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EMG based Design and Evaluation of Micro Macro Neural Network for Rollover Support Trunk Orthosis

Takeshi Ando, *Student Member, IEEE*, Jun Okamoto, Mitsuru Takahashi, and Masakatsu G. Fujie, *Senior Member, IEEE*

***Abstract*— An EMG controlled intelligent orthosis was developed to support the rollover movement of cancer bone metastasis patients. In this paper, the validation of the developed signal processing algorithm to recognize the rollover was focused. Firstly, the ElectroMechanicalDelay of the internal oblique muscle was measured as the about 65 (msec). Secondly, it was confirmed that the rollover movement was recognized about 65 (msec) before the movement started. Therefore, the developed Micro Macro Neural Network (MMNN) recognized the rollover movement using the EMG signal as quick as possible. Finally, the robustness of the developed MMNN was discussed by conducting the experiment to discriminate between the rollover and turning out. We proposed and developed the original algorithm in which the logical XOR operation was added to the MMNN, because the MMNN which learned the characteristics of the only rollover recognized the turning out movement as the rollover movement perfectly. When the proposed algorithm that combined the MMNN and XOR operator was used, the rollover and turning out movements were discriminated 83%.**

I. Introduction

CANCER bone metastasis patients suffer from severe pain when they attempt movements such as rollover that include trunk twisting. Currently, there is a customized hard orthosis to restrict the range of trunk movement. However, the hard orthosis is not always used, because the hard orthosis strongly and constantly restrains movement and, therefore, puts a lot of physical pressure on patients. As a result of not using the hard orthosis, some patients become bedridden. In this research, we focused on the rollover movement as the movement including the trunk rotational movement, because it is a first step out of a bedridden condition – of course, it also is one of the major ADL (Activities of Daily Living).

We have been developing an intelligent trunk orthosis to support rollover by restricting the trunk rotational ROM (Range Of Motion) only when the rollover is conducted. The intelligent trunk orthosis realizes the patient's rollover by himself or herself without the pain and the prevention of bedridden in the terminal care.

As shown in Fig. 1, the intelligent orthosis is composed three core technologies; 1) the detection of patient's intention on the rollover using the surface EMG signal [1], 2) the recognition of the rollover using an original neural network known as the MMNN [2] (See Section II), and 3) trunk rotational ROM restriction using the pneumatic rubber actuator [3]. So far, on the EMG signal processing, the MMNN was proposed [2] and methodology to design the structure of MMNN was developed [10]. The contribution of this paper is to evaluate the response performance and the robustness in recognizing the rollover under the simulated terminal care environment using the developed neural network. Ultimate goal of this paper is that the methodology to design the recognition and control system in the intelligent trunk orthosis is established.

This paper is organized as follow: Section II introduces the concept of the intelligent trunk orthosis; Section III explains the timing of the muscle activation in the rollover movement, Section IV shows the timing of recognizing the rollover, Section V presents the discrimination between the rollover and turning out movements; finally, Section VI presents a summary and a look at future work.

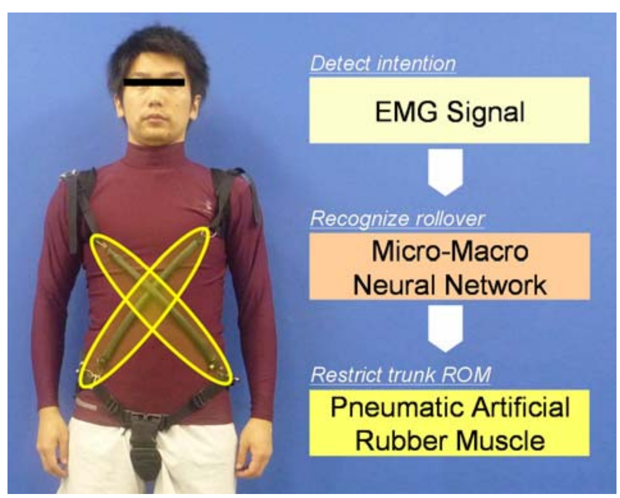

Fig. 1. Intelligent trunk orthosis to support rollover. Note that, in this orthosis, the rollover is recognized using the EMG signal and the original neural network. After that, rollover is supported by restricting trunk rotational movement using the pneumatic artificial rubber muscle

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Takeshi Ando is with the Faculty of Science and Engineering and Graduate School of Advanced Science and Engineering, Waseda University, Tokyo Japan (corresponding author; e-mail: ando@aoni.waseda.jp).

