Evaluation for Independent Quantization Learning Predictive Coding Using Electrocardiogram

Shunsuke Kobayakawa and Hirokazu Yokoi

***Abstract*—**This paper is presented a method for improving predictive coding. The method is the independent quantization predictive coding as its two predictors are learning. Its coding process is characterized in independently processing quantizations of an original series signal and a prediction series signal to eliminate quantization errors. It is performed to reduce prediction error as the predictors using error-convergence neuron network are learning. The method is the lossless data compression with the highest compression ratio, if quantization step size for an original series signal is the same as one when the signal was obtained. Then, computer simulations to evaluate its compression ratio were executed for a normal sinus rhythm electrocardiogram with using input-delay second-order Volterra neuron networks for neuron networks in an error-convergence neuron network predictor. As a result, the compression ratio was 1.71. In addition, an obtained quantization error series signal is more compressed with cabinet. Its compression ratio was 2.02. This method can be expected to perform excellent predictive coding for every signal with functional relationships between inputs and a prediction.

***Keywords*—**Accuracy, Electrocardiogram, Lossless data compression, Neuron network, Predictive coding.

I. INTRODUCTION

THE error-convergence neuron network predictor (ECNNP) designed by S. Kobayakawa [1] can be used for predictors of predictive coding as an application [2]. The data compression ratio of predictive coding elevates by its prediction accuracy high, and the evaluation to its performance becomes high. It is necessary to evaluate prediction accuracy of the ECNNP, that is, its generalization capability, though its complete learning without error is confirmed, when it is used as this predictor.

There are on-line learning and off-line learning when the learning method for the ECNNP is roughly classified. The learning styles concerning a neuron network (NN) at each step are simultaneous learning which is concerning every datum at the same time, and sequential learning which is independently finished up every NN at each step. These learning are executed from an NN at low step in order of an NN at high step using a teacher signal to an NN at the down step signal, which is an error signal which is simply obtained from an output signal and a teacher signal of an NN at the up step. Even an NN which expresses one system, characteristics of its output signal is different to each input signals of learned and unlearned, if its generalization capability is not enough. Therefore, a highly accurate and error-free output signal at all is obtained for learned input signals. However, it is difficult for unlearned input signals. This cause is thought that an output signal of an NN at the down step prove convergence for an output error signal of an NN at the up step oppositely. Because an output signal of the NN at the down step has only characteristics to compensate an output signal of the NN at the up step for learned input signals though characteristics of an output signal of the NN at the up step is different to learned input signals and unlearned input signals.

The prediction of a predictor used for typical predictive coding influences the quantization errors always [3]. Therefore, high accurate reconstruction series signal cannot be obtained from the quantization error series signal. Then, highly accuracy predictive coding has been designed to eliminate the problem by S. Kobayakawa. This is called independent quantization predictive coding (IQPC) [1]. The coding process is characterized in independently processing quantizations of an original series signal and a prediction series signal. Therefore, the quantization error series signal is unaffected by the prediction. That is, quantization errors by IQPC are only one by the original series signal.

Most signals of recent are quantized, when they are obtained. Therefore, a quantizer for original series signal with IQPC is often unnecessary. An original series signal without errors with IQPC can be completely reconstructed if quantization step size for the original series signal then is the same as one for IQPC. That is, this is a lossless data compression. In a past research by A. Fukunaga et al. [4], the method in which this is limited to the lossless compression of the image data is. In addition, F. Alexa et al. [5] and R. Logeswaran [6] applied NNs and Generalised Regression NNs to predictors of lossless predictive coding, respectively. Moreover, the improvement of the compression ratio can be expected with using ECNNPs for predictors of IQPC.

