Chapter 125
Pattern Discrimination of Mechanomyogram Using a Delta-Sigma Modulated Probabilistic Neural Network

Keisuke Shima and Toshio Tsuji

Abstract This paper proposes a discrimination method for mechanomyogram using probabilistic neural network based on delta-sigma modulation. The proposed method includes a statistical model so that the posterior probability for the given input patterns can be estimated. Also, the 1-bit pulse signals with delta-sigma modulators used in this paper improves the calculation speed of the probabilistic neural network implemented in the hardware. Finally, discrimination experiments were conducted using the mechanomyogram measured from an amputee.

Keywords Mechanomyogram · neural network · delta-sigma modulation

Introduction

Bioelectric signals such as electromyograms and electroencephalograms reflect the internal conditions of the human body including the intention regarding body motions. If the motion intention can be estimated from biological signals, it could be used as a control signal for artificial limbs and human-machine interfaces.

The present paper explores the utilization of the mechanomyogram (MMG) [1] for the human-machine interfaces [2, 3]. Unlike electromyograms and electroencephalograms, it is not affected by the change of skin impedance caused by sweating. For the human-machine interfaces, the discrimination of multiple motions is necessary, as well as the estimation of muscular force from the measured MMG signals.

The probabilistic neural networks (PNNs) [4] have been applied to the pattern discrimination problems for bioelectric signals such as electromyograms. Our research group proposed a PNN for the pattern discrimination of bioelectric signals, which is called a log-linearized Gaussian mixture network (LLGMN) [5]. Then, the LLGMN has been used to develop various human-machine interfaces such as myoelectric prosthetic hands [6]. In such systems, the software implementation of

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the LLGMN on a general-purpose computer was adopted; however, it has not been applied to human-machine interfaces because of the difficulty to reduce the size of the interface device to be portable.

In this paper, for the aim of estimation of forearm motions from MMGs in a digital hardware, we propose a feature extraction and discrimination method using PNN based on delta-sigma modulation. As delta-sigma modulation and statistical model are included in PNN, the proposed method can realize high accuracy discrimination for the MMGs.

MMG Discrimination Using the Delta-Sigma Modulated PNN

The MMG signals can be measured using acceleration sensors which are attached to the forearm. Then, full-wave rectification and smoothing process by a second low-pass filter, whose cut-off frequency is f_d [Hz], are carried out for the measured MMG. The normalized signals, the sum of which for all channels makes 1, are converted into the input vector $x(t) = [x_1(t), x_2(t), \ldots, x_L(t)]^T$ for time t and are used for pattern discrimination. Also, the user's force information for $x(t)$ is defined as follows:

$$RMS_i(t) = \sqrt{\frac{1}{n}\sum_{\tau=0}^{n-1} MMG_i(t-\tau)^2}, \qquad (125.1)$$

$$F_{MMG}(t) = \frac{1}{L}\sum_{i=1}^{L} \frac{RMS_i(t) - RMS_i^{st}}{RMS_i^{max} - RMS_i^{st}}, \qquad (125.2)$$

where $MMG_i(t)$ is the preprocessed MMG signal from the ith acceleration sensor; and RMS_i^{max} and RMS_i^{st} are the average of $RMS_i(t)$ at the maximum voluntary contraction of the muscle and at rest, respectively. When $F_{MMG}(t)$ exceeds threshold M_d of the motion occurrence, the movement is estimated from the input vector $x(t)$ using the PNN.

The LLGMN using delta-sigma modulation [7] is used as the discrimination method for MMG, which is based on the Gausian mixture model and the log-linear model of the probability density function (pdf). First, the input vector $x \in \Re^d$ is converted into the modified vector $X \in \Re^H$ as follows:

$$X = \left[1, x^T, x_1{}^2, x_1 x_2, \cdots, x_1 x_L, x_2^2, x_2 x_3, \cdots, x_2 x_L, \cdots, x_L{}^2\right]^T, \qquad (125.3)$$

where $x_i, i = 1, 2, \ldots, d$, are the elements of x and $H = 1 + L(L+3)/2$. The first layer consists of H units corresponding to the dimension of X and the identity function is used for activation of each unit. In the second layer, each unit receives the output of the first layer weighted by the weight $w_h^{(k,m)}(h = 1, 2, \ldots, H; k = 1, \ldots, K; m = 1, \ldots, M_k)$ and outputs the posterior probability of each Gaussian component. Here, K denotes the number of classes, and M_k is the number of Gaussian

