Adaptive Postural Control for Trans-Femoral Prostheses Based on Neural Networks and EMG Signals

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Gait control capacity for most trans-femoral prostheses is significantly different from that of a normal person, and training is required for a long period of time in order for a patient to walk properly. People become easily tired when wearing a prosthesis or orthosis for a long period typically because the gait angle cannot be smoothly adjusted during wearing. Therefore, to improve the gait control problems of a trans-femoral prosthesis, the proper gait angle is estimated through surface EMG(electromyogram) signals on a normal leg, then the gait posture which the trans-femoral prosthesis should take is calculated in the neural network, which learns the gait kinetics on the basis of the normal leg's gait angle. Based on this predicted angle, a postural control method is proposed and tested adaptively following the patient's gait habit based on the predicted angle. In this study, the gait angle prediction showed accuracy of over 97%, and the posture control capacity of over 90%.

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1. Introduction

The number of all-limb paralytics, or those with hemiplegia, paralysis in the lower half of the body, upper or lower limb amputees has increased because of industrial or traffic accidents. In Japan, Kawato succeeded in robotic control in 1994, leading to the development of artificial arm and leg for sufferers from disastrous accidents (Koike and Kawato[1]). In 2000, Barreto (Florida University, USA) presented a study for artificial arm control using the EMG signal(Barreto[2,3]). These studies made it possible to commercialize artificial arms or legs. Nevertheless, there were considerable problems that remained unsolved. Commercialized orthoses or prostheses have gait angles quite different from those of a normal person. They require a long period of training so that the wearer can walk properly. Besides, patients become more easily fatigued when they walk with a prosthesis or orthosis for a long period. One of the main factors is that patients cannot control the gait posture angle as smoothly as a normal person can. During one gait period (from one position to the next same position), the lower limb draws an arc, and the gait refers to a repetition of this period. This gait phase is influenced by inherent reflection capacity, the learned activity, the kinematics aspect of both lower limbs, personal features, central and peripheral nervous system, and heart and lung capacity(Esquenanzi[4], Ozkaya[5]). The gait angle of each joint depends on a patient's gait habit, physical size and so on. Therefore, in the case of a patient whose lower limb is amputated, it is hard to obtain his/her normal gait pattern. Therefore, to solve this problem, a new method was investigated for controlling the optimal gait posture according to patient's gait habit using a neural network, which has a capacity for learning. For implementation, the gait angle was predicted by using a surface EMG signal(Wang[6], Enderle[7], Metin Akay[8]) on a normal lower limb, and then, based on this angle, the gait posture was predicted for the prosthesis from the neural network that learned the gait kinematics. The posture was then adaptively controlled through a multi-neural network. In this study, the gait angle prediction capacity and the control capacity system were analyzed.

2. Trans-femoral prosthesis modeling

A trans-femoral prosthesis was modeled for a patient whose limb below the femoral joint was amputated. Generally, prosthesis motion consists of the interaction between the three joints (coxa, knee joint, and ankle joint) and the feet; therefore, it should be kinetically modeled on this interaction(Kalanovic[9]). However, for kinetics modeling of the trans-femoral prosthesis, the ankle joint was fixed, and the coxa was assumed to be controlled by the amputee. Fig. 1 shows the modeling structure of the trans-femoral prosthesis. If the torque to control the coxa is controlled by the amputee while controlling the trans-femoral prosthesis, the control target becomes the knee joint. Therefore, the structure of the trans-femoral prosthesis and the kinematical feature of the gait are quite similar to that of a pendulum. In this research, the lower limb prosthesis was modeled after a pendulum to interpret the dynamic two-dimension coordinates. The following procedure was taken to obtain the torque (τ_k) to control the knee joint. For modeling the trans-femoral prosthesis in this study, the symbols of the mechanical parameters are shown in Table 1.

In Fig. 1, the angle was set as negative if the joint flexes; positive if the joint extends on the basis of the vertical direction of the rectangular coordinate ($\theta_h = \theta_k = 0$). The coxa was set up as the origin ($x = 0$, $y = 0$).

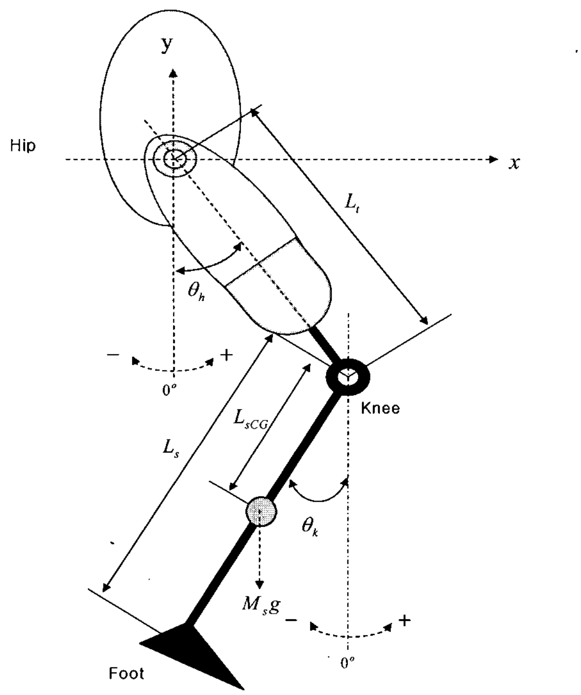

Fig. 1 The trans-femoral prosthesis model

Table 1 Defined the symbols for modeling trans-femoral prosthesis

θ_h, θ_k	Angles of hip and knee
L_t, L_s	Lengths of thigh and shank
L_{sCG}	Distance from knee joint to the center of mass of the shank
M_t,	Mass of the thigh
M_s	Sum of the masses of the foot and the shank
I_t, I_s	Inertial moments for the thigh and shank
x_k , y_k	Joint location of the knee
g	Gravitational constant

