \lvert +60[\text{deg.}]\rvert)/q = 12$	-
	m	$\Delta q = (\lvert -60[\text{deg.}]\rvert + \lvert +60[\text{deg.}]\rvert)/q = 12$ $m_q = (-60[\text{deg.}]) + \Delta q * k$ *for* $k = 0,1,2,....,q$	-
	w	-0.5~0.5	0.5~0.5

angle signals of each joint included vibrating noise that occurred while the patient was walking. The noise signals were filtered using a 500th-order moving average filter (MVF). The absolute value signals, $E_L(n)$, were filtered using a 40th-order low-pass filter in which the cutoff frequency was 2 Hz. The amplified EMG signal, filtered EMG signal, joint angles, and filtered angle signals are shown in Fig. 6. These results were obtained upon walking five steps.

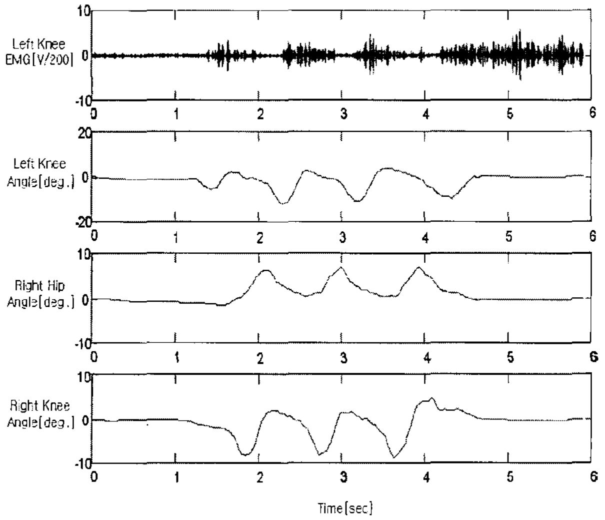
4.2. Knee angles prediction of normal lower limb and gait angles prediction

Table 1 gives the structures of the RBFNN and MLNN used to predict the knee angles of the normal lower limb and the gait angles. Three cases were considered when evaluating the performance of the proposed method based on the neural networks structure.

The first case was walking on a normal road. The second case was standing up from a chair. The third case was sitting down on a chair. The predicted results for these respective cases are given in Figs. 7, 8, and 9

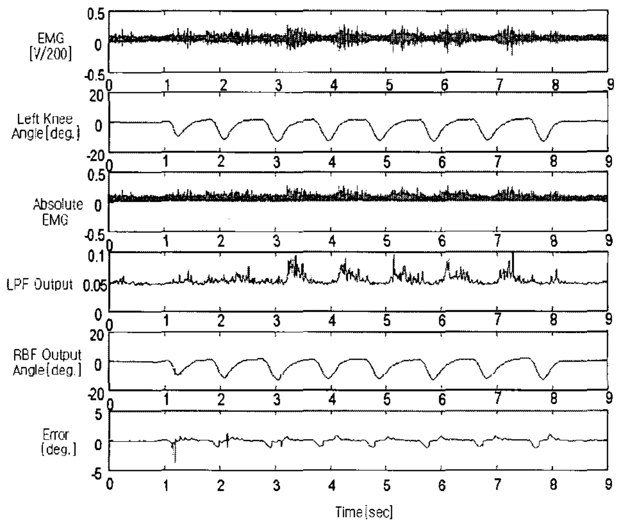


(a) The measured signals with noise.

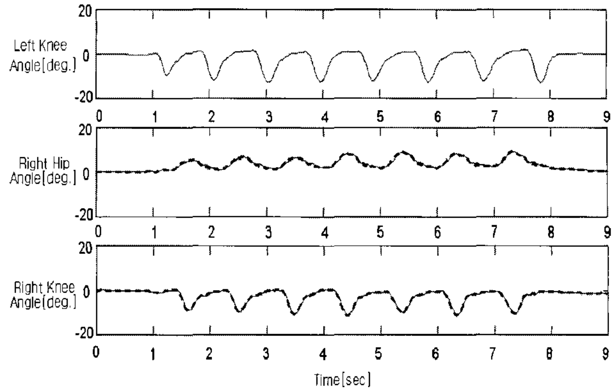


(b) The filtered signals.

Fig. 6. The measured EMG and angle signals using the implemented interface.

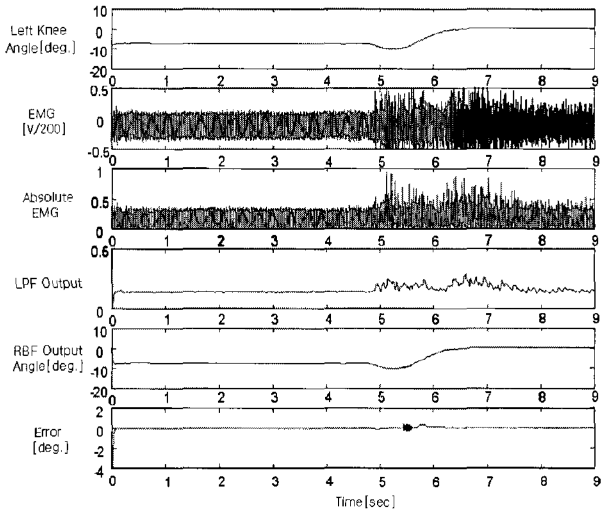


(a) The estimated knee angle during gait.