Jun Okamoto is with the Faculty of Science and Engineering, Waseda University, Tokyo, Japan.

Mitsuru Takahashi (M.D.) is the chief, Division of Orthopaedic Oncology, Shizuoka Cancer Center, Shizuoka, Japan.

Masakatsu G. Fujie is with the Faculty of Science and Engineering, Waseda University, Tokyo, Japan.

II. INTELLIGENT TRUNK ORTHOSIS

A. Micro Macro Neural Network to Recognize Rollover

Since the recognition of rollover is based on noisy and complex EMG signals, a highly robust system that is unaffected by the possible misalignment of electrodes or individual differences is necessary to recognize EMG signals accurately. A Neural Network (NN) is one of the learning machines that use EMG signals to recognize movement [4]-[9]. However, most related studies share the same problems, that is, the misrecognition and recognition reaction delay.

We have designed and constructed a new neural network known as Micro Macro Neural Network (MMNN) to recognize slower movement such as the rollover accurately with quick response [10]. The MMNN is able to recognize the rollover more correctly and steadier using the long past time-series data of the EMG signal. Basically, we upgraded the traditional Time Delay Neural Network (TDNN), in which a delay is introduced in the network and past data (the data collected before the current measurement point) is set as the input signal of the network, to MMNN (Fig. 2). The MMNN can handle an increased amount of input data to the neural network without increasing the number of calculations. The MMNN is composed of the Micro Part, which detects a rapid change in the strength of the EMG signal, and the Macro Part, which detects the tendency of the EMG signal toward a continuing increase or continuing decrease, to improve the response time and accurate recognition of the rollover movement based on the EMG signal as input.
Traditional TDNN is defined in our network as the Micro Part. As can be seen in Fig. 2, the data for $-T_{micro} < t < 0$ is the Micro Part, and the data for $-(T_{macro} + T_{micro}) < t < -T_{micro}$ is the Macro Part. In addition, the input data in the Macro Part is divided into several T_{ARV} (msec), and the average rectified value (ARV) of the EMG signal among the T_{ARV} values is defined as the input value of the Macro Part.

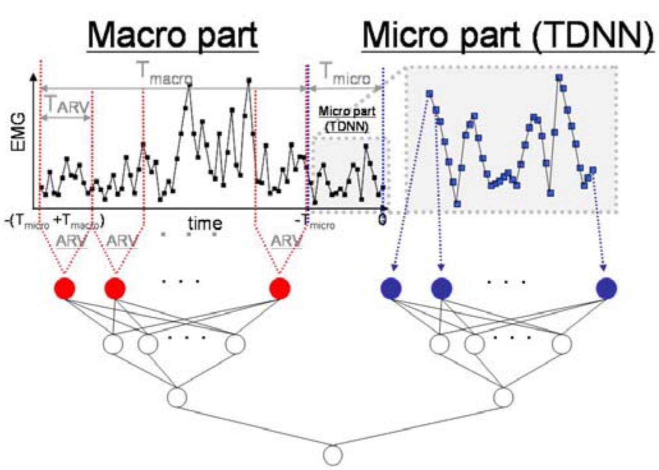


Fig. 2. Micro Macro neural network. Note that MMNN is divided into the Micro Part and the Macro Part.

The relations between each pair of units in both the Macro Part and the Micro Part are shown in (1), (2), and (3) above.

$$net_i^m = \sum_{j=1}^{n_{m-1}} \omega_{ij}^m x_j^{m-1} + \theta_i^m \tag{1}$$

$$x_i^m = f(net_i^m) \tag{2}$$

$$f(net) = 1/(1 + \exp(-u_0 net)) \tag{3}$$

where m = 2 and 3, i = 1,…,n_m, n_m is the number of the m^{th} layer unit, $\omega^m{}_{ij}$ is the weight between the $(m\text{-}1)^{th}$ layer's i^{th} unit and the m^{th} layer's j^{th} unit, $x^m{}_i$ i is the output of the m^{th} layer's i^{th} unit, $\theta^n{}_i$ is the threshold in the m^{th} layer's i^{th} unit, and u_0 is the constant to decide the gradient of the sigmoid function.