The locations of the knee and the center of gravity of the shank can be expressed as follows:

$$x_k = L_t sin\theta_h \tag{1}$$

$$y_k = -L_t cos\theta_h \tag{2}$$

$$x_{sCG} = -L_t sin\theta_h + L_{sCG} sin\theta_k \tag{3}$$

$$y_{sCG} = -L_t cos\theta_h - L_{sCG} cos\theta_k \tag{4}$$

If Eqs. (1) and (2) are differentiated with respect to time (t), the velocity can be expressed as:

$$\dot{x}_{sCG} = -\dot{\theta}_h L_t cos\theta_h + \dot{\theta}_k L_{sCG} cos\theta_k \tag{5}$$

$$\dot{y}_{sCG} = \dot{\theta}_h L_t sin\theta_h + \dot{\theta}_k L_{sCG} sin\theta_k \tag{6}$$

In Eqs. (5) and (6), the velocity vector ($\boldsymbol{v}_s$) of the center of gravity of the shank can be expressed as:

$$\boldsymbol{v}_s = \begin{bmatrix} \dot{x}_{sCG} \\ \dot{y}_{sCG} \end{bmatrix} \tag{8}$$

$\boldsymbol{v}_s^T \boldsymbol{v}_s$ is expressed in Eq. (9).

$$\begin{aligned} \boldsymbol{v}_s^T \boldsymbol{v}_s &= \begin{bmatrix} \dot{x}_{sCG} \\ \dot{y}_{sCG} \end{bmatrix}^T \begin{bmatrix} \dot{x}_{sCG} \\ \dot{y}_{sCG} \end{bmatrix} \\ &= \dot{x}_{sCG}^2 + \dot{y}_{sCG}^2 \\ &= L_t^2 \dot{\theta}_h^{\,2} + L_{sCG}^2 \dot{\theta}_k^{\,2} + 2 L_t L_{sCG} \\ &\quad \dot{\theta}_h \dot{\theta}_k \cos(\theta_h - \theta_k) \end{aligned} \tag{9}$$

Based on Eqs. (5) to (9), kinetic energy (T) and potential energy (U) of the shank are obtained as:

$$\begin{aligned} T &= \frac{1}{2} m \boldsymbol{v}^T \boldsymbol{v} + \frac{1}{2} I_s \dot{\theta}_k^2 \\ &= \frac{1}{2} M_s \{ L_t^2 \dot{\theta}_h^{\,2} + L_{sCG}^2 \dot{\theta}_k^{\,2} \\ &\quad + 2 L_t L_{sCG} \dot{\theta}_h \dot{\theta}_k \cos(\theta_h - \theta_k) \} \\ &\quad + \frac{1}{2} I_s \dot{\theta}_k^2 \end{aligned} \tag{10}$$

$$U = -M_s g (L_t cos\theta_h + L_{sCG} cos\theta_k) \tag{11}$$

From Eqs. (10) and (11), the knee joint torque is obtained as Eq.(13) by the Lagrange equation(Mckerrow10).

$$\begin{aligned} L &= T - U \\ &= \frac{1}{2} M_s \{ L_t^2 \dot{\theta}_h^{\,2} \\ &\quad + 2 L_t \dot{\theta}_h L_{sCG} \dot{\theta}_k cos(\theta_h - \theta_k) \\ &\quad + L_{sCG}^2 \dot{\theta}_k^{\,2} \} + \frac{1}{2} I_s \dot{\theta}_k^{\,2} + M_s g L_t cos\theta_h \\ &\quad + M_s g L_{sCG} cos\theta_k \end{aligned} \tag{12}$$

$$\begin{aligned} \tau_k &= \frac{d}{dt} \left(\frac{\partial L}{\partial \dot{\theta}_k} \right) - \frac{\partial L}{\partial \theta_k} \\ &= M_s L_t L_{sCG} \ddot{\theta}_h \cos(\theta_h - \theta_k) \\ &\quad + (M_s L_{sCG}^2 + I_s) \ddot{\theta}_k \\ &\quad - M_s L_t L_{sCG} \dot{\theta}_h^{\,2} \sin(\theta_h - \theta_k) \\ &\quad + M_s g L_{sCG} \sin\theta_k \end{aligned} \tag{13}$$

3. Proposed trans-femoral prosthesis control system

Human gait depends on gait speed, posture, road surface, and patient's gait habit. Therefore, to obtain normal gait features for a femur

