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# Pattern Discrimination of Raw EMG Signals Using a New Recurrent Neural Network

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**Abstract**

In this paper, a new recurrent neural network called a Recurrent Log-Linearized Gaussian Mixture Network (R-LLGMN) is proposed. This network includes a Hidden Markov Model (HMM) in its structure and weight coefficients in the network can be learned using the well-known back-propagation through time algorithm. Then, a pattern discrimination of a time series of EMG signals is performed. Experimental results show that the R-LLGMN can successfully classify raw EMG signals and realize a kind of signal processing similar to low-pass filtering.
**Key Words:** Neural network, Gaussian mixture model, Hidden Markov model, EMG.

## 1 Introduction

A pattern discrimination for a time series of bioelectric signals such as the electroencephalogram (EEG) and the electromyogram (EMG) is a key technique, when various signals measured from a human body are utilized as means of a human-machine interface. In order to deal with such bioelectric signals effectively, at least the following points should be taken into account:

1. Since the signals include high frequency components, an adequate signal processing such as low-pass filtering is necessary in order to extract meaningful information for the human interface.
2. To command an electric device by using a bioelectric signal, a pattern discrimination of the bioelectric signal is needed to generate appropriate commands, and the discrimination performance has to be high.
3. For robust discrimination against the differences among individuals and the change of environment, a learning ability should be adopted.

Among many kinds of bioelectric signals, this paper focuses on the EMG signals. Since the EMG accompanied by muscular contraction includes information about the muscles contributing to human movements, the EMG is expected as a means of the human-machine interface, especially, for prosthetic hands and arms.

Up to the present, many studies have been reported on the pattern discrimination problem of EMG signals using neural networks (NNs) [1]-[13]. Hiraiwa *et al.* [1] used the back-propagation neural network (BPN) for the estimation of five finger motions. They reported that the five finger motions, the joint torque and the angles were successfully estimated simultaneously. Also, Kelly *et al.* [2] proposed a pattern discrimination method which combines the BPN and the Hopfield neural network, and discriminated motions of forearm from the EMG signal measured by one pair of electrodes. Tsuji *et al.* [3][4] used a NN including a statistical model [3] and the entropy of output signals [4] for estimation of forearm motions. Koike and Kawato [5] used the BPN to construct a forward dynamics model of the human arm which maps the EMG signals to arm trajectories. Farry *et al.* [6] proposed a method to remotely operate a robot hand by classifying the motion of human hand from the frequency spectrum of EMG signals. Huang and Chen [7] constructed several feature vectors from the integral of the EMG, the zero-crossing and the variance of the EMG, and 8 motions were classified using the BPN. Nishikawa *et al.* [8] succeeded to estimate 10 motions from the EMG signals using the Gabor transformation and the BPN.

While the BPN is utilized in most of the previous studies, Tsuji *et al.* proposed the log-linearized Gaussian mixture network (LLGMN) [9] based on a log-linear model and a Gaussian mixture model. The LLGMN can acquire the log-linearized Gaussian mixture model through learning and calculate the *a posteriori* probability. Using the LLGMN incorporated with a Neural Filter (NF) [10], which is a sort of recurrent neural network, in order to cope with time-varying characteristics of bioelectric signals, the non-stationary time sequence of the EMG signals [11][12] were successfully discriminated. Then, this method is used for the EMG based human assisting manipula-