The output data of the Micro part and Macro part is defined as the input data of the Integrated Layer. In the Integrated layer, the output signal is calculated using also (1), (2) and (3).

B. Rollover support mechanism by restricting trunk ROM

We have also developed a mechanism using a pneumatic artificial rubber muscle (PARM) to restrict the range of the trunk twisting movement [3] – in our system, PARM, which is often used to support some movement actively [11] –[14], supports rollover passively.

The length from the right acrominon to the left ASIS becomes longer when the trunk is twisted to the right. On the other hand, the relations between the distances are reversed when the trunk is twisted to the left.

Therefore, the progress of the trunk twisting movement can be stopped when the change of the distances between the acrominon and ASIS is limited to less than a constant value.

The PARMs are arranged on the lines that connect the right (left) acrominon to the left (right) ASIS. Additionally, the PARMs that connect the right (left) acrominon with the left (right) ASIS contract when the patient starts to rotate his trunk to the right (left). As a result, the ROM of the trunk is limited, based on the length of the intelligent orthosis and on the stiffness (and length) of the constricted PARM. The interface of the intelligent orthosis is normally soft and unrestraining, but it should become hard when the rollover movement is started. This change from soft to hard could be controlled by PARM that limits the distance from the acrominon to the ASIS.

Depending on the types of the rollover movement, the contracted PARMs are different. We focused our attention on the differences in the motion during the first stage of rollover. Referring to the related work [15][16], we were able to divide rollover into three types: an Upper Limb Precedent Type (ULPT), Lower Limb Precedent Type (LLPT), and Lower Limb Flexion Type (LLFT). In the ULPT, the start of upper limb motion comes before that of pelvis rotation. In the LLPT, the start of pelvis rotation comes before that of upper limb motion, without using the reaction force of the lower limb. In the LLFT, the start of pelvis rotation comes before that of upper limb motion, with using the reaction force of the lower limb (with the knee bent).

For example, in case of turning over toward right side of the subject as shown in Figs. 3(a), 4(a) and 5(a), the length from the right acrominon to left ASIS in ULPT and that from left acrominon to right ASIS in LLPT and LLFT become longer. Therefore, the PARM arranged from the right acrominon to left ASIS in ULPT and that from left acrominon to right ASIS in LLPT and LLFT are contracted to restrict the trunk rotational movement in rollover movement.

III. Measurement Experiment of ElectroMechanical Delay in Rollover Movement

A. ElectroMechanical Delay (EMD)

Generally, there is the time delay between the mechanical output, that is, the movement ventilation and force generation, and muscle discharge. This phenomenon is known as the ElectroMechanical Delay (EMD) [17][18].

The EMD is about 20 – 100 (msec), which depends on the type of muscle contraction, the velocity of the contraction, the muscle length, the load to the muscle and so on. In the related studies, the EMD in the simple movement such as the knee extension was measured. However, the EMD in the rollover movement is not measured.

B. Objective

In the intelligent trunk orthosis, the rollover movement needs to be recognized by using the MMNN as quick as possible after the EMG signal is generated.

The objective of this section is to measure the EMD in the rollover movement to estimate the time delay of the recognition after the rollover starts in the next section.

So far, we have qualitatively analyzed the surface EMG signal as an input signal for the intelligent orthosis to recognize the rollover movement [1]. As a result, the EMG signal of the internal oblique muscle is selected as the input signal, because its signal is generated quicker and stronger than the EMG signals of other muscles. Therefore, the EMD of the internal oblique muscle in the rollover movement is measured.