Then, purposes of this study are a confirmation of compensating effect of an output signal of the NN at the down step in an ECNNP when it is used with generalization, evaluation for generalization capability of the ECNNP, and

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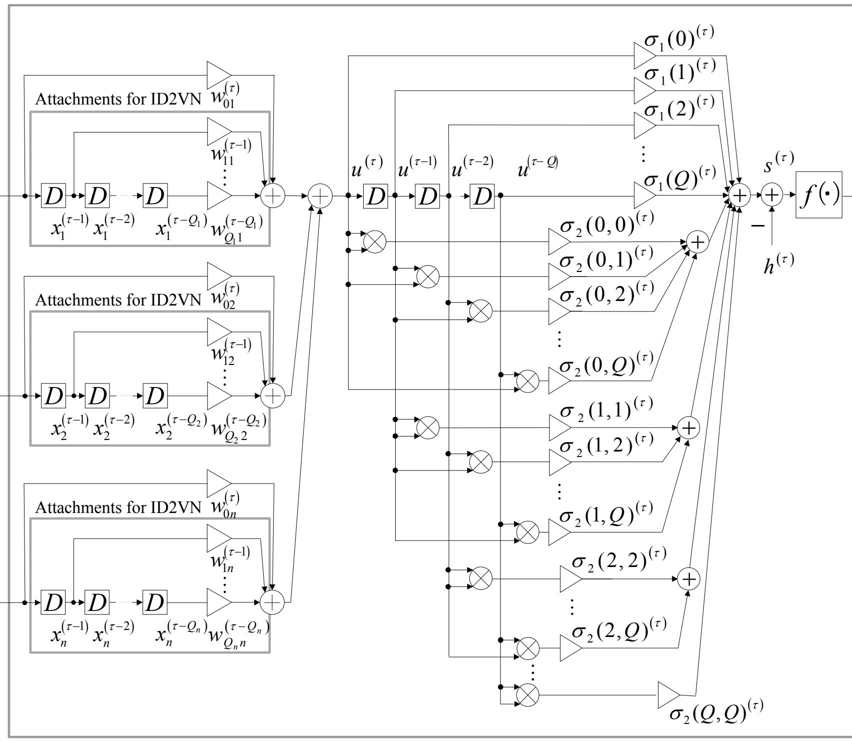


Fig. 1 Second-order Volterra neuron or input-delay second-order Volterra neuron

improvement of predictive coding with an ECNNP. As a result, the compensating effect can be confirmed. Moreover, three original techniques concerning the independent quantization learning predictive coding (IQLPC), which predictive coding is performed as the ECNNP is learning for an unlearned input signal, the means to reduce values of an error series signal, and the double compression using IQLPC and cabinet (CAB) are described. And, the computer simulations to evaluate its compression ratio were executed for a normal sinus rhythm electrocardiogram (ECG) with using input-delay second-order Volterra NNs (ID2VNNs) which input-delay NN [7] and second-order Volterra NN are combined proposed by J. Miyoshi et al. [8], [9] for NNs in the ECNNP.

II. Construction of Predictor

A. Second-Order Volterra Neuron

Fig. 1 shows a second-order Volterra neuron (2VN) designed by H. Yokoi [10]–[12]. Its I/O characteristics are shown in (1) to (3).

$$u^{(\tau)} = \sum_{i=1}^{n} w_i^{(\tau)} x_i^{(\tau)} \tag{1}$$

$$s^{(\tau)} = \sum_{p=0}^{Q} \sigma_1(p)^{(\tau)} u^{(\tau-p)} + \sum_{p=0}^{Q}\sum_{q=p}^{Q} \sigma_2(p,q)^{(\tau)} u^{(\tau-p)} u^{(\tau-q)} - h^{(\tau)} \tag{2}$$

$$z^{(\tau)} = f(s^{(\tau)}) = A\tan^{-1}(s^{(\tau)}) \tag{3}$$

where u is the input weighted sum, x_i is the i^{th} input signal, w_i is the i^{th} connection weight, s is the input sum, D is a delay element, Q is the filter order, σ_1 is the prediction coefficient of the first-order term corresponding to the signal obtained from between from the first delay element input to the Q^{th} delay element output, σ_2 is the prediction coefficient of the second-order term corresponding to the product of combinations of all two signals included in combinations of the same signal obtained from between from the first delay element input to the Q^{th} delay element output, h is the threshold, z is the output signal, f is the output function, A is the output coefficient, τ is discrete-time which is an integer value. w_i, h, σ_1, and σ_2 are changed by training.