components in class k. The relationships between the input of unit $\{k, m\}$ in the second layer $^{(2)}I_{k.m}$ and the output $^{(2)}O_{k.m}$ are defined as

$$^{(2)}I_{k.m} = \sum_{h=1}^{H} {}^{(1)}O_h w_h^{(k,m)}, \qquad {}^{(2)}O_{k.m} = \frac{\exp\left[{}^{(2)}I_{k.m}\right]}{\sum_{k'=1}^{K}\sum_{m'=1}^{M_{k'}} \exp\left[{}^{(2)}I_{k'.m'}\right]}, \qquad (125.4)$$

where $w_h^{(K.M_k)} = 0$. The third layer consists of K units, and the function between the input and the output is described as

$$^{(3)}O_k = {}^{(3)}I_k = \sum_{m=1}^{M_k} {}^{(2)}O_{k.m} . \qquad (125.5)$$

Delta-sigma modulation is a technique in which the input signal such as multi-bit signals and analog signals is converted into a 1-bit pulse signal, and it has been attracting interests in various fields such as acoustics and communications [8]. The structure of a bipolar-type delta-sigma modulator (DSM) is shown in Fig. 125.1, where the output takes the values "-1" and "$+1$. " In this figure, the bold line represents multi-bit signals and the thin line 1-bit signals. The output y of the circuit can be expressed in the form of

$$v = \frac{z^{-1}}{1 - z^{-1}} \{x - \tau y\}, \qquad y = \begin{cases} 1 & (v \geq 0) \\ -1 & (v < 0) \end{cases} \qquad (125.6)$$

where x is the input, v is the integrated value of the quantization error, and $\tau > 0$ is the feedback gain. Here, "-1" and "$+1$" are represented by the low level and the high level in the hardware, respectively.

The structure of the LLGMN based on delta-sigma modulation is shown in Fig. 125.2. The network consists of 1-bit adders, 1-bit multipliers, weight multipliers using DSM, and so on. Here, the input data are normalized to its minimum value of -1 and maximum value of $+1$ as a prerequisite for pattern discrimination, due to the restriction of the calculable ranges of the 1-bit pulsed NNs. First, the input vector $x(t)$ is interpolated using the linear interpolation method at a sampling frequency f_h [Hz], and nonlinearly transformed using the $(H - L - 1)$ 1-bit multipliers. Next, for
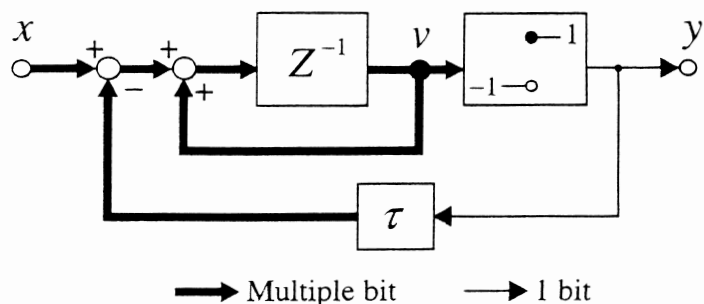