C. Experimental Methodology

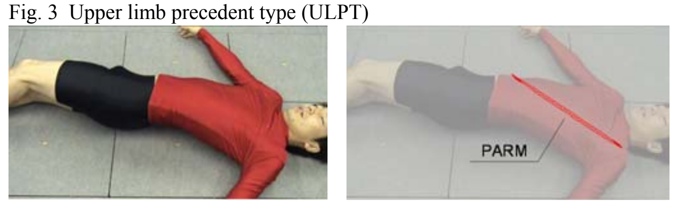
In this research, rollover movements were performed thirty times in advance by each of three young, healthy male subjects. The rollover is conducted to the right side of the subject as shown in Fig. 3. We gave the subjects a detailed account of our experimental objectives, explained that they were entitled to stop the experiment whenever they desired, and obtained their consent.

The EMG electrodes (Biometrics inc., active electrode made by AgCl, electrode distance: 20 (mm), sampling frequency: 1(kHz)) were put on the right and left internal oblique muscles with considering to avoid innervation band.

The acceleration sensor (ACL300, Biometrics inc., sampling frequency: 1(kHz)) were set at the position of the left acrominon and anterior superior iliac spine (ASIS).

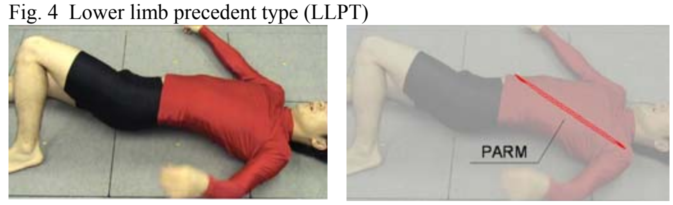
(a) Characteristic motion (b) Contraction of PARM

Fig. 3 Upper limb precedent type (ULPT)



(a) Characteristic motion (b) Contraction of PARM

Fig. 4 Lower limb precedent type (LLPT)



(a) Characteristic motion (b) Contraction of PARM

Fig. 5 Lower limb flexion type (LLFT)

The data of the EMG and acceleration was synchronized using DataLog (Biometrics inc., P3X8).

As shown in Fig. 6, the EMD was defined and measured based on the following steps;

1) The average and standard deviation of the EMG signal and acceleration data in the resting state were calculated as the μ_{emg}, μ_{acc} , σ_{emg} and σ_{acc}.

2) The threshold of the EMG signal and acceleration data were defined as Th_{emg} and Th_{acc} as follow based on the statistics of Gaussian distribution.

$$Th_{emg} = \mu_{emg} \pm 3\sigma_{emg} \tag{4}$$

$$Th_{acc} = \mu_{acc} \pm 3\sigma_{acc} \tag{5}$$

3) The time when the EMG data of right or left IO muscle and acceleration data of the acrominon or ASIS became larger than the thresholds multiple times between 20 (msec) was defined as the t_{emg} and t_{acc}.

4) The EMD was calculated as the difference between the time that the rollover started, t_{acc}, and the time that the EMG to conduct the rollover, t_{emg}.

$$EMD = t_{acc} - t_{emg} \tag{6}$$

D. Result and Discussion

An example of EMG and acceleration data is shown in Fig. 7. The EMD of the internal oblique muscle in the rollover movement was 67.6±20.1 (msec). The variation of the EMD among the subjects was not confirmed.

The required specification of the developed neural network to recognize the rollover movement is that the rollover movement is recognized about 65 (msec) before the rollover starts.

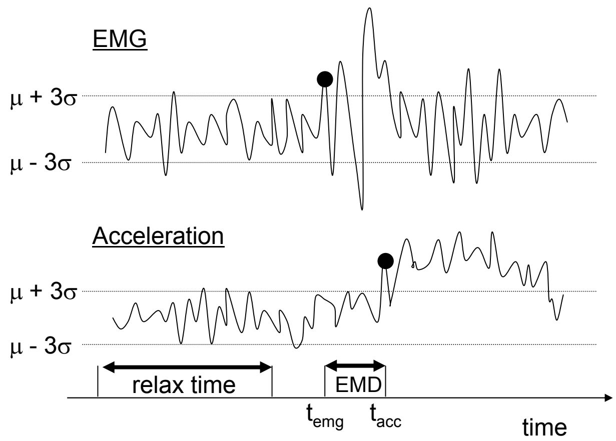
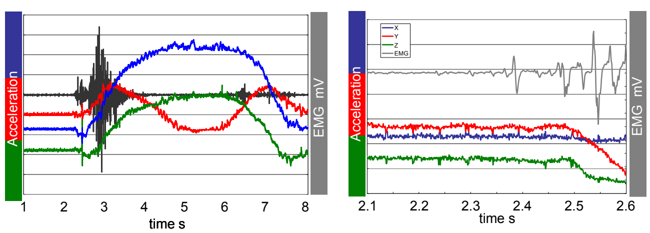