B. Input-Delay Second-Order Volterra Neuron

Fig. 1 shows an input-delay second-order Volterra neuron (ID2VN) also. Its I/O characteristics are shown in (4) to (6).

$$u^{(\tau)} = \sum_{i=1}^{n}\sum_{p=0}^{Q_i} w_{pi}^{(\tau)} x_i^{(\tau-p)} \tag{4}$$

$$s^{(\tau)} = \sum_{p=0}^{Q} \sigma_1(p)^{(\tau)} u^{(\tau-p)} + \sum_{p=0}^{Q}\sum_{q=p}^{Q} \sigma_2(p,q)^{(\tau)} u^{(\tau-p)} u^{(\tau-q)} - h^{(\tau)} \tag{5}$$

$$z^{(\tau)} = f(s^{(\tau)}) = A\tan^{-1}(s^{(\tau)}) \tag{6}$$

where w_{pi} is the connection weight corresponding to signal obtained from between from the first delay element input to the

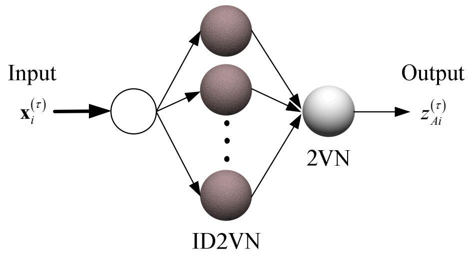


Fig. 2 Input-delay second-order Volterra neuron network

Q_ith delay element output concerning the ith input signal, Q_i is the number of delay elements concerning the ith input signal. w_{pi}, h, σ_1, and σ_2 are changed by training.

C. Input-Delay Second-Order Volterra Neuron Network

An ID2VNN is constructed of ID2VNs in middle layer and a2VN in output layer. This is used for three-layer networks of one or two input one output in an ECNNP. The ID2VNN is shown in Fig. 2.

D. Error-Convergence Neuron Network Predictor

A nonlinear predictor used for predictive coding and its principle must be improved to obtain high accuracy, though it is more appropriate than a linear predictor [13] when a nonlinear signal is predicted. Here is a method to improve the learning capability of an NN at each step in an error-convergence neuron network (ECNN) [14], [15] for a nonlinear predictor used for predictive coding. This is an ECNNP. The learning for a nonlinear predictor using NNs is easier by strengthening of functional relationships between signals from past to present and a prediction signal. Therefore, the learning for an NN at the first step in the ECNN is comparatively easy. However, the learning for an NN at the high step is difficult, because it is guessed that the functional relationships weaken by rising of the number of steps. Then, the NN at each step in the ECNN is used as a predictor to strengthen functional relationships between its input signals and one teacher signal.

Moreover, the learning capability of the NN can be elevated by increasing the number of input signals which have functional relationships to a teacher signal [16]. Fig. 3 is redesigning of an ECNN to realize it. The I/O characteristics of ECNNP are shown in (7) to (17). Initial conditions for NNs from the second step are shown in (14). I/O relations of NNs in the ECNNP are shown in (16). An output signal of the ECNNP is shown in (17). A teacher signal to the ECNNP is shown in (18).

$$i,\ j,\ n_{\mathrm{in}} \in Z \tag{7}$$

$$n_{\mathrm{in}} \geq 1 \tag{8}$$

$$\mathbf{x} = \left(x_1, x_2, \cdots, x_{n_{\mathrm{in}}}\right) \tag{9}$$

$$\mathbf{A}_{\mathrm{in}i} = \left(a_{i1}, a_{i2}, \cdots, a_{in_{\mathrm{in}}}\right) \qquad \left(1 \leq i \leq n\right) \tag{10}$$

$$x_{Aij} = a_{ij} x_j \qquad \left(1 \leq i \leq n;\ 1 \leq j \leq n_{\mathrm{in}}\right) \tag{11}$$

$$\mathbf{x}_1^{(\tau)} = \left(x_{A11}^{(\tau)}, x_{A12}^{(\tau)}, \cdots, x_{A1n_{\mathrm{in}}}^{(\tau)}\right) \tag{12}$$

$$\mathbf{x}_i^{(\tau)} = \left(Ae_{\mathrm{in}i} x_{ij}^{(\tau)}, x_{Ai1}^{(\tau)}, x_{Ai2}^{(\tau)}, \cdots, x_{Ain_{\mathrm{in}}}^{(\tau)}\right) \quad \left(2 \leq i \leq n;\ 1 \leq j \leq n_{\mathrm{in}}\right) \tag{13}$$

