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Micro Macro Neural Network to Recognize Slow Movement: EMG based Accurate and Quick Rollover Recognition

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1. Introduction

The wearable robots to support many kinds of movements have been developed for the elder and disabled people all over the world (Hayashi et al., 2005, Furusho et al., 2007, Kawamura et al., 1997), because we are facing the elder dominated society. A surface ElectroMyoGram (EMG) signal, which is measured a little before the start of the movement, is expected as the trigger signal of movement support.

We have been also developing an EMG controlled intelligent trunk corset, shown in Fig. 1, to support rollover movement, since it is one of the most important activities of daily living (ADL). Especially, the rollover movement of bone cancer metastasis patients is focused as the target movement. The bone cancer metastasis patients feel sever pain when they conduct the rollover movement. The core of the intelligent trunk corset system is a pneumatic rubber muscle that is operated by the EMG signals from the trunk muscle. As shown in Fig. 2, in our study, we first analyzed the EMG signal (Ando et al., 2007) that is used as the input signal for the intelligent corset to recognize a rollover movement. Second, we proposed an original neural network algorithm to recognize the rollover quickly and with high accuracy (Ando et al., 2008a). Finally, we developed the mechanisms of the intelligent corset to assist rollover movement using the pneumatic rubber actuator (Ando et al., 2008b).

In this chapter, the proposed original neural network, called the Micro-Macro Neural Network (MMNN), is introduced. In addition, the methodology to determine the optimal structure of the MMNN to recognize the rollover movement is established. This paper is organized as follows; Section 2 summarizes the related neural network to recognize some movements based on the EMG signal. Section 3 discusses the traditional neural network known as Time Delay Neural Network (TDNN) and MMNN structures, Section 4 establish the methodology to determine the optimal structure of MMNN, and the rollover recognition result using the optimal MMNN is compared with that using traditional TDNN. Section 5 presents a summary and future work.

2. Related neural network to recognize movement using EMG signal

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, individual differences, or surrounding electrical conditions is necessary to recognize EMG signals accurately. A Neural Network (NN) is one of the learning machines that use EMG signals to recognize movement (Kuribayashi et al., 1992, Fukuda et al., 1999, Wang et al., 2002, Kiguchi et al., 2003, Hou et al., 2004, Zecca et al., 2002). NN is capable of nonlinear mapping, generalization, and adaptive learning. There are generally two kinds of NN that recognize a time series-signal. One is the Time Delay Neural Network (TDNN) (Waibel, 1989), 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. The other is the Recurrent Neural Network (RNN) (Kelly et al., 1990, Tsuji et al., 1999), which uses feedback from the output signal of the output layer as the input signal of the input layer. To avoid needless time-stretch properties and to reduce calculation amounts and costs, we selected TDNN as the base neural network for the work reported here.

Many researchers have used TDNN to recognize movements from EMG signals. For example, Hincapie et al. (Hincapie et al., 2004) estimated the movement of the affected side of a patient by using EMG data of the unaffected side in their development of a prosthetic upper limb. Hirakawa et al. (Hirakawa et al., 1989) and Farry et al. (Farry et al., 1996) recognized movement using frequency domain information of the EMG signal. Huang et al. (Huang et al., 1999) proposed the feature vector, composed of an integrated EMG, Zero Crossing and variance, to recognize eight-finger movement. Finally, Nishikawa et al. (Nishizawa et al., 1999) recognized ten kinds of movements using a Gabor-transformed EMG signal.