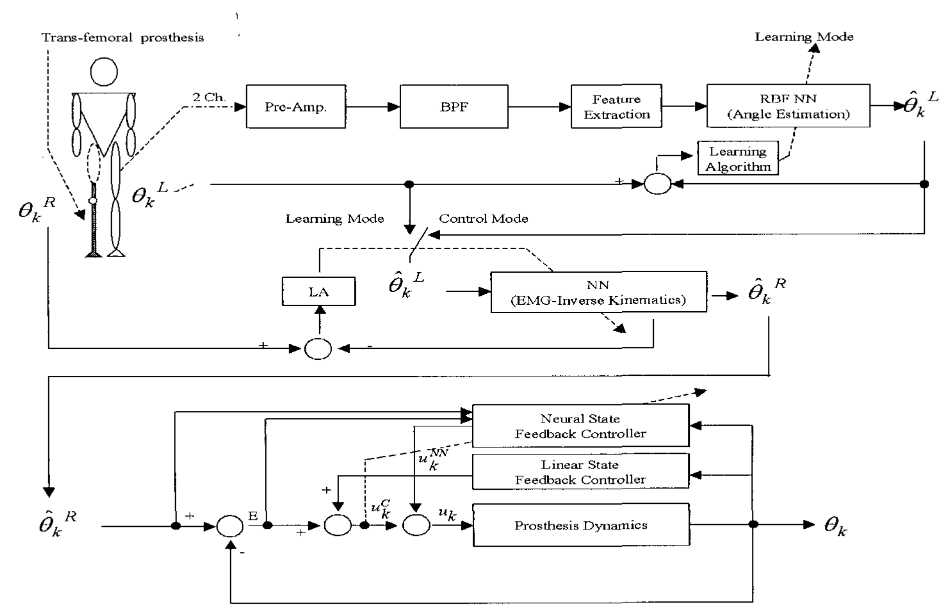

Fig. 2 The proposed control structure to control the gait posture of the trans-femoral prosthesis

amputee, the control structure and method are proposed as shown in Fig. 2 . In the proposed control method, the gait dynamics was trained in the neural network. The gait dynamics followed by the gait habit of a normal person whose gait feature is similar to the femur amputee. The knee joint angle of the prosthesis was then predicted while walking on the basis of the EMG signal from the femur muscle of the amputee. The predicted angle was set up as the control input to control the posture of the knee joint of the prosthesis. In this technique, the gait feature of the injured lower limb of the amputee was assumed to be similar to that of a normal person's; thus the amputee's EMG was used. To measure and control the gait posture angles of the amputee, a general angle sensor (encoder, tilt sensor, etc.) should be attached to the amputee although this generally causes inconvenience while walking. Therefore, EMG was used to sense the joint angles while the amputee's walking was not hindered. This method using the EMG signal is used features of EMG; when the knee joint flexes or extended, the EMG energy of femur muscles increases or decreases (Barreto[2,3], Wang[6], Enderle[7]). In this study, the control structure and technique are suggested to realize the same gait posture of the patient whose one-side lower limb is lost as normal person's (Fig. 2). In the proposed method, the neural network first learned normal person's gait manner, which was similar to the patient. Second, the hip joint angle and the knee joint posture of the artificial leg for walking were estimated based on the EMG signals from the femoral muscle. Third, the estimated angles were inputted into the controller to control the angles of the artificial leg joints from the knee joint angle. In other words, the EMG signal, which varied depending on the gait patterns, was obtained from the femoral muscle involved in the knee joint movements to filter with a low-pass filter, and then the absolute value of the EMG signal was inputted into the RBF neural network(Lee[11], Zurada[12], Lee[13]) to estimate the knee joint angle. Then, using the estimated knee joint angle as a reference signal of the controller, the hip joint angle and the knee joint angle of the artificial leg were predicted. After that, the predicted angle was set up as the reference value of the adaptive posture controller.

3.1 EMG-based knee and gait angle prediction for a normal gait

This study proposes a method of predicting the posture angle of prosthesis from the EMG signal coming from the normal side. The neural network learns the gait feature of the normal lower limb of the amputee whose one lower limb was amputated, so that a more effective posture of the prosthesis joint can be predicted. Its structure and the signal processing method are as shown in Fig. 3. The proposed method to predict the gait angles used two neural networks as shown in Figs. 4 and 5.

Fig. 4 shows the structure to predict the knee joint angle on the normal side of the subject from the EMG signal. The RBF neural network was used, which was robust in processing biomedical signals that normally show much noise(Lee11). As shown in Fig. 3, the EMG signal of the rectus-femoris and the knee joint angle were sampled and acquired at 1 kHz frequency. In the experimentation, the acquired signals included the noises in EMG signal and knee angles signal. These noises are 60 Hz frequency generated from the power line, the random signal and the vibration noise of sensors generated from patient's walking.