Fig. 6 Definition of the ElectroMechanicalDelay



(a) Rollover movement (b) Start timing of rollover

Fig. 7 EMG and acceleration data in rollover movement. Gray line is EMG and blue, red and green lines are X, Y and Z axis data of acceleration.

IV. Recognition of Rollover by TDNN and MMNN

A. Objective

Based on the EMD measured in the section III, the response characteristic of the developed MMNN in recognizing the rollover is evaluated by comparing with that of traditional TDNN.

B. Experimental Methodology

The rollover movements were performed thirty times in advance by each of three young, healthy male subjects. EMG signals obtained from the right and left internal oblique (IO) muscle were selected as the input signals. The EMG signals were sampled at a rate of 1000 (Hz), rectified with a second-order, low-pass filter with a cut-off frequency of 20 (Hz). The EMG signal is calculated in PC (operating frequency: 650 (MHz), BUS: PC104, and OS: QNX 6.2).

Furthermore, by synchronizing the EMG data with the data of a 3D motion-capture system (VICON612, sampling frequency: 100(Hz) and accuracy: 1(mm)), the start of rollover movement was recognized.

For the learning machine in this research, we selected the three-layer feed-forward type TDNN and MMNN and the back propagation method with momentum term, which is a standard neural network for recognizing time-series signals.

The number of the input layer units, the hidden layer and the output layer of the traditional TDNN were 75, 38 and 1, respectively. On the other hand, the structure of the MMNN was T_{ARV} = 40 (sec), N_{macro} = 40 and N_{miccro} = 10 [3]. The number of hidden and output layers' units was determined based on" the Rule of thumb."

As the learning data for every rollover type, 20% of the data (18 out of 90 rollovers – 30 for each of the three subjects) was randomly selected. The other 80% of the data was used as test data. Because the numbers of learning and test data were small, the k-fold cross validation estimation (k = 5) was used to prevent degradation of the accuracy based on the selection of learning data.

The recognition results of the test data were evaluated according to the response by the indexes presented below.

The response time, $t_{response}$, is the time from the start of the rollover movement to the recognition of the rollover movement by the neural network. The time when the rollover starts was determined by the 3D motion-capture system.

C. Result and Discussion

The examples of the recognition result were shown in Fig. 8. It was confirmed that the MMNN recognized the rollover quickly with the high accuracy. The average $t_{response}$ for MMNN was -65 (S.D. 55) (msec). The average $t_{response}$ for TDNN was -25 (S.D. 59) (msec). Therefore, by comparing with the EMD, it was confirmed that the recognition timing of MMNN was the almost same as the timing that the EMG was generated to start the rollover movement. On the other hand, the recognition time of TDNN was about 40 (ms) later than the timing that the EMG was generated to start the rollover movement.

It was confirmed that original neural network algorithm with enough specification on the response time was developed. In addition, this response time of the MMNN is enough to compensate the actuation delay of the pneumatic rubber muscle due to the compressive property of the air, because the actuation delay is about 30 (msec).

V. Discrimination of Rollover and Turning Out

A. Objective

In section IV, it was confirmed that the developed MMNN had enough specification to recognize the rollover movement. However, the bone cancer metastasis patients conduct not only the rollover movement but also the turning out movement on the bed. The bone cancer metastasis patients who are not the osteoporosis patients don't feel the pain when they conduct the turning out movement, which includes not the trunk rotational movement but the trunk anteflexion movement. Therefore, the pneumatic rubber muscle need not to contract when the turning out movement is performed. The objective of this section is to develop the signal processing method to discriminate between the rollover movement and the turning out movement.