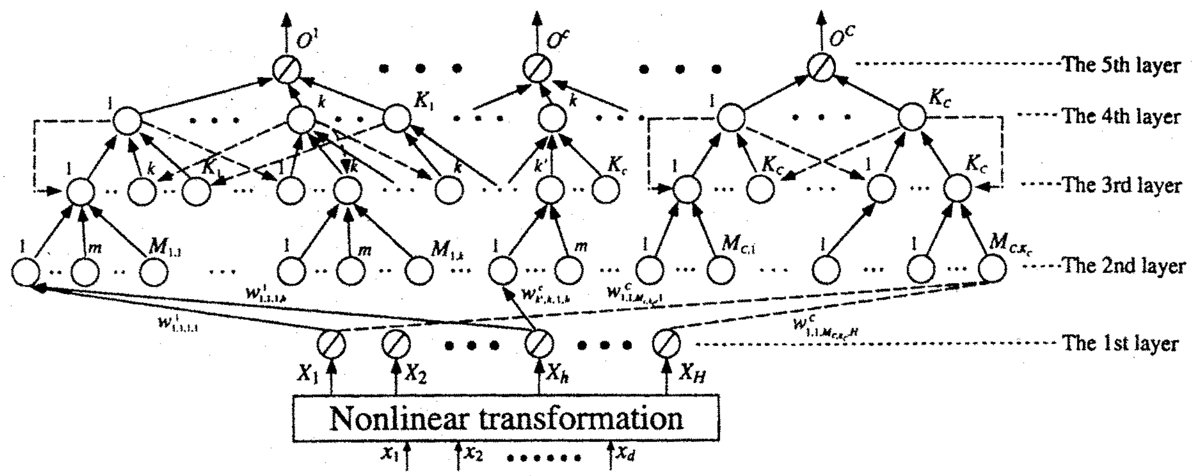


Fig. 1: The structure of the R-LLGMN

tor system [13]. However, since it was very difficult to perform the filtering and the discrimination simultaneously, conventional methods adopted a sequential scheme in which two processes were performed independently. As a result, since the NN was used for only the pattern discrimination, optimization of the whole processing was almost impossible and it was hard to gain a high performance of discrimination, especially for non-stationary signals.

In this paper, a novel NN, a Recurrent Log-Linearized Gaussian Mixture Network (R-LLGMN) is proposed by introducing recurrent connections into the LLGMN to classify a time sequence of bioelectric signals. Since this network is composed of a feedforward NN including a Gaussian mixture model and feedback connections from output to input, the filtering process and the pattern discrimination are unified together and realized in a single network. The R-LLGMN includes a hidden Markov Model (HMM) [14] in its structure and can regulate the weight coefficients based on the learning scheme of the back-propagation through time (BPTT) algorithm [15]. The R-LLGMN ensures the filtering process and the pattern discrimination to be achieved at the same time and can attain high discrimination ability.

## 2 Network Structure

The structure of a proposed network in this paper is shown in Fig. 1. This network is a five-layer recurrent NN with a feedback connection between the 3rd layer and the 4th layer. First of all, the input vector $\mathbf{x}(t) = [x_1(t), x_2(t), \cdots, x_d(t)]^{\mathrm{T}} \in \Re^d (t = 1, \ldots, T)$ is pre-processed with a non-linear computation and converted into the modified vector $\mathbf{X} \in \Re^H$:

$$\begin{aligned}\mathbf{X(t)} &= [1, \mathbf{x}(t)^{\mathrm{T}}, x_1(t)^2, x_1(t)x_2(t), \cdots, \\ &\quad x_1(t)x_d(t), x_2(t)^2, x_2(t)x_3(t), \\ &\quad \cdots, x_2(t)x_d(t), \cdots, x_d(t)^2]^{\mathrm{T}}. \end{aligned} \quad (1)$$

The first layer consists of $H$ units corresponding to the dimension of $\mathbf{X}$(the dimension $H$ is determined as $H = 1 + d(d+3)/2$) and the identity function is used for activation of each unit. Each unit in the first layer is defined as

$$^{(1)}I_h(t) = X_h(t), \quad (2)$$

$$^{(1)}O_h(t) = {}^{(1)}I_h(t), \quad (3)$$

where $^{(1)}I_h$ and $^{(1)}O_h$ denote the input and the output, respectively, of the $h$th unit in the first layer.

Unit$\{c, k, k', m\}$ ($c = 1, \cdots, C$ ; $k, k' = 1, \ldots, K_c$ ; $m = 1, \ldots, M_{c,k}$) in the second layer receives the output of the first layer weighted by the coefficient $w^c_{k',k,m,h}$. The relationship between the input and the output in the second layer is defined as

$$^{(2)}I^c_{k',k,m}(t) = \sum_{h=1}^{H} {}^{(1)}O_h(t) w^c_{k',k,m,h}, \quad (4)$$

$$^{(2)}O^c_{k',k,m}(t) = \exp\left({}^{(2)}I^c_{k',k,m}(t)\right). \quad (5)$$

where $C$ is the number of classes, $K_c$ is the number of states, $M_{c,k}$ is the number of the components of the Gaussian mixture distribution corresponding to the class $c$ and the state $k$ [9].