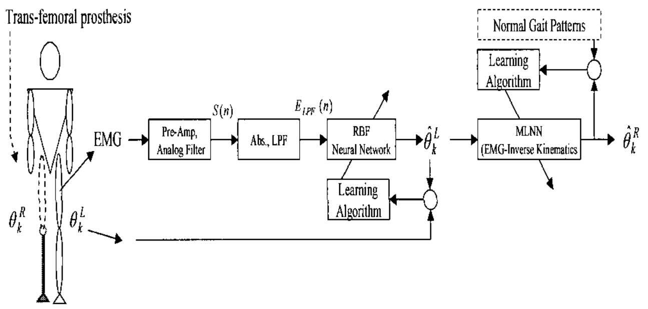

Fig. 3 Structure of gait angle prediction for prostheses using RBFNN and MLNN

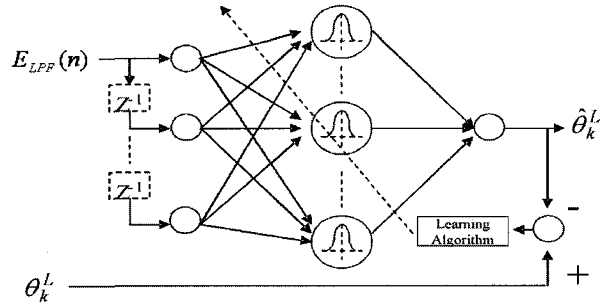

Fig. 4 Knee angle estimator using the RBF neural network

In this study, the used two filters to reject the noises are the MAF(moving average filter) and BPF(band pass filter). The vibration noise of the sensor was filtered with the 500-order MVF that has the characteristic of the cutoff frequency 1.2[Hz]. And the random noise included in the measured EMG was pre-processed with band pass filter(41 order FIR filter) with a cut-off frequency of 20 - 300Hz (Enderle7) for removal. And the absolute energy process was computed as in Eq. (14)

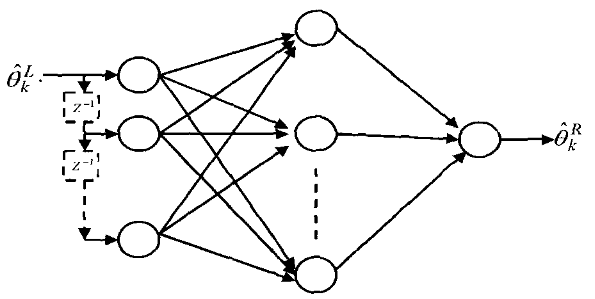

Fig. 5 Structure of gait angles prediction based on stimulated knee angle and multi-layer neural networks

to obtain the EMG signal when the knee joint bent and extended. The low-pass filter of the FIR structure with the cut-off frequency of 200Hz was used to filter the noise as in Eq. (15) to obtain the EMG signal envelope.

$$S_{ABS}(n) = |S(n)| \tag{14}$$

$$E_{LPF}(n) = \sum_{k=0}^{K-1} S_{ABS}(n-k)w_k \tag{15}$$

The extracted feature signal was inputted into the RBF neural network as in Figs. 2 and 3. The structure of the neural network for learning is shown in Fig. 4. The knee joint angle θ_k^L on the normal side was set as the desired value, and the neural network learned to minimize the prediction error $E(n)$ of the knee joint angle. After the neural network completed learning, the knee joint angle was predicted for forward operation. The following equation is the angle prediction.

$$\begin{aligned}\hat{\theta}_k^L(n) &= NN_{RBF}(i_{RBF}) \\ &= \sum_{r=1}^{R} w_r(exp[-\sum_{q=1}^{Q}\frac{(i_{RBF}(q)-m_{rq})^2}{\sigma_{rq}^2}]) \\ & q=1,2,\ldots,Q,\ r=1,2,\ldots,R\end{aligned} \tag{16}$$

where, $i_{RBF}=[E_{LPF}(n),,,E_{LPF}(n-q-1)]$ is the input vector of RBF neural networks; m_{rq} is the center value of the r-th RBF function for the q-th input; σ_{rq} is the distribution of the r-th RBF function for the q-th input. The learning of the RBF neural network was used to minimize the prediction difference $E(n)$ between the knee joint angle θ_k^L on the normal side and the predicted knee joint angle $\hat{\theta}_k^L$.

$$E(n) = \frac{1}{2}(\theta_k^L - \hat{\theta}_k^L)^2 \tag{17}$$

Optimal m_{rq}, σ_{rq} and w_r for the neural network learning are shown in Eqs. (18) to (20).

$$\begin{aligned}\Delta w_r &= -\eta_w \frac{\partial E(n)}{\partial w_r} \\ &= \eta_w(\theta_k^L-\hat{\theta}_k^L)\ (exp[-\sum_{q=1}^{Q}\frac{(i_{RBF}(q)-m_{rq})^2}{\sigma_{rq}^2}])\end{aligned} \tag{18}$$

$$\begin{aligned}\Delta m_{rq} &= -\eta_m \frac{\partial E}{\partial m_{rq}} \\ &= \eta_m 2\,(exp[-\sum_{q=1}^{Q}\frac{(i_{RBF}(q)-m_{rq})^2}{\sigma_{rq}^2}]) \\ &\quad \frac{(i_{RBF}(q)-m_{rq})}{\sigma_{rq}^2}(\theta_k^L-\hat{\theta}_k^L)\cdot w_r\end{aligned} \tag{19}$$

$$\begin{aligned}\Delta \sigma_{ji} &= -\eta_\sigma \frac{\partial E}{\partial \sigma_{ji}} \\ &= \eta_\sigma 2\,(exp[-\sum_{q=1}^{Q}\frac{(i_{RBF}(q)-m_{rq})^2}{\sigma_{rq}^2}]) \\ &\quad \cdot \frac{(i_{RBF}(q)-m_{rq})^2}{\sigma_{rq}^3}(\theta_k^L-\hat{\theta}_k^L)w_r\end{aligned} \tag{20}$$