Fig. 1. Intelligent trunk corset to support rollover movement

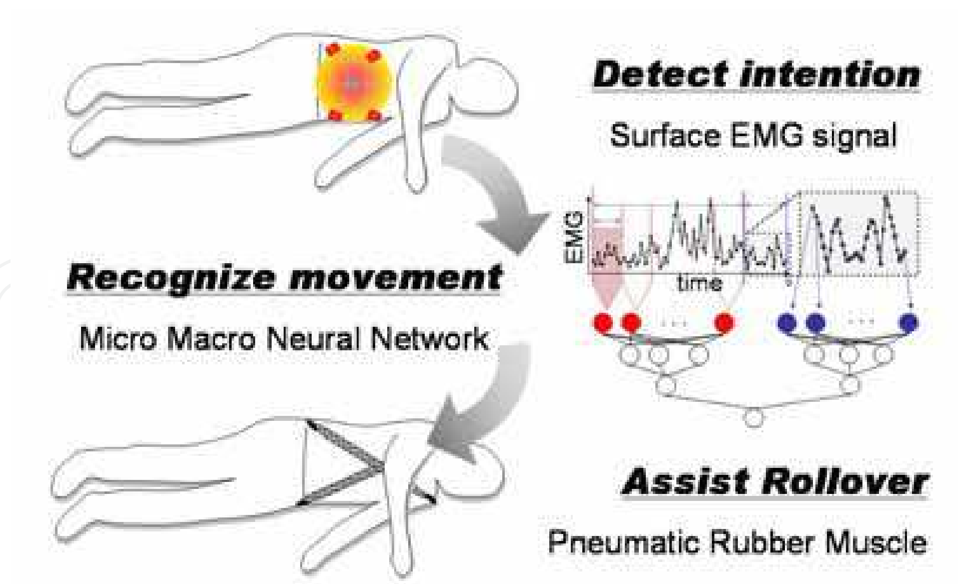


Fig. 2. Concept of the intelligent corset using EMG signal, original neural network and pneumatic actuator.

However, all of these related research efforts share two common problems, which are slow response time and incorrect recognition of the movement. Consequently, we previously proposed the original algorithm called the Micro Macro Neural Network (MMNN), 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. However, the methodology to design or optimize the structure of the MMNN is not established, because there are many parameters to determine the structure of the MMNN.

3. Micro - Macro Neural Network (MMNN)

3.1 Traditional Time Delay Neural Network

For the learning machine in this research, we selected the three-layer feed-forward type of Time Delay Neural Network (TDNN) as the structure of the network and the back propagation (BP) method with a momentum term as the leaning algorithm, which is a standard neural network to recognize time-series signals. In addition, we selected the sequential adjustment method to modify the weight and threshold of each unit. The relations between each pair of units in the TDNN are shown in (1), (2), and (3).

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

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

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

where m = 2 and 3, i = 1,…,n_m, n_m is the number of the m^{th} layer unit, ω^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, θ^m_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.

In this study, the number of input layer units was typically 75, and, that is, the input of the input layer was EMG signals, *semg (t-i)* (i=0,1,...,74). In other words, the time it took the TDNN system to recognize the rollover movement from the inputted EMG data was 0.075 (msec) (Zecca et al., 2002).

3.2 Concept of Micro-Macro Neural Network

Using TDNN, previous researchers focused on upper limb movement, which is a relatively fast movement. Since the movement takes only a short time, less time-series EMG data is inputted into the system. The advantage of this short data length is that there are fewer calculations to be done and, therefore, less cost; the disadvantage is that less input data means more false recognitions.

We focused on the rollover movement, which is a relatively slow movement. Since the movement takes a relatively long time, it is possible to have more time-series EMG data inputted into the system.

We checked the impact of past time-series EMG data using TDNN on the recognition result. The structure of TDNN was as follows: the number of input layer units was 1700, the number of hidden layer units was 850, and the number of output layer units was 1. We determined the number of input units as 1700 based on our EMG experiment (Ando et al., 2007), which showed that the shortest time spent on rollover was 1.7 (sec) without taking into account the time for any previous rollover movement.

To check the importance of each unit in TDNN, the contribution rate of the weight of each input unit was calculated by (4).

$$R_{contribution}(i) = \frac{\sum_{j=1}^{N/2} \left|\omega_{ij}^{m}\right|}{\sum_{i=1}^{N}\sum_{j=1}^{N/2}\left|\omega_{ij}^{m}\right|} \times 100 \quad (4)$$

where $R_{contribution}(i)$ is the contribution rate of the weight of input unit i, whose data is the EMG data of i (msec) before the current measured point, N = 1700, m = 2.