The input into a unit $\{c, k, k'\}$ in the third layer integrates the outputs of units $\{c, k, k', m\}$ ($m = 1, \ldots, M_{c,k}$) in the second layer. The output in the third layer is that input weighted by the previous output in the fourth layer. The relationship in the third layer is defined as

$$^{(3)}I^c_{k',k}(t) = \sum_{m=1}^{M_{c,k}} {}^{(2)}O^c_{k',k,m}(t), \quad (6)$$

$$^{(3)}O^c_{k',k}(t) = {}^{(4)}O^c_{k'}(t-1)^{(3)}I^c_{k',k}(t), \quad (7)$$

where $^{(4)}O^c_{k'}(0) = 1.0$ for the initial state.

The fourth layer receives the integrated outputs of units $\{c, k, k'\}$ in the third layer. The relationship in the fourth layer is defined as

$$^{(4)}I^c_k(t) = \sum_{k'=1}^{K_c} {}^{(3)}O^c_{k',k}(t), \quad (8)$$

$$^{(4)}O^c_k(t) = \frac{^{(4)}I^c_k(t)}{\sum_{c'=1}^{C}\sum_{k'=1}^{K_{c'}} {}^{(4)}I^{c'}_{k'}(t)}. \quad (9)$$

At last, a unit $c$ in the fifth layer integrates the outputs of $K_c$ units $\{c, k\}$ $(k = 1, \ldots, K_c)$ in the fourth layer. The relationship in the fifth layer is defined as

$$^{(5)}I^c(t) = \sum_{k=1}^{K_c} {}^{(4)}O^c_k(t), \quad (10)$$

$$^{(5)}O^c(t) = {}^{(5)}I^c(t). \quad (11)$$

The output of the network $^{(5)}O^c(t)$ corresponds to the *a posteriori* probability of the input vector $\mathbf{x}(t)$ for the class $c$, while only the weight coefficients $w^c_{k',k,m,h}$ between the first layer and the second layer are adjusted by learning.

## 3 Relation between R-LLGMN and Hidden Markov Model

This section proves that the R-LLGM can be regarded as a NN which introduces a log-linearized Gaussian mixture model into the HMM [14].

First, let us consider a dynamic model, where there are $C$ classes in this model and each class $c$ $(c \in \{1, \ldots, C\})$ is composed of $K_c$ states. For the given time series $\tilde{\mathbf{x}} = \mathbf{x}(1), \mathbf{x}(2), \cdots, \mathbf{x}(t), \cdots, \mathbf{x}(\mathrm{T})$, where $\mathbf{x}(t) \in \Re^d$, the *a posteriori* probability for class $c$, $P(c|\tilde{\mathbf{x}})$, is derived as [14]

$$P(c|\tilde{\mathbf{x}}) = \sum_{k=1}^{K_c} P(c, k|\tilde{\mathbf{x}}), \quad (12)$$

$$P(c, k|\tilde{\mathbf{x}}) = \frac{\alpha^c_k(\mathrm{T})}{\sum_{c'=1}^{C}\sum_{k'=1}^{K_{c'}} \alpha^{c'}_{k'}(\mathrm{T})}. \quad (13)$$

$$\alpha^c_k(t) = \sum_{k'=1}^{K_c} \alpha^c_{k'}(t-1)\gamma^c_{k',k} b^c_k(\mathbf{x}(t)) \ (t > 1), \quad (14)$$

$$\alpha^c_k(1) = \pi^c_k b^c_k(\mathbf{x}(1)), \quad (15)$$

where $\gamma^c_{k',k}$ is the probability of the state changing from $k'$ to $k$ in class $c$, and $b^c_k(\mathbf{x}(t))$ is defined as *a posteriori* probability for state $k$ in class $c$ corresponding to $\mathbf{x}(t)$. Also the *a priori* probability $\pi^c_k$ equals to $P(c, k)|_{t=0}$.