$$x_{ij}^{(\tau)} = 0 \qquad \left(\tau \leq 0;\ 2 \leq i \leq n;\ 1 \leq j \leq n_{\mathrm{in}}\right) \tag{14}$$

$$x_{ij}^{(\tau)} = x_j^{(\tau)} - \sum_{k=1}^{i-1} z_k^{(\tau-1)} \qquad \begin{pmatrix} \tau > 0 \\ 2 \leq i \leq n \\ 1 \leq j \leq n_{\mathrm{in}} \end{pmatrix} \tag{15}$$

$$z_{Ai}^{(\tau)} = f_i\left(\mathbf{x}_i^{(\tau)}\right) \qquad \left(1 \leq i \leq n\right) \tag{16}$$

$$z^{(\tau)} = \hat{x}_j^{(\tau+1)} \qquad \left(1 \leq j \leq n_{\mathrm{in}}\right) \tag{17}$$

$$y^{(\tau)} = x_j^{(\tau+1)} \qquad \left(1 \leq j \leq n_{\mathrm{in}}\right) \tag{18}$$

where Z is whole number, a suffix of the NN is the step number, $\mathbf{x}$ is the input signal vector, $\mathbf{A}_{\mathrm{in}i}$ is the amplification factor vector of input signals at the ith step, a_i is the amplification factor of an input signal at the ith step, x_{Ai} is the input signal after amplification at the ith step, suffixes of a_i and x_{Ai} are input signal numbers, $\mathbf{x}_i$ is the input signal vector after amplification at the ith step, x_{ij} is the input error signal at the ith step to input signal x_j to the ECNNP, $Ae_{\mathrm{in}i}$ is an amplification factor of the input error signal at the ith step, z_i is the output signal to NN_i after restoration, z_{Ai} is the output signal of NN_i, f_i is the n_{in} variables function when i is 1 or the $n_{\mathrm{in}} + 1$ variables function when i is 2 or more to show I/O relation of NN_i, $\hat{x}_j$ is the prediction to x_j, y is the teacher signal to the ECNNP, y_{iA} is the teacher signal to NN_i after amplification, A_i is the amplification factor of the teacher signal to NN_i.

II. Independent Quantization Learning Predictive Coding

Model parameters of predictors used for typical predictive coding were decided by learning etc., and fixed beforehand according to signal characteristics to a predictive object. Therefore, there are problems which the amplitude of error series signal of the predictive coding is large, when its generalization capability is poor and a predictive object is a time-variant system [17]. A. Romero et al. [18] introduced adaptive predictors to improve this problem. Moreover, there is a problem which quantization errors of the predictor is included, because an error series signal which is obtained from an original series signal and a prediction series signal, is quantized with a quantizer. This problem is eliminated with IQPC. Process of IQPC is shown in Fig. 4. Here, a method to improve the first problem is proposed. It is IQLPC which the prediction with predictors of IQPC is executed as the predictors are learning. This is shown in Fig. 5. Principle of IQLPC is as follows.

Two same predictors for a coding process and a decoding process of IQLPC are learnable. They are preprocessed by