As a result, it was found that the weights of units in the range of -1 to -10 (msec) were higher than those of the other units in TDNN (See Fig. 3). It is natural that the EMG data nearest to the time of measurement has a large impact on the recognition result. However, it is worth noting that the contribution rate of the inputted EMG data before -10 (msec) is almost constant. Even though the importance of data from 10-75 (msec) before is the same as that of data from 76-1700 (msec) before, the latter data was not used to recognize the rollover movement in the traditional TDNN (See Section 3.1). Therefore, in the traditional TDNN,

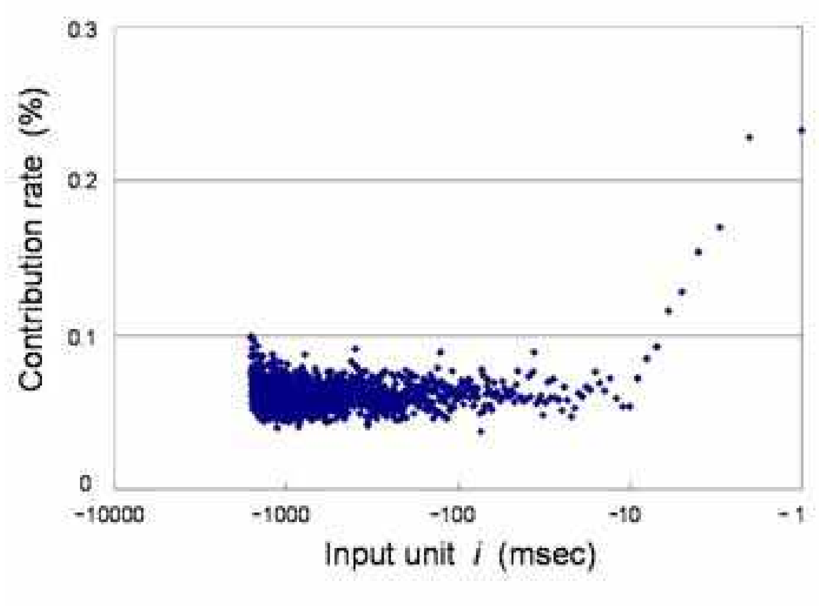


Fig. 3. Contribution rate as a function of input unit

whose input unit number was 75 (msec), a later response and a higher incidence of false recognition were evident.
When long past time-series EMG data is used in TDNN, the advantage of this long data length is that more input data means faster response and less false recognition. The disadvantage is the large amount of calculations and its cost.
In the proposed Micro Macro Neural Network (MMNN), some of the long past time-series data was compressed. Therefore, the amount and cost of the calculations do not increase.
The basic concept of the Micro Macro Neural Network (MMNN) is to use the long past time-series EMG data to discriminate the movement accurately and quickly without increasing the calculation cost by compressing some of the long past data.

3.3 Structure of the Micro-Macro Neural Network

Basically, we upgraded the traditional TDNN to MMNN (Fig. 4). The most important feature of MMNN is that it can handle an increased amount of input data to the neural network without increasing the number of calculations. Traditional TDNN is defined in our network as the Micro Part. The input data, ${}_{micro}x_n^1$ in the Micro Part is defined as following;

$$ {}_{micro}x_n^1 = semg\ (t - n + 1) \tag{5}$$

where $n = 1,2,....,N_{micro}$, and N_{micro} is the number of input unit in Micro part

As can be seen in Fig. 5, 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, ${}_{macro}x_n^1$ 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, calculated by (6), is defined as the input value of the Macro Part.

$$ {}_{macro}x_n^1 = \frac{\sum_{i=t-(n-1)T_{ARV}}^{t-nT_{ARV}} |semg(i)|}{T_{ARV}} \tag{6} $$

where $n = 1,2,\ldots,N_{macro}$
Therefore, the number of input units of the Macro Part is expressed by the following equation:

$$ N_{macro} = T_{macro} / T_{ARV} \tag{7} $$

where N_{macro} is the number of input units of 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.
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).