When the *a posteriori* probability of state $k$ in class $c$ corresponding to $\mathbf{x}(t)$, $b^c_k(\mathbf{x}(t))$, is approximated by summing up $M_{c,k}$ components of Gaussian mixture distribution [9][16], $\gamma^c_{k',k} b^c_k(\mathbf{x}(t))$ in the right side of (14) can be derived with the form

$$\gamma^c_{k',k} b^c_k(\mathbf{x}(t)) = \sum_{m=1}^{M_{c,k}} \gamma^c_{k',k} r_{c,k,m}\, g(\mathbf{x}(t); \boldsymbol{\mu}^{(c,k,m)}, \Sigma^{(c,k,m)}) \quad (t > 1), \quad (16)$$

where $r_{c,k,m}$, $\boldsymbol{\mu}^{(c,k,m)} \in \Re^d$ and $\Sigma^{(c,k,m)} \in \Re^{d\times d}$ stands for the mixing proportion, the mean vector and the covariance matrix of each component $\{c, k, m\}$, respectively. Using the mean vector $\boldsymbol{\mu}^{(c,k,m)} = (\mu_1^{(c,k,m)}, \ldots, \mu_d^{(c,k,m)})^{\mathrm{T}}$ and the inverse of the covariance matrix $\Sigma^{(c,k,m)-1} = [s_{ij}^{(c,k,m)}]$, the right side of (16) can be rewritten as

$$\begin{aligned} &\gamma^c_{k',k} r_{c,k,m}\, g(\mathbf{x}(t); \boldsymbol{\mu}^{(c,k,m)}, \Sigma^{(c,k,m)}) \\ &= \gamma^c_{k',k} r_{c,k,m} (2\pi)^{-\frac{d}{2}} |\Sigma^{(c,k,m)}|^{-\frac{1}{2}} \\ &\quad \times \exp\left[-\frac{1}{2}\sum_{j=1}^{d}\sum_{l=1}^{j}(2-\delta_{jl}) s_{jl}^{(c,k,m)} x_j(t) x_l(t)\right. \\ &\quad + \sum_{j=1}^{d}\sum_{l=1}^{d} s_{jl}^{(c,k,m)} \mu_j^{(c,k,m)} x_l(t) \\ &\quad \left. - \frac{1}{2}\sum_{j=1}^{d}\sum_{l=1}^{d} s_{jl}^{(c,k,m)} \mu_j^{(c,k,m)} \mu_l^{(c,k,m)}\right], \end{aligned} \quad (17)$$

where $\delta_{ij}$ is the Kronecker delta: $\delta_{ij} = 1$ when $i = j$ and $\delta_{ij} = 0$ when $i \neq j$, and $|\cdot|$ stands for the matrix determinant. Also, $x_i(t)$ $(i = 1, 2, \cdots, d)$ is the element of $\mathbf{x}(t)$. Then, taking logarithm of (17), we get

$$\gamma^c_{k',k} b^c_k(\mathbf{x}(t)) = \sum_{m=1}^{M_{c,k}} \xi^c_{k',k,m}(t), \quad (18)$$

$$\begin{aligned} &\xi^c_{k',k,m}(t) \\ &\triangleq \log \gamma^c_{k',k} r_{c,k,m}\, g(\mathbf{x}(t); \boldsymbol{\mu}^{(c,k,m)}, \Sigma^{(c,k,m)}) \\ &= {\boldsymbol{\beta}^c_{k',k,m}}^{\mathrm{T}} \mathbf{X}(t), \end{aligned} \quad (19)$$

where $\mathbf{X}(t) \in \Re^H$ is defined as

$$\begin{aligned} \mathbf{X}(t) = \ &(1, \mathbf{x}(t)^{\mathrm{T}}, x_1(t)^2, x_1(t)x_2(t), \cdots, x_1(t)x_d(t), \\ &x_2(t)^2, x_2(t)x_3(t), \cdots, x_2(t)x_d(t), \\ &\cdots, x_d(t)^2)^{\mathrm{T}}, \end{aligned} \quad (20)$$

and $\boldsymbol{\beta}^c_{k',k,m} \in \Re^H$ is the appropriate coefficients vector [9].