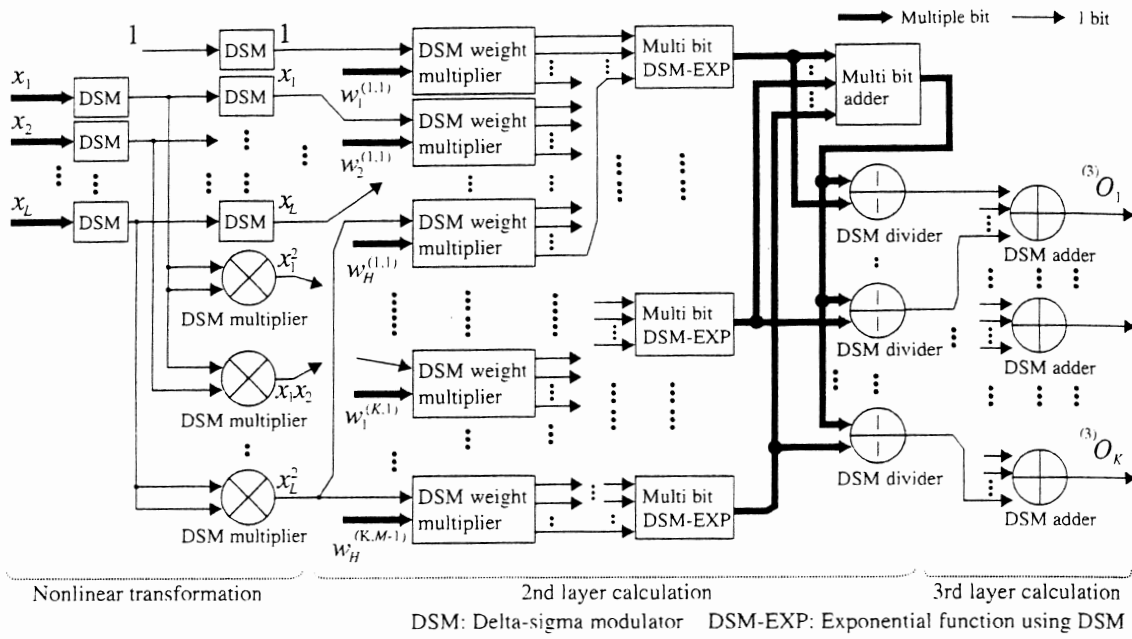**Fig. 125.1** Delta-Sigma modulator [8]

Fig. 125.2 Structure of an LLGMN using delta-sigma modulation

the calculation of the weight coefficients, the input function of the second layer is converted as follows:

$$
{}^{(2)}I_{k,m} = \sum_{h=1}^{H}\sum_{n=1}^{N}{}^{(1)}O_h\frac{w_h^{(k,m)}}{N}, \tag{125.7}
$$

where N is an arbitrary positive integer. Further, the exponential function included in (125.4) is approximated as follows by using the Taylor series:

$$
\exp[{}^{(2)}I_{k,m}] = \prod_{h=1}^{H}\prod_{n=1}^{N}\exp\left[{}^{(1)}O_h\frac{w_h^{(k,m)}}{N}\right]
$$
$$
\cong \prod_{h=1}^{H}\prod_{n=1}^{N}\left[\sum_{c=0}^{C}\frac{1}{c!}\left({}^{(1)}O_h\frac{w_h^{(k,m)}}{N}\right)^{c}\right], \tag{125.8}
$$

where C is the order of the Taylor series ignoring the high-order terms greater than $C+1$. Because the range of the values for the input functions of the second layer (see (125.7)) are restricted between -1 and $+1$ using the appropriate value of N, each term of the right-hand side of (125.8) can be calculated in a range of values between -1 and $+1$. The output function (125.4) in the second layer is then realized by using multipliers and dividers, after it is demodulated to multi-bit signals using low-path filters. Finally, the outputs of the network are calculated by (125.5) by using the 1-bit adder from the outputs in the second layer. Thus, the posterior probabilities of input patterns can be calculated using DSMs.

Experiments

In order to verify the validity of the proposed method, we implemented the delta-sigma modulated PNN on a field programmable gate array (FPGA), and MMG discrimination experiments were conducted. MMG patterns were measured from four healthy subjects (A–D: male) and a right forearm amputee (E: male). First, we measured the acceleration signals at four locations of a forearm using acceleration sensors ($L = 4$, NIHON KOHDEN Corporation) with each subject. The measured signals were recorded at a sampling frequency of 1 [kHz], and filtered by the second band-path filter (bandwidths: 30 – 150 [Hz]) to extract the MMG. The subject was asked to perform the following four motions ($K = 4$) continuously: M1: hand opening, M2: hand grasping, M3: wrist extension, and M4: wrist flexion (see Fig. 125.3). Parameters of proposed method were set as $f_{cut} = 0.5$ [Hz], $f_h = 25$ [MHz], $M_k = 2$, $N = 30$, and $C = 4$.