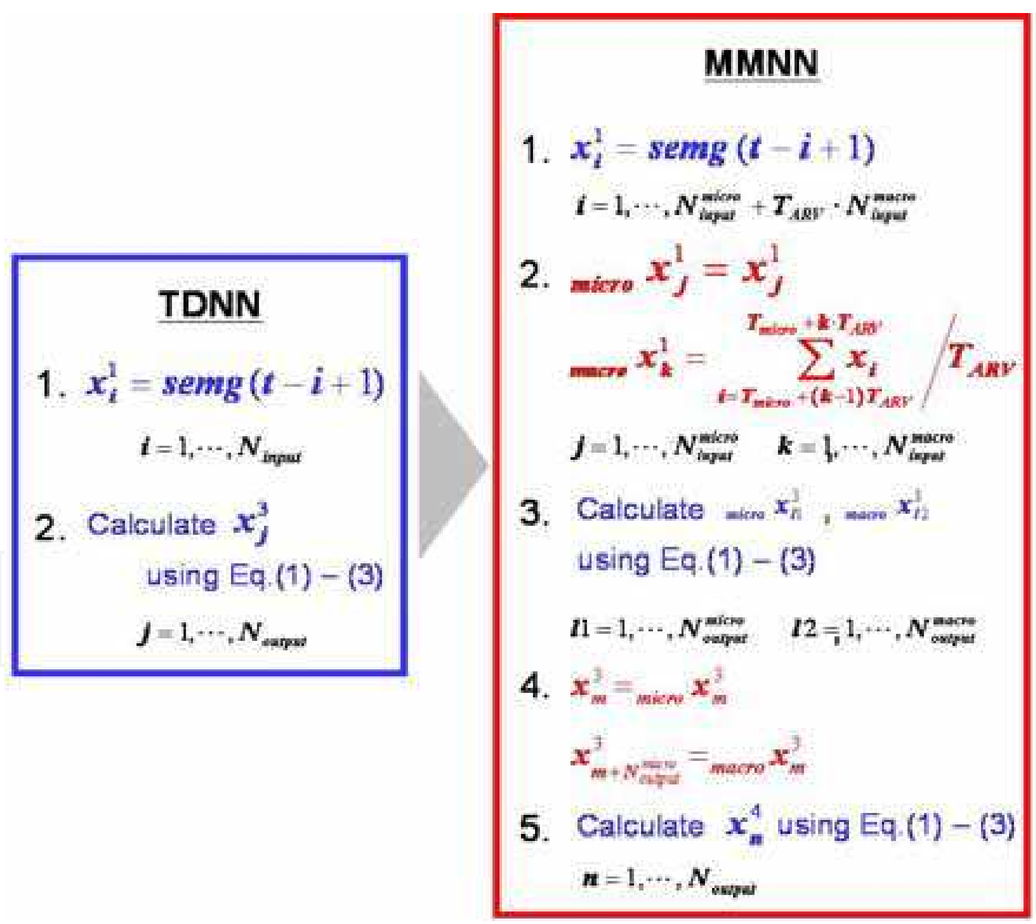


Fig. 4. Development of MMNN algorithm from TDNN algorithm

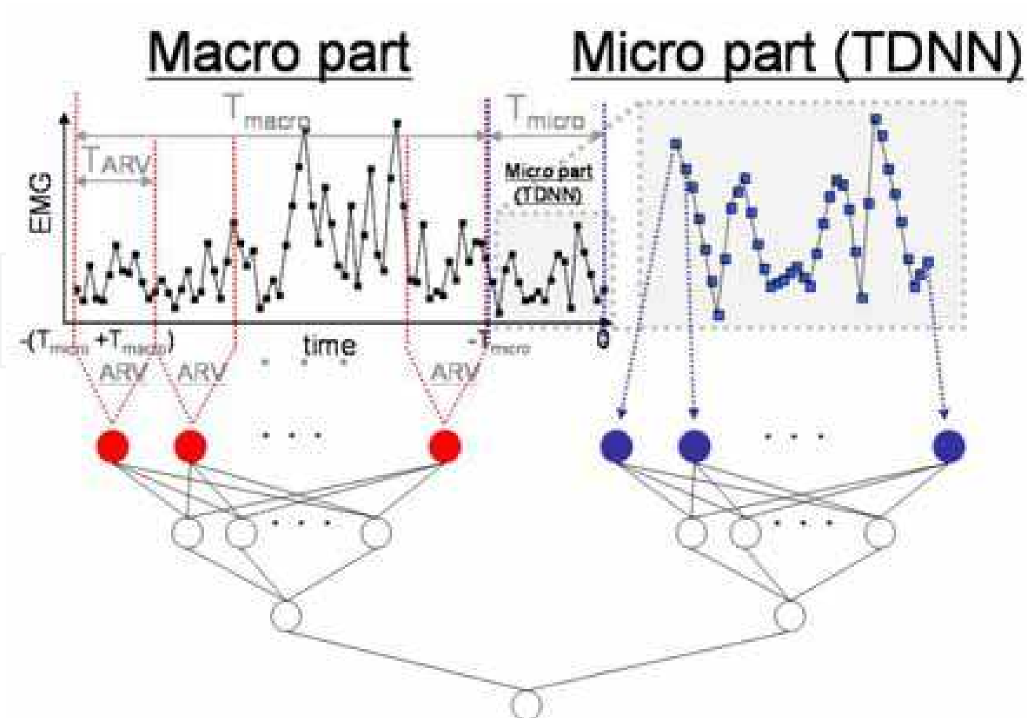


Fig. 5. Micro Macro neural network. Note that MMNN is divided into the Micro Part and the Macro Part. The Micro Part is TDNN using the data for T_{micro} as the input signal. The input data of the Macro Part uses the data for T_{macro}, which is the ARV of the EMG signal among all T_{ARV} values.

4. Optimal structure of proposed MMNN and rollover movement recognition

4.1 Objective

The structure of the MMNN is complex, because many parameters determine the structure of the MMNN. In this section, based on the contribution rate shown in Fig. 3 and an experiment about rollover recognition using MMNN, the optimal parameters in MMNN are determined.

4.2 Methodology of rollover recognition experiment

We defined the rollover movement as a continuous movement involving a deliberate change of posture from a supine position to a lateral or prone position. In this research, rollover movements were performed thirty times in advance by each of three young, healthy male subjects. EMG signals obtained from the internal oblique (IO) muscle were selected as the input signals based on our previous study (Ando et al., 2007). 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), and normalized by the 100% maximal voluntary contraction (MVC) method (Zaman et al., 2005, Kumar et al., 1989), which shows the ratio of muscle activity in the MVC of the IO muscle to the measured EMG signal (Helen et al., 2002).

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 (Kuribayashi et al., 1992, Fukuda et al., 1999). 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 time required to recognize the rollover was measured using TDNN. Furthermore, by synchronizing the EMG data with the data of a 3D motion-capture system, VICON612 (sampling frequency; 100 (Hz) and measurement accuracy; 1 (mm)) , the start of rollover movement was recognized.

4.3 Evaluation index

The recognition results of the test data were evaluated according to the response by the indexes presented below.