Equation (20) describes the nonlinear pre-process for the first layer in R-LLGMN (see (1)), and $\xi^c_{k',k,m}$ can be expressed as the product of the coefficient vector $\beta^c_{k',k,m}$ and the modified input vector $\mathbf{X} \in \Re^H$. Hence, the model can be expressed as the neural network structure by using $\beta^c_{k',k,m}$ as the weight coefficients.

However, most of elements of $\beta^c_{k',k,m}$ are constrained by the statistical properties of the parameter $s_{i,j}^{(c,k,m)}$, and these constraints may cause a difficult problem in the learning procedure: how to satisfy the constraints during the learning of the weight coefficients. Therefore the new variable $Y^c_{k',k,m}$ and the new coefficient vector $\mathbf{w}^c_{k',k,m}$ are introduced to get rid of the constraints:

$$\begin{aligned} Y^c_{k',k,m}(t) &\equiv \xi^c_{k',k,m}(t) - \xi^C_{K_C,K_C,M_{C,K}}(t) \\ &= \left(\beta^c_{k',k,m} - \beta^C_{K_C,K_C,M_{C,K}}\right)^{\mathrm{T}} \mathbf{X}(t) \\ &= \mathbf{w}^c_{k',k,m}{}^{\mathrm{T}}\mathbf{X}(t), \end{aligned} \tag{21}$$

where $\mathbf{w}^C_{K_C,K_C,M_{C,K}} = 0$ by definition.

This new parameter $\mathbf{w}^c_{k',k,m}$ has no constraints and is used as the weight coefficient in this paper. Subsequently, equation (14) can be rewritten in the form as

$$\begin{aligned} a^c_k(t) &= \sum_{k'=1}^{K_c} a^c_{k'}(t-1)\gamma^c_{k',k} b^c_k(\mathbf{x}(t)) \\ &= \sum_{k'=1}^{K_c} a^c_{k'}(t-1)\exp\left[Y^c_{k',k,m}(t)\right] \\ &\qquad (t > 1). \end{aligned} \tag{22}$$

Comparing (12),(13),(20),(21),(22) in the HMM with (1)-(11) in the R-LLGMN, we can see that the R-LLGMN includes the HMM as a special case and regards the coefficient vector $\mathbf{w}^c_{k',k,m}$ as a weight coefficient vector. Then, the weight coefficients are modified so as to optimize an energy function via learning with the BPTT [15]. In this paper, the log-likelihood function is used as the energy function [9], and the terminal learning [17] algorithm is incorporated with the BPTT.

## 4 Pattern Discrimination of Raw EMG Signals

In order to show effectiveness of the proposed NN, discrimination experiments of time series of the EMG signals were performed. In the previously proposed methods for discrimination of the intended motion of an operator, the smoothed EMG signals [2][3] or the extracted characteristics in a fixed time window [1][7][6] have been used as the input vector to the NN. However, these processings result in considerable phase delay and time delay caused by the low-pass filtering and the time window operation. To avoid such delay, in this paper, raw EMG signals without any preprocessing are used as the input to the R-LLGMN.

### 4.1 Experimental Conditions

Experiments were performed with four subjects (A: an amputee, B, C, D: normal) who had been experienced to manipulate the EMG signals. The EMG signals were measured from 6 electrodes ($L$=6: four channels at the forearm, and two at the upper arm) and 6 forearm and hand motions ($C$=6 : flexion, extension, pronation, supination, grasp, hand opening) were classified in the experiments.

The electrodes (NT-511G, NT-512G: NIHON KOHDEN Corp.) for EMG measurements are made of Ag/AgCl with the diameter 0.012 [m]. Distance between electrodes was set as 0.03 m. The measured EMG signals were amplified and filtered out with the low-pass filter (cut-off frequency, 100[Hz]) in a multitelemeter (Web5000: NIHON KOHDEN Corp.) and digitized by an A/D converter (sampling frequency, 200 [Hz]; and quantization, 12 [bits]) after they were amplified (70 [dB]). The $L$ channel EMG signals are denoted by $EMG_i(s)$ ($i = 1, \cdots, L; s = 1, \cdots, S$), where $S$ is the number of all data.