TABLE I Comparison of the recognition timing and EMD

	timing of EMG generated or motion recognized before motion start msec	S.D. msec
EMD	68	20
TDNN	25	59
MMNN	65	55

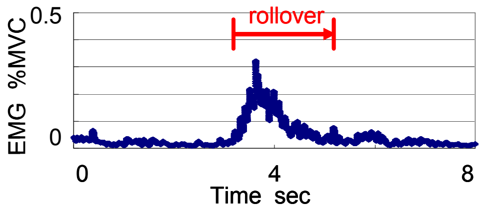


Fig. 8(a) Input signal to NN

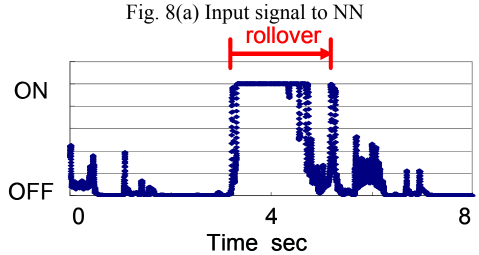


Fig. 8 (b) Output signal from the TDNN

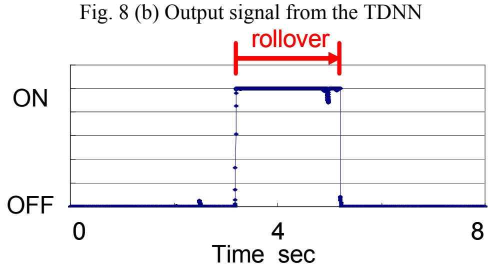


Fig. 8 (c) Output signal from the MMNN

Fig. 8 Comparison between recognition of rollover by TDNN and MMNN. Note that output of TDNN shown in Fig. 8 (b) fails to recognize the rollover at 0-2 (msec) and 5-7 (msec); moreover, it does recognize the rollover after the movement starts. In contrast, as shown in Fig. 8 (c), MMNN recognizes the rollover correctly before the movement starts. EMG signal data is included for reference as Fig 8(a).

B. Experimental Methodology

The rollover movements and turning out movement were performed thirty times in advance by each of three young, healthy male subjects. The EMG signals were measured at the position of the right and left internal oblique muscles. The measurement conditions were the same as those shown in section IV B. In the learning step of the MMNN, the EMG signal of only rollover movements were used with the same condition as those in section IV B. In other word, performance of discriminating the turning out movement was evaluated by using the MMNN which learned the characteristics of the rollover movement.

C. Result and Discussion

1) Step 1: Normal signal processing;

When the signal processing applied in section IV (Fig. 9) was used, the rollover was recognized accurately. However, the turning out movement was also recognized as the rollover movement in every trial, because the internal oblique muscles were activated in the turning out movement (Fig. 10). Therefore, it was confirmed that it was difficult to apply the MMNN which learnt the characteristic of the only rollover movements to discriminate between the rollover and turning out movements.

2) Step 2: XOR operation added signal processing;

In *step 1*, it was confirmed that the EMG signals of the right and left internal oblique muscles were generated at the almost same moment. Based on this characteristic of the turning out movement, we propose an original algorithm to discriminate between the rollover and turning out movements. As shown in Fig. 11 and TABLE II, the algorithm is based on the logical XOR operator as follow;

-- *If* the MMNNs for both right and left IO muscles recognizes rollover, *then* turning out movement.

-- *If* the MMNNs for neither right nor left IO muscles recognizes rollover, *then* non movement (stop).

-- *If* the MMNNs for either right or left IO muscles recognizes rollover, *then* rollover movement and support based on the section II B.