where, η_w, η_σ, and η_m are learning constants. As shwon in Fig. 5, the multilayer neural network was used to estimate the hip joint and the knee joint angles of the artificial leg during walking, based on the estimated knee joint angle of the normal leg. Thus, a new identification method is proposed on the dynamics for patient's walking pattern. To estimate the hip joint and knee joint angles of the artificial leg of the patient whose one-side leg is lost, this proposed method obtains physically similar person's gait angle and uses the data for learning the gait angle estimator. The EBPA(error back-propagation algorithm) of the multi-neural network was used for the learning algorithm(Zurada12, Lee13). The input vector i_{NN} of the gait angle prediction neural network is the knee joint angle $\hat{\theta}_k^L$ predicted from the EMG, and the output $\hat{\theta}_k^R$ allows for the prediction of the posture angle θ_k^R for each joint of the prosthesis during walking. The corresponding operation process is shown in Eq. (22).

$$\begin{aligned}i_{NN} = [&\hat{\theta}_k^L(n), \hat{\theta}_k^L(n-1), \hat{\theta}_k^L(n-2), \\ &\ldots, \hat{\theta}_k^L(n-j-1)]\end{aligned} \tag{21}$$

$$\hat{\theta}_k^R(n) = \lambda_2 \sum_{k=1}^{K} w_k \lambda_1 \sum_{j=1}^{J} w_{jk} i_{NN}(j) \tag{22}$$

where, λ_1, λ_2 are the activation functions. To minimize the prediction error $E(n)$ between $\hat{\theta}_k^R(n)$ and $\theta_k^R(n)$, Δw_{jk} and Δw_k were adjusted and learned through the error back propagation algorithm as follows:

$$E(k) = \frac{1}{2}[\theta_k^R(n) - \hat{\theta}_k^R(n)]^2 \tag{23}$$

$$\triangle w_{kj} = -\eta\frac{\partial E}{\partial w_{kj}},\quad \eta > 0 \tag{24}$$

$$\triangle w_{ji} = -\eta\frac{\partial E}{\partial w_{ji}},\quad \eta > 0 \tag{25}$$

Based on the weight information in the neural network learned from the normal person's gait data, the gait posture angle for each joint of the prosthesis was predicted using the knee joint angle $\hat{\theta}_k^R(n)$ which was predicted simply in a forward direction of the neural network during walking.

3.2 Design of adaptive controller to control the knee joint of the prosthesis

In this study, the posture of the prosthesis was controlled through the predicted gait angle $\hat{\theta}_k^R$ of the knee joint and the controller as in Fig. 6. In this neural network controller, the linear controller was arranged in parallel, the neural network repeated the desired period, which was learned and controlled on-line, so that the desired gait posture angle $\hat{\theta}_k^R$ could be obtained while the forward error was back-propagated through the neural network. The gait angle was learned through several learning cycles, and the neural network learned and controlled the inverse dynamics of the prosthesis for convergence. In other word, the adaptive controller was used to control the posture of the knee joint adaptively according to the amputee's gait features.

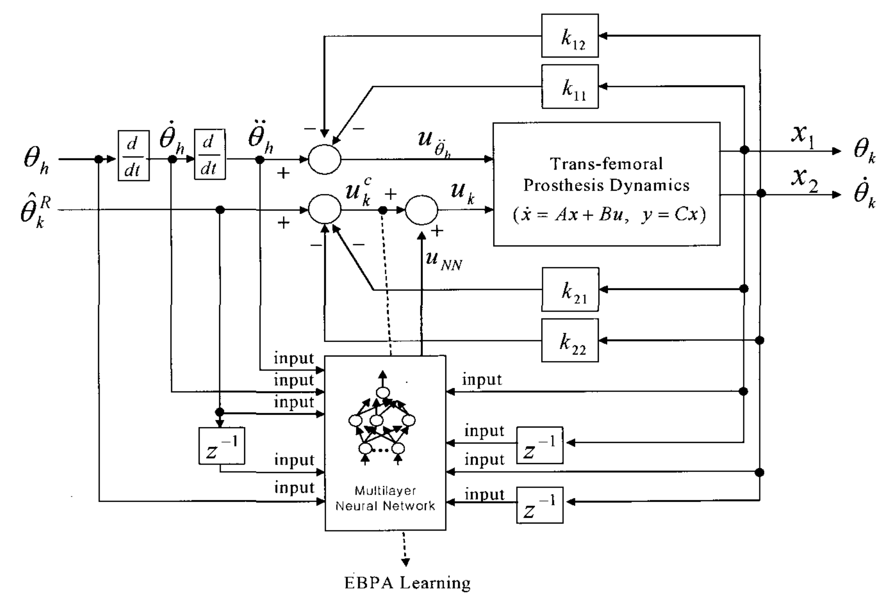

Fig. 6 Neural network controller for posture control of knee prosthesis

3.2.1 Design of the linear controller

The controller in this study consists of the LQR controller and the neural network controller trained order to adaptively control the posture of the knee joint. The used physical parameters of the prosthesis model for controlling the posture are in shown Table 2. Table 2 is obtained from patient's prosthesis who limb below the femoral muscle was amputated.