Then, the integral EMG (IEMG) $\alpha(t)$ were obtained calculating moving average within the teacher vector length $T$ of the R-LLGMN after $EMG_i(s)$ were rectified:

$$\alpha(s) = \frac{1}{L}\sum_{i=1}^{L} \frac{\overline{EMG_i}(s)}{\overline{EMG_i}^{max}}, \tag{23}$$

$$\overline{EMG_i}(s) = \frac{1}{T}\sum_{j=0}^{T-1} |EMG_i(s-j)|, \tag{24}$$

where $\overline{EMG_i}^{max}$ is the premeasured IEMG of each channel under the maximum voluntary contraction (MVC). Also, it should be noted that $EMG_i(s-j) = 0$ when $s - j < 0$. In this paper, $\alpha(t)$ is used for the recognition of the beginning and ending of motions: When $\alpha(t)$ is over the motion appearance threshold $\alpha_d$, the motion is regarded as having occurred.

The input vector $\mathbf{x}(t) = [x_1(t), x_2(t), \cdots, x_d(t)]^{\mathrm{T}}$ ($t = 1, \ldots, T$) to the R-LLGMN is the normalized $EMG_i(t)$ with $\alpha(t)$ as

$$x_i(t) = \alpha^{-1}(T)EMG_i(t). \tag{25}$$

This normalization enables to estimate the motion from a pattern of all channels as well as the amplitude of the raw EMG signals.

### 4.2 Discrimination Results

First, discrimination experiments for non-stationary time series of EMG signals were carried out. The subject was an amputee who is a 51 year-old man whose forearm, 3 cm from the left wrist joint was amputated when he was 18 years old by an accident (subject A). He has never used the EMG controlled hand and usually uses a cosmetic hand.

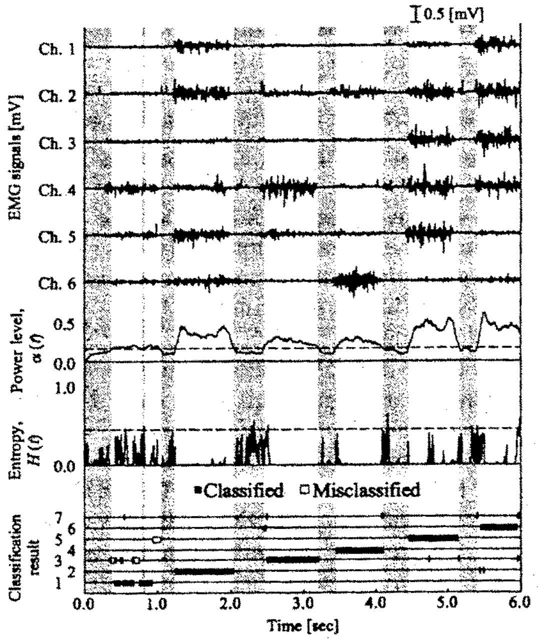


Fig. 2: An example of the discrimination result for non-stationary EMG signal (subject A)

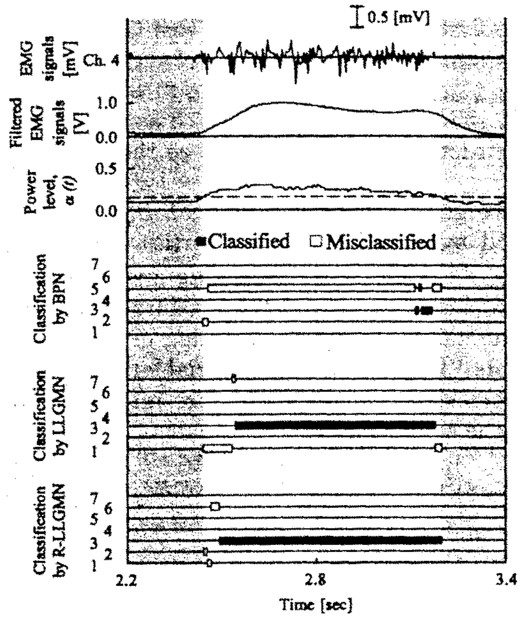


Fig. 3: Changes of the discrimination results by three types of neural netoworks (subject A)