(1) 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 .

$$t_{response} = t_{recognition} - t_{movement} \tag{8}$$

where $t_{recognition}$ is the time when the rollover is recognized, and $t_{movement}$ is the time when the rollover starts.

(2) Movement recognition rate before starting movement, P_{start}

$$P_{start} = N_{before} / N_{total} \tag{9}$$

where P_{start} is the ratio of N_{before}, the number of times rollover was recognized before the movement started to N_{total}, the total number of rollover movements.

(3) Number of false recognition rate, N_{false}
N_{false} is the number of times when false recognition occurred, that is, the times that NN recognized a rollover movement even though no rollover was actually conducted.

4.4 Structure of TDNN and recognition result

As stated above, for the learning machine in this research, we selected the three-layer feed-forward type NN and the back propagation method with momentum term, which is a standard neural network for recognizing time-series signals. The number of input layer units was 75. The unit numbers of the hidden layer and the output layer were 38 and 1, respectively.
As shown in Fig. 6 (b), when TDNN was used, the recognition results were as follows: $t_{response}$ was -25 (S.D. 59) (msec), P_{start} was 38% (138 out of 360 trials), and N_{false} was 151 out of 360 trials.

4.5 Optimal structure of MMNN and recognition result

The structure of MMNN was resolved based on many parameters.
First, in the Micro Part, which is the traditional TDNN, the number of input layer units was fixed at 10 (T_{micro} = 10 (msec) in Fig. 4), because the contribution rates in -1 ~ -10 (msec) are higher than those at other input times, as shown in Fig. 2. The number of hidden layer units

was fixed at 5, and the number of output layer units was fixed at 1. The number of hidden layer units was determined based on the "rule of thumb" as follow;

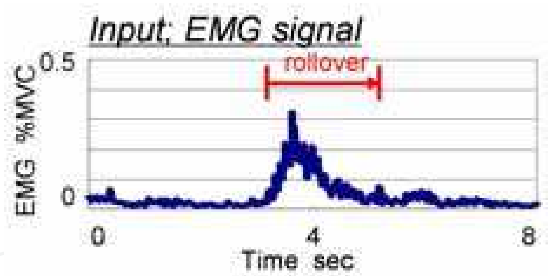
$$N_{hidden} = (N_{input} + N_{output}) \ / \ 2 \quad (10)$$

where N_{hidden}, N_{input}, and N_{output} are the numbers of hidden layer, input layer and output layer units.