An example of the measured MMG of subject E is shown in Fig. 125.4. In this figure, four channels of the input MMG are shown. The discrimination rates of the MMG measured from five subjects are shown in Fig. 125.5, which are represented by the software implementation of the LLGMN using C language and the hardware implementation of the LLGMN using DSMs. From this figure, we confirmed that the proposed method has a high accuracy of pattern discrimination in digital hardware. The discrimination rates of all the trials were 94.3 ± 1.65 [%] and 92.48 ± 2.38 [%],
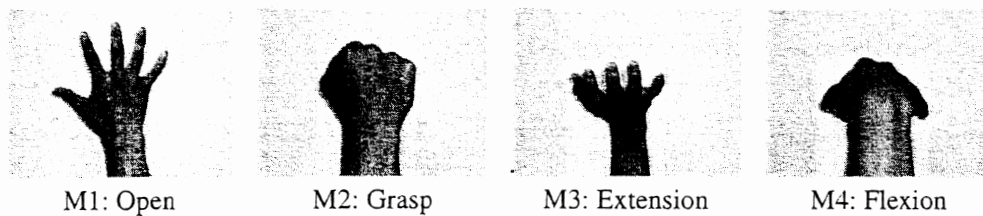

M1: Open   M2: Grasp   M3: Extension   M4: Flexion

Fig. 125.3 Forearm motions used in the experiments
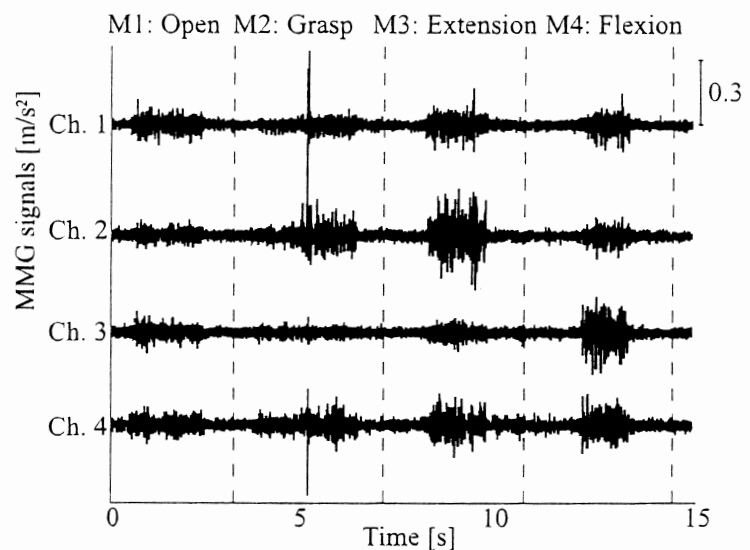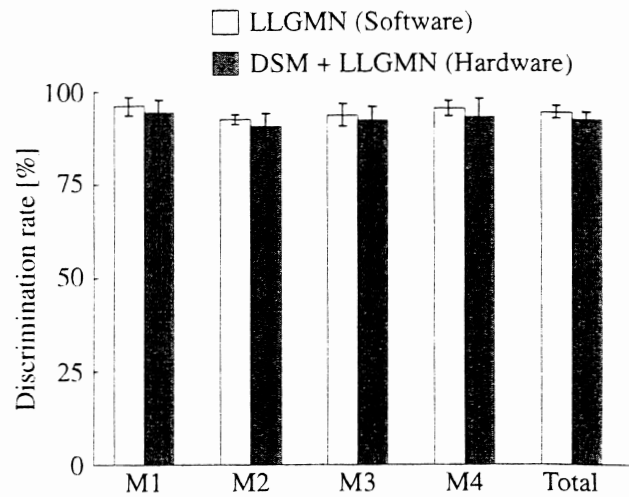

Fig. 125.4 Measured MMG signals of each motion (a forearm amputee)

Fig. 125.5 Discrimination results of forearm motions with all subjects

respectively. It should be noted that the feature extraction of the MMG was implemented in the software, and only discrimination of the MMG patterns is performed by an FPGA.

Conclusions and Future Work

In this paper, we proposed the MMG discrimination method using a delta-sigma modulated PNN in digital hardware. Since the discrimination rates of the proposed PNN was 92.48 ± 2.38 [%], it can be concluded that the proposed method has a high performance in the case of the MMG discrimination. In the future, we plan to study the human-machine interface in digital hardware using the proposed method.

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