Table 2 The physical parameters of the prosthesis used in the simulation

Parameter	Units	Trans-femoral Prosthesis
L_t	[m]	0.42
L_{sCG}	[m]	0.18
L_s	[m]	0.51
M_t	[kg]	8.1
M_s	[kg]	4.5
I_t	[kg · m²]	0.06
I_s	[kg · m²]	0.11

The proposed control method is that the LQR controller operates in the early stage of the process, and the neural network controller, which learns the amputee's gait features, operates when the learning the neural network is converged. To design the LQR controller, the necessary and sufficient condition of that all roots of an system equation(Eq.(28), obtained from Table 2) should be controllable (Eq.27) and observable (Eq.(28)).

$$\dot{\boldsymbol{x}} = \boldsymbol{A}\boldsymbol{x} + \boldsymbol{B}\boldsymbol{u}$$
$$\boldsymbol{y} = \boldsymbol{C}\boldsymbol{x} \tag{26}$$

In Eq.(26), the state vector $\boldsymbol{x}$ is $[\theta_k\ \dot{\theta}_k]^T$, the input vector $\boldsymbol{u}$ is $[u_{\ddot{\theta}_h}\ u_k^c]^T$ and $\boldsymbol{A}$, $\boldsymbol{B}$, $\boldsymbol{C}$, $\boldsymbol{D}$ are as follows:

$$\boldsymbol{A} = \begin{bmatrix} 0 & 1 \\ -0.5394 & 0 \end{bmatrix}, \boldsymbol{B} = \begin{bmatrix} 0 & 0 \\ -1.33 & 3.91 \end{bmatrix}, \boldsymbol{C} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

Accordingly, the trans-femoral model of this study are controllable and observable because the values of the controllability(Eq. 27) and observation(Eq. 28) are n_c=2 and n_o=2.

$$rank([B\ AB\ AB^2, ..., AB^{n-1}]) = n_c \tag{27}$$

$$rank(\begin{bmatrix} C \\ CA \\ \cdot \\ \cdot \\ CA^{n-1} \end{bmatrix}) = n_o \tag{28}$$

The prosthesis models in this study are effective for measuring all states; thus, all states can give feedback. Accordingly, the LQR controller(Eq.(30)) controls the posture of the trans-femoral prosthesis. The optimal gain matrix $\boldsymbol{K}$(Eq.(31)) of the LQR controller to minimize the cost function J is obtained by solution $\boldsymbol{P}$ of the steady-state Riccati equation(Ogata16) as $\boldsymbol{PA} + \boldsymbol{A}^T\boldsymbol{P} - \boldsymbol{PBRB}^T\boldsymbol{P} + \boldsymbol{Q} = 0$.

$$J = \int_0^\infty (\boldsymbol{x}'\boldsymbol{Q}\boldsymbol{x} + \boldsymbol{u}'\boldsymbol{R}\boldsymbol{u})\,dt \tag{29}$$

$$\begin{bmatrix} u_{\ddot{\theta}_h} \\ u_k^c \end{bmatrix} = -\boldsymbol{K}\boldsymbol{x} = \begin{bmatrix} -k_{11}\theta_k - k_{12}\dot{\theta}_k \\ -k_{21}\theta_k - k_{22}\dot{\theta}_k \end{bmatrix} \tag{30}$$

$$K = \begin{bmatrix} k_{11} & k_{12} \\ k_{21} & k_{22} \end{bmatrix} = \begin{bmatrix} -0.28 & -0.38 \\ 0.82 & 1.13 \end{bmatrix} \tag{31}$$

where Q and R are defined as Eq. (32) to obtain the gain matrix.

$$Q = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad R = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{32}$$

3.2.2 Design of the neural network adaptive controller

The learning of the FELC(forward error learning controller(Sigeru15)) minimizes the error function E shown in Eq. (33). The desired output from Eq. (33) is $\hat{\theta}_k^R$.