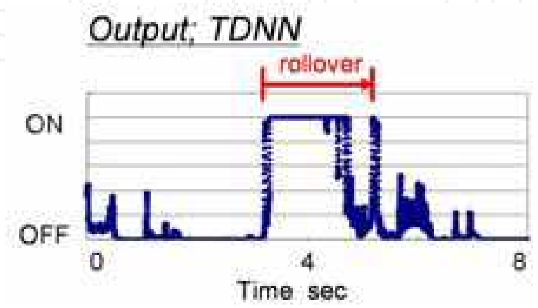
Second, the optimal structure of the Macro Part was determined as follows. The value of T_{ARV} was changed from 5 to 100 (T_{ARV} = 5, 10, 15,…., 100), and the value of N_{macro}, the number of input layer units, was changed from 5 to 70 (N_{macro} = 5, 10,15,…., 70). Additionally, according to the rule of thumb, the number of hidden layer units was set at N_{macro} /2 (if N_{macro} was even) or (N_{macro} +1)/2 (if N_{macro} was odd). Based on our EMG experiment (Ando et al., 2007), which showed that the shortest time spent on rollover was 1.7 (msec), we applied (11) when we calculated the response time for each rollover movement using MMNN, without taking into account the time for any previous rollover movement.

$$\begin{aligned} T_{ARV} \times N_{macro} &\le 1700 - N_{micro} \\ &= \ 1700 - 10 = 1690 \end{aligned} \quad (11)$$

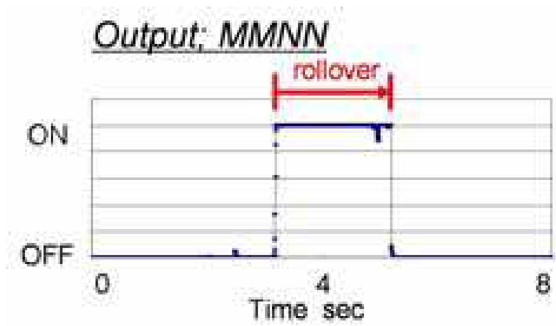
We obtained the best results for response with changing values of T_{ARV} and N_{macro} when T_{ARV} = 40 (sec) and N_{macro} = 40. With these conditions, the average $t_{response}$ for MMNN was -65 (S.D. 55) (msec). The average $t_{response}$ for TDNN was -25 (S.D. 59) (msec). Negative values mean the rollover was recognized before the movement started. Therefore, the recognition time of MMNN was 40 (S.D. 49) (msec) faster that that of TDNN.
Furthermore, as shown in Table 1, the P_{start} was 86% (310 out of 360 times), and N_{false} was only 50 in 360 trials.
Figure 6 shows an example of MMNN (T_{ARV} = 40 (msec), N_{macro} = 40). When the results of TDNN in Fig. 6(b) and the MMNN in Fig. 6(c) are compared, the following observations are clear: TDNN registers a false recognition four times, and, most importantly, the response speed in recognizing rollover is faster, steadier, and more accurate when MMNN is used than when TDNN is used.



(a) Input signal to NN



(b) Output signal from the TDNN



(c) Output signal from the MMNN

Fig. 6. Comparison between recognition of rollover by TDNN and MMNN. Note that TDNN fails to recognize the rollover at 0-2 (msec) and 5-7 (msec); however, it does recognize the rollover after the movement starts. In contrast, MMNN recognizes the rollover before the movement starts. EMG signal data is included for reference.

Neural Network	P_{start} %	N_{false}
TDNN	38	51/360
MMNN	86	150/360

Table 1. P_{start} and N_{false} of TDNN and MMNN

4.6 Discussion

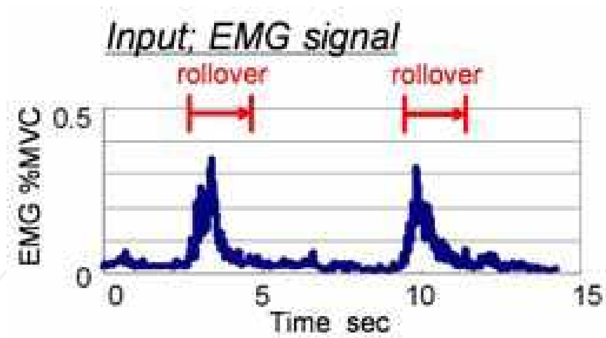
In Section 4.5, the effectiveness of MMNN in recognizing the rollover is shown in comparison with the effectiveness of TDNN.