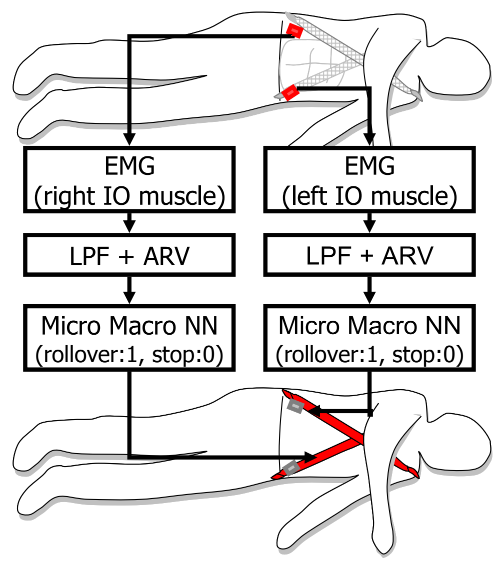


Fig. 9 Signal processing using the MMNN which learnt the characteristic of the only rollover movement

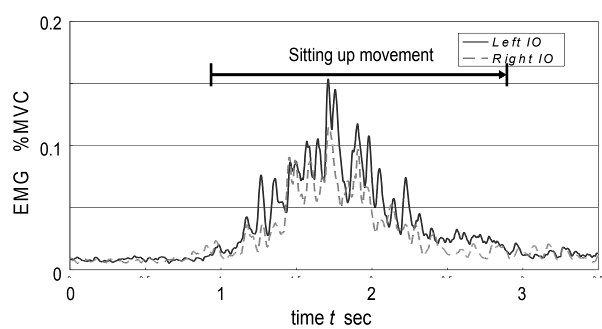


Fig. 10 The EMG signals of IO muscles in turning out movement

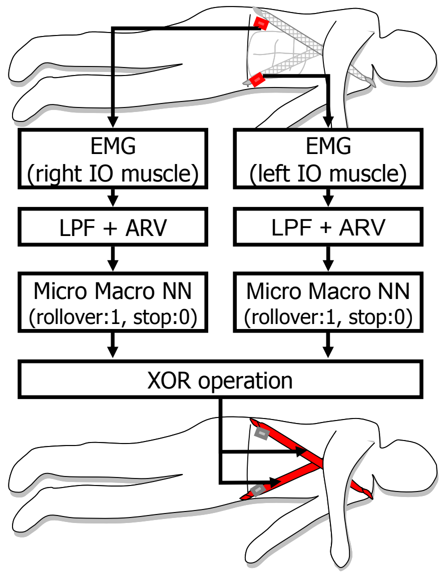


Fig. 11 Signal processing using the MMNN and logical XOR operation to discriminate between the rollover and turning out

TABLE II Discrimination between rollover and turning out movements

		Right IO muscle	
		ON	OFF
Left IO muscle	ON	TURNING OUT	ROLLOVER (Pneumatic muscle contraction from right ASIS to left acrominon)
	OFF	ROLLOVER (Pneumatic muscle contraction from left ASIS to right acrominon)	STOP, NO MOVE

By applying the proposed algorithm, the 83 % turning out movements were recognized as the turning out. On the other hand, the recognition rate of the rollover was not decreased comparing with that using the MMNN which learnt the characteristic of the only rollover movement.

VI. CONCLUSION

We have been developing the intelligent trunk orthosis to support the rollover movement of the cancer bone metastasis patients. In this paper, the validation of the developed signal processing algorithm to recognize the rollover was focused. Firstly, the EMD of the internal oblique muscle was measured as the about 65 (msec). Secondly, it was confirmed that the rollover movement was recognized about 65 (msec) before the movement started. Therefore, the MMNN recognized the rollover movement using the EMG signal as quick as possible. Finally, the robustness of the developed MMNN was discussed by conducting the experiment to discriminate between the rollover and turning out. We proposed and developed the original algorithm in which the logical XOR operation was added to the MMNN to discriminate these two movements, because the MMNN which learned the characteristics of the only rollover was difficult to discriminate them. When the combination of the MMNN and XOR operator was used, the rollover and turning out movements were discriminated 83%. Therefore, we developed the signal processing algorithm to support the rollover movement of the bone cancer metastasis patients.

In future, the more robust on- line recognition system will be developed and we will test the effectiveness of the total system in clinical tests with cancer patients in terminal care.

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