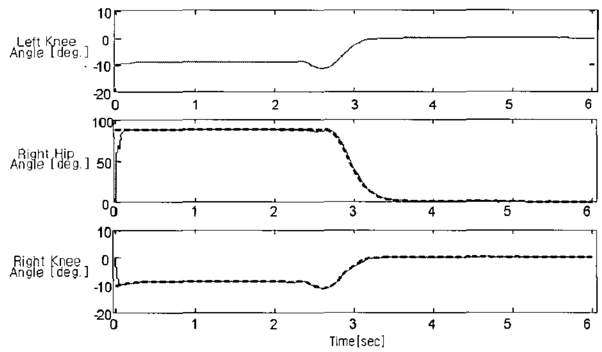


(b) The estimated angles during gait.
(- - - : Desired angles, — : MLNN).

Fig. 7. Predicted posture angles when walking.



(a) The estimated knee angle when standing up.



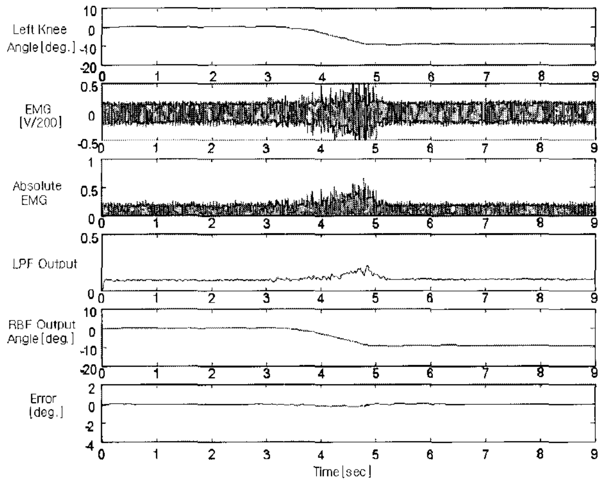
(b) The estimated angles when standing up.
(- - - : Desired angles,— : MLNN)

Fig. 8. Predicted posture angles when standing up.

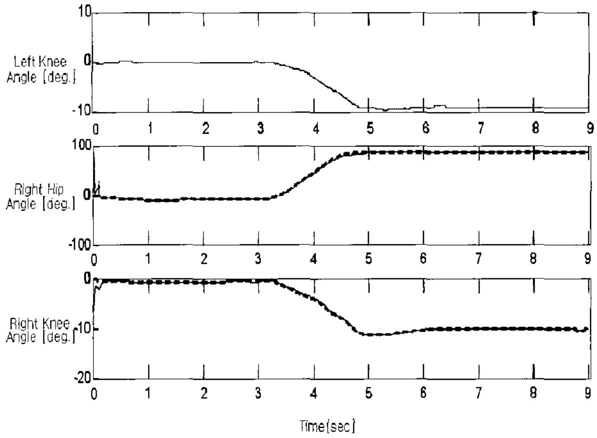
Tables 2 and 3 summarize the performance index. In these tables, the estimated average error of each joint was 0.25, giving the estimated posture angle with 97.5% accuracy. This accuracy should be expected if the estimator was available for controlling the motion of an artificial leg while walking. The estimated angle was set as the reference signal for the posture controller.

Table 2. Errors of the predicted knee angle of the RBFNN for the normal limb.

Cases	Absolute mean error [deg.]	Total mean error [deg.]
gait	0.18	0.083
standing up	0.05	
sitting down	0.03	
Continuous actions (gait→ sitting down→ standing up)	0.07	



(a) The estimated knee angle when sitting down.



(b) The estimated angles when sitting down.
(- - - : Desired angles, —— : MLNN)

Fig. 9. Predicted posture angles when sitting down.

Table 3. Errors of the gait angles of MLNN based on the predicted knee angle.

Cases	Absolute Mean Error		Total Mean Error	
	Hip	Knee	Hip	Knee
Gait	0.14	0.23	0.4	0.1
Standing up	0.61	0.06		
Sitting down	0.68	0.08		
Continuous actions (gait→ sitting down→ standing up)	0.17	0.03		

5. CONCLUSION

This study proposed an estimation technique for predicting the posture angles of patients' orthotics or prostheses. Experimentally, the accuracy of the estimated gait posture angle using the proposed method was 97.5%. The reference input could be used to control the postures of orthotics and prostheses. Therefore, orthotics and prostheses using this method should have a very beneficial effect in paralyzed patients or amputees.

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