In this section, the output signal of not only optimal MMNN but also the output of the Micro part and Macro part in the recognition of the rollover movement is discussed to show the characteristics of MMNN. In other words, first, the number of input layer units in TDNN was 10, and the input of the input layer was defined to show the characteristics of the Micro part as EMG signals, *semg (t-i)* (i=0,1,..., 9). Second, the number of input layer units in TDNN

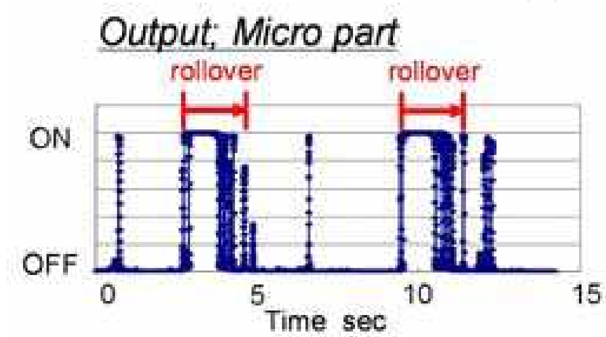
was 40, and the input of the input layer was defined to show the characteristics of the Macro part as the average reflected values among 40 (msec).
Table 2 shows the result of recognition time and the number of the false recognition using the TDNN (Input: 75 (msec) raw EMG signal), MMNN (Input: 10 (msec) raw EMG and 40 ARV EMG among 40 (msec)), only Micro Part (Input: 10 (msec) raw EMG) in MMNN and only Macro Part (Input: 40 ARV EMG among 40 (msec)) in MMNN. The response times using only the Micro part and the Macro part were $t_{response}$ = -50 (S.D. 26) (msec) and $t_{response}$ = 1 (S.D. 55) (msec). The number of false recognitions using only the Micro part and only the Macro part was N_{false} = 210 (in 360 times) and N_{false} = 56 (in 360 times).
When the input data was short past time-series data, the response time was short and the stability of the recognition was low. However, when the input data was the ARV of 40 (msec), the response time became longer and the stability increased.
The response time $t_{respons}$ did not show a significant difference (p < 0.05) between the optimized MMNN and TDNN using 10 (msec) time-series data as did the input data, that is, when using the only Micro part in MMNN. In addition, the number of false recognitions was almost the same when the number in the optimized MMNN was compared with that in TDNN using the ARV of 40 (msec), that is, when using the only Macro part in MMNN. Therefore, the advantages of quick response in the Micro part (See Fig. 7 (b)), and the stable recognition of the Macro part (See Fig. 7 (c)), are combined in the developed optimal MMNN. As a result, the MMNN is an NN that features quick response and little false recognition (See Fig. 7 (d)).

Neural Network	$t_{response}$ *msec*	N_{false}
TDNN (Input: 75 (msec) raw EMG)	-25 (S.D. 59)	150/360
MMNN (Input: 10 (msec) raw EMG and 40 ARV EMG among 40 (msec))	-65 (S.D. 55)	51/360
Only Micro part in MMNN (Input: 10 (msec) raw EMG)	-50 (S.D. 26)	210/360
Only Macro part in MMNN (Input: 40 ARV EMG among 40 (msec))	1 (S.D. 55)	56/360

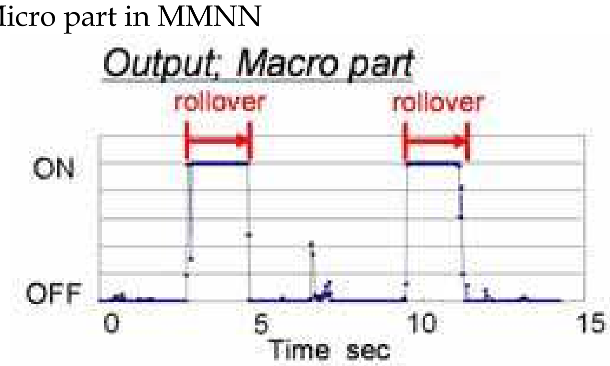
Table 2. Features of TDNN, MMNN, and Micro and Macro parts of MMNN