Figure 2 shows an example of the discrimination result. In the figure, the EMG signals, the IEMG $\alpha(t)$, the entropy $H(t)$ calculated from the output probability of the R-LLGMN, the discrimination results of the R-LLGMN are shown, while he performed 6 motions (1: open, 2: grasp, 3: flexion, 4: extension, 5: pronation, 6: supination, 7: discrimination suspension), continuously. In the R-LLGMN, the parameters of the network are set as: $K_1 = K_2 = 1$, $M_{1,1} = M_{2,1} = 1$, $T = 20$, $L = 5$, $\alpha_d = 0.155$. The discrimination rate was about 92.3 % in this experiments. The output of the R-LLGMN is considerably smooth and the entropy is low during motions except for the motion 1.

Figure 3 shows the signals magnified from 2.2 [s] to 3.4 [s] in Fig. 2 during the wrist extention motion. In the figure, the EMG signal of the channel 4, the smoothed EMG signal which is rectified and filtered out by the second order Butterworth low-pass filter (cut-off frequency, 1.0[Hz]), the IEMG $\alpha(t)$, the discrimination results of the BPN, the LLGMN, the R-LLGMN are shown. The BPN and the LLGMN used the smoothed EMG signals as the input vector [9], while the R-LLGMN the raw EMG signals. It can be seen from the figure that there is a considerable phase delay between the raw EMG and the filtered EMG signals, which causes the ill-discrimination in the results of the BPN and the LLGMN. On the other hand, using the raw EMG signals, the R-LLGMN achieves a high discrimination performance comparing to the others. It should be noted that the discimination rates of the BPN and the LLGMN decreased considerably when the cut-off frequency of the low-pass filter increased. The increase of the cut-off frequency results in filtered EMG signals containing high frequency components, so that the learning of the NNs becomes very difficult.

Table 1: Discrimination results for non-stationary EMG signals

| Type of the methods | | BPN | LLGMN | R-LLGMN |
|---|---|---|---|---|
| Subject A (Amputee) | *CR* | 70.1 | 89.3 | 91.2 |
| | *SD* | 10.8 | 0.0 | 1.3 |
| Subject B (Normal) | *CR* | 80.5 | 82.9 | 94.1 |
| | *SD* | 8.1 | 0.0 | 0.4 |
| Subject C (Normal) | *CR* | 78.9 | 88.3 | 90.4 |
| | *SD* | 4.1 | 0.0 | 0.9 |
| Subject D (Normal) | *CR* | 75.8 | 85.9 | 91.0 |
| | *SD* | 4.5 | 0.0 | 1.8 |
| Total | *CR* | 76.3 | 86.6 | 91.8 |
| | *SD* | 6.9 | 0.0 | 1.1 |

*CR* : Classification rate [%], *SD* : Standard deviation [%]

Table 3 shows the discrimination results for four subjects using three different NNs. The mean values and the standard deviations of the discrimination rates are computed for 10 kinds of initial weights, which are randomly chosen. The EMG signals measured during 6 motions in about 18 [s] were used. In the LLGMN, the number of components were set as $M_1 = M_2 = 1$, and the number of training data 50 for each motion. In the BPN, the first and last layer consists of 6 units, and the second and third layer consists of 10 units. Also, the same training data as the LLGMN are used.

From the table, it can be seen that the R-LLGMN attained the best discrimination rates. Because the R-LLGMN contains the dynamic statistical model, it can utilize time history of the EMG signals.

## 5 Conclusions

In this paper, the new recurrent neural network, the R-LLGMN, has been proposed to perform a pattern discrimination for a time series of bioelectric signals. The R-LLGMN is a recurrent NN including a Gaussian mixture model and a feedback connection from output to input. Therefore, this network ensures the filtering process and the pattern discrimination to be achieved at the same time.

The discrimination experiments for the non-stationary time series of raw EMG signals have been carried out to examine the discrimination capability of the proposed network. The results of discrimination experiments showed that the R-LLGMN performs the filtering process as well as the pattern discrimination together in the same network architecture and can realize a relatively high discrimination rate.

Future research will be directed toward improving the learning algorithm for the application of the discrimination of various bioelectric signals.

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