$$E = \frac{1}{2}\sum_{k=1}^{K}(\hat{\theta}_k^R(n) - \theta_k(n))^2 \tag{33}$$

In this study, the used activation functions of this neural network

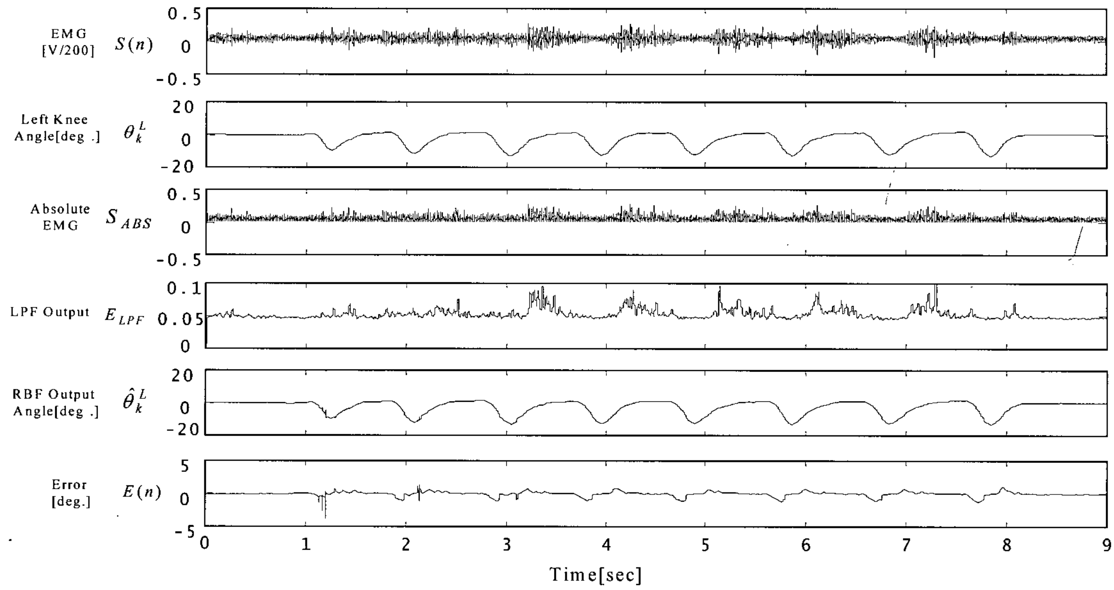

Fig. 8 Results of the estimated knee angle and EMG signal processing in the case of gait

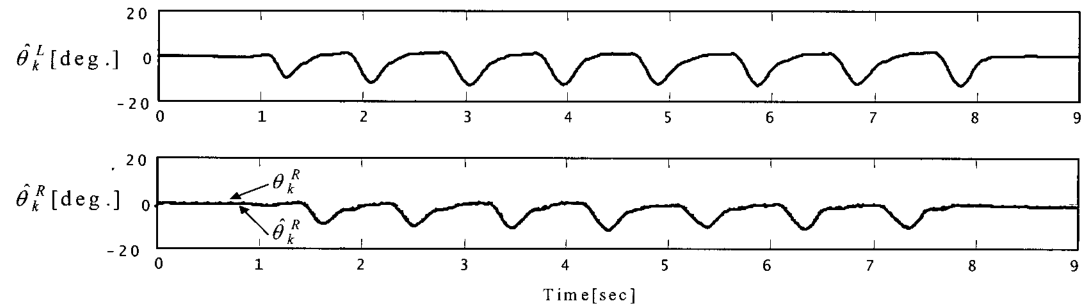

Fig. 9 Result of the Estimated angles during gait

controller are the linear functions $net = f(net)$ and the learning algorithm used the EBPA(error back-propagation algorithm) to train the plant Jacobian, $\partial\theta_k/\partial u_k$. The overall control output u_k is the sum of the output u_k^C of the linear controller and the output u_k^{NN} of the neural network controller as $u_k = u_k^c + u_k^{NN}$.

4. Experiment and results

4.1 Design of the analog interface to measure EMG and gait angle

The analog sensor interface was designed to obtain the EMG signal first so that the effectiveness of the proposed prosthesis control system could be verified. Because the EMG signal amplitude required was 20 to 30mV and the frequency required was 20 to 300Hz when the sensor interface circuit was designed, electrodes were attached to the skin above the femur muscle and amplified 200 times. A band pass filter of 20 to 300Hz and 60Hz band reject filter were designed to remove noise included in the amplified EMG signal. The TILT SA1(DAS14) tilt sensor with the angle range of ±60[deg.] was used to measure the lower limb angle while walking. Fig. 7 shows the implemented system. The EMG sensor was attached to the femur muscle while the tilt sensor was attached to measure the joint angle at the center of the shin length. The joint angle and the EMG signal were then measured from each lower limb.

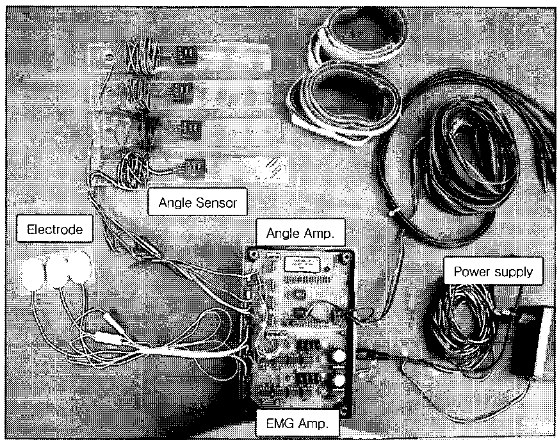

Fig. 7 The implemented measurement system

4.2 EMG measurement and digital signal process

The EMG signals and the gait data are obtained using Biopac's MP100 at the sampling frequency of 1 kHz. The EMG signal and gait angles are measured for three step walking sets, and the vibration noise from each sensor caused by muscle vibration while walking was removed with the moving average filter (order=500). The cut-off frequency was set at 20 to 300Hz, and the band pass filter (order=59) with the FIR filter structure having the characteristics of the hamming window function removed the noise from the EMG signal.