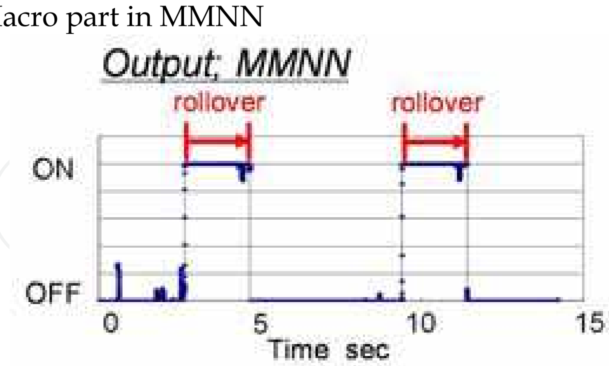
(a) Input signal to the NN



(b) Output from the Micro part in MMNN



(c) Output from the Macro part in MMNN



(d) Output from the MMNN

Fig. 7. Comparison with the output of TDNN, Micro part in MMNN, Macro Part in MMNN and MMNN. Note that the EMG signal is included for reference as (a). (b) is the output of Micro part and shows the quick and unstable response. (c) is the output of Macro part and shows the slow and stable response and (d) is output of MMNN and show quick and stable response.

5. Summary and future work

We have been studying patients with cancer bone metastasis who have a very short time to live. Specifically, we have developed the EMG controlled intelligent corset to support the rollover movement.

In this paper, we described an original neural network that we developed, called the Micro Macro Neural Network (MMNN), for the purpose of recognizing and responding to the rollover movement based on inputted EMG signals.

First, the structure of the MMNN was optimized with N_{micro} = 10 in the Micro part and N_{macro} = 40 and T_{ARV} = 40 in the Macro part, and then the response and accuracy of the MMNN were analyzed. After that, the response and accuracy of the optimized MMNN in recognizing the rollover movement were compared with those of the traditional TDNN. Test results showed that recognition in MMNN was 40 (S.D. 49) (msec), which is quicker than the recognition in TDNN. Additionally, the number of false recognitions in MMNN was only one third of those in TDNN. Hence, we can verify that our MMNN is effective and useful in recognizing rollover based on inputted EMG signals, which are noisy and vary considerably from individual to individual. In addition, by comparing the recognition results of only the Micro part and only the Macro part, we found that the advantages of quick response in the Micro part and stable recognition in the Macro part are features of MMNN.

In the future, we will incorporate MMNN into our rollover support system that uses pneumatic rubber muscles, and then we will test the effectiveness of the total system in clinical tests with cancer patients in terminal care.

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Recent Advances in Biomedical Engineering

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The field of biomedical engineering has expanded markedly in the past ten years. This growth is supported by advances in biological science, which have created new opportunities for development of tools for diagnosis and therapy for human disease. The discipline focuses both on development of new biomaterials, analytical methodologies and on the application of concepts drawn from engineering, computing, mathematics, chemical and physical sciences to advance biomedical knowledge while improving the effectiveness and delivery of clinical medicine. Biomedical engineering now encompasses a range of fields of specialization including bioinstrumentation, bioimaging, biomechanics, biomaterials, and biomolecular engineering. Biomedical engineering covers recent advances in the growing field of biomedical technology, instrumentation, and administration. Contributions focus on theoretical and practical problems associated with the development of medical technology; the introduction of new engineering methods into public health; hospitals and patient care; the improvement of diagnosis and therapy; and biomedical information storage and retrieval. The book is directed at engineering students in their final year of undergraduate studies or in their graduate studies. Most undergraduate students majoring in biomedical engineering are faced with a decision, early in their program of study, regarding the field in which they would like to specialize. Each chosen specialty has a specific set of course requirements and is supplemented by wise selection of elective and supporting coursework. Also, many young students of biomedical engineering use independent research projects as a source of inspiration and preparation but have difficulty identifying research areas that are right for them. Therefore, a second goal of this book is to link knowledge of basic science and engineering to fields of specialization and current research. The editor would like to thank the authors, who have committed so much effort to the publication of this work.

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