4.3 Gait angle prediction and experimental results using the EMG

The neural network structure was specified with the parameters in Table 3 to predict the knee joint angle of the amputee's normal lower limb using the EMG while walking by the amputee based on the pro-

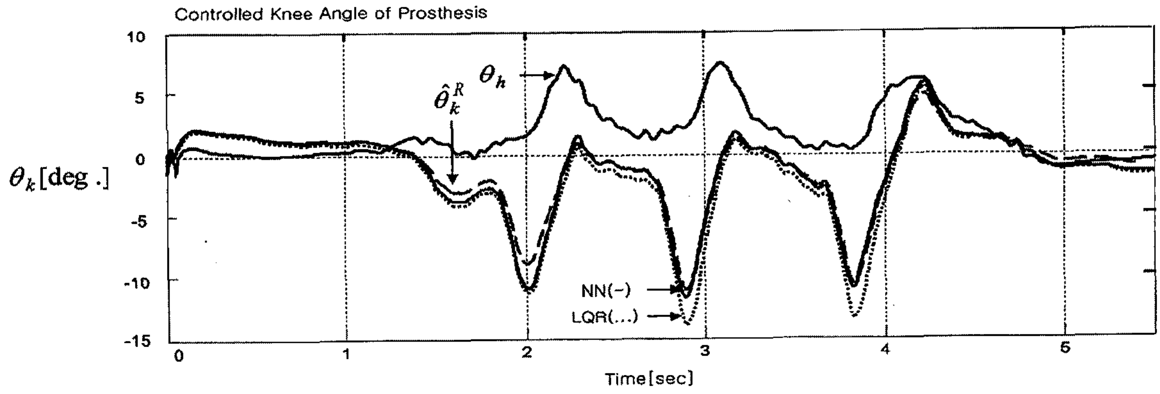

Fig. 10 Results of adaptive posture control for the knee during the gait

posed technique shown in Figs. 3 and 4. The prediction result of the neural network after learning is shown in Fig. 8. The knee joint angle error of the normal lower limb was measured as an average 0.1809° for 8 sets in the gait period.

Table 3 Parameters of LPF(lowpass filter) and neural networks to predict gait angles

LPF		Neural Networks		
			RBF	MLNN
Cutoff frequency	200[Hz]	Input Neurons	20	100
Orders	59	Hidden Neurons	10	20
Window	Hamming	Output Neurons	1	2
Structure of filter	FIR	Activation Function	Gaussian	Linear
		Learning Rate	0.1	0.1

4.4 Gait angle prediction and the posture control of the Prosthesis

As shown in Figs. 3 and 5, the gait posture angle of each joint of the prosthesis was predicted using the knee joint predicted simply in the forward direction of the neural network while walking. It was based on the weight information of the neural network learned from the normal gait data. The parameters in Table 3 were specified to verify the prediction effect of the gait angle which the prosthesis should take while walking. The result is shown in Fig. 9. In the experimental result, the prediction error for the knee joint posture angle, which the prosthesis should take, turned out to be 0.23[deg.] for 8 sets in the gait period. Therefore, the accuracy of the knee joint angle prediction of the prosthesis based on the EMG signal was 97.6%. Thus, this accuracy is expected to be available as each joint predictor for controlling the posture of the knee joint of the prosthesis while walking. Using this predicted angle, the reference signal was set up for the posture controller in this research.

4.5 Gait posture control experiment and results

The proposed posture controller shown in Figs. 2 and 6 was designed and simulated in order to verify the performance of the control technique. In the experimentation, the used structure of the neural network for controlling the posture of the trans-femoral prosthesis included 14 input neurons, 20 hidden layers, and 1 output layer in the time delay neural network formation. The activation function was linear. The inputs of the control neural network are the hip joint angle $\theta_h(n)$, acceleration $\ddot{\theta}_h(n)$ and angular velocity $\dot{\theta}_h(n)$ of the normal lower limb, each first delay component $(\ddot{\theta}_h(n-1), \dot{\theta}_h(n-1), \theta_h(n-1))$, control error $(e_k(n), e_k(n-1))$, the predicted knee joint angle for the prosthesis$(\hat{\theta}_k(n), \hat{\theta}_k(n-1))$, the output of the state feedback controller $(u_k^C(n), u_k^C(n-1))$ and overall control output $(u_k(n), u_k(n-1))$. In controlling the prosthesis, first, the LQR controller was controlled, then, the posture was controlled adaptively through learning convergence in the neural network controller. Eq. (31) was used for the gain of the LQR controller. Fig. 10 shows the result of controlling the posture of the prosthesis knee joint when the neural network was twice taught to learn. Table 4 shows the average error of the neural network controller during the third gait period. In this result, the neural network controller was able to properly control its learning process per amputee's gait state.

Table 4 Errors of posture control using the neural controller

Simulation item	Mean error	
	LQR	NN
gait(cycles=3)	3.2706	1.3575

5. Conclusions

To restore gait capacity when wearing the prosthesis and to make it similar to that of a normal person, the posture control technique of the trans-femoral prosthesis was proposed using the learning capacity of the artificial neural network, and its performance was gauged through the experiments. The surface EMG signal of the normal lower limb was used to extract the current gait angle, and then, the gait posture of the prosthesis was predicted from the neural network which learned normal gait kinematics based on the angle. The adaptive posture was then controlled using the artificial neural network. The results revealed that the average error of the knee joint angle prediction out of the EMG of the normal lower limb was 0.1809[deg.], which is quite acceptable for actual applications. The prediction error of the posture angle, which the prosthesis should take while walking, was 0.2255[deg.]. The accuracy of the angle prediction was 97.6%, which showed that the posture angle obtained while the amputee was walking could be used as the controller input. For controlling the posture of the trans-femoral prosthesis from the predicted knee joint posture angle, it showed an improvement of up to 90% from the LQR controller. Therefore, it is estimated that the trans-femoral prosthesis can be properly controlled following the amputee's gait habits, and we may expect the amputee would show signs of less fatigue when walking with the prosthesis.

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