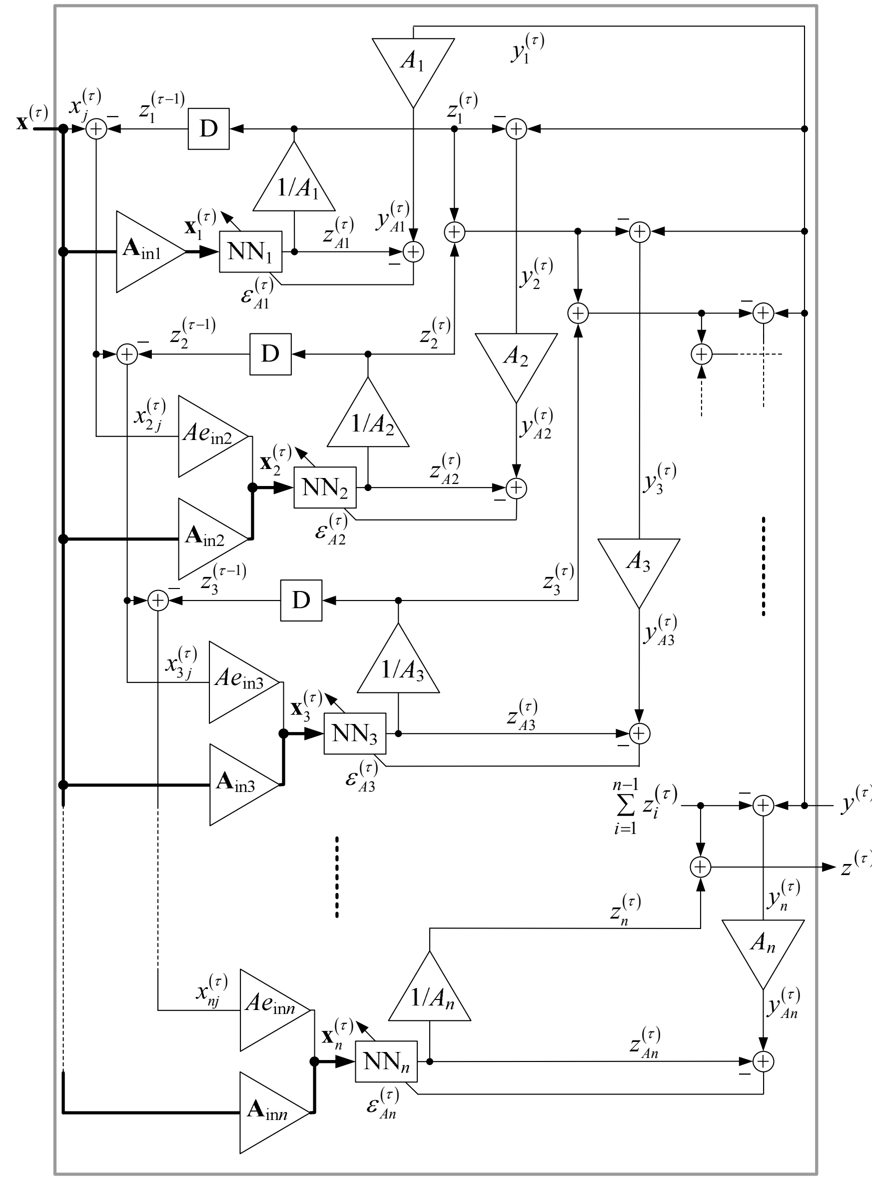


Fig. 3 Error-convergence neuron network predictor

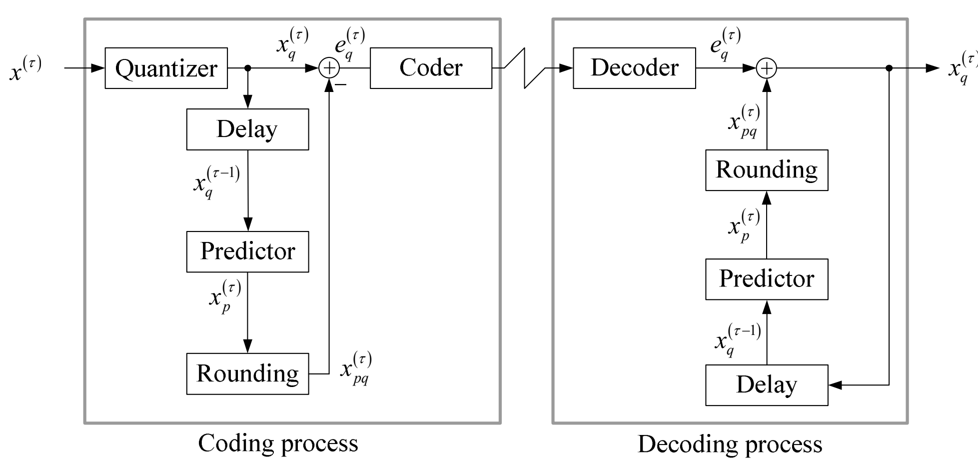


Fig. 4 Independent quantization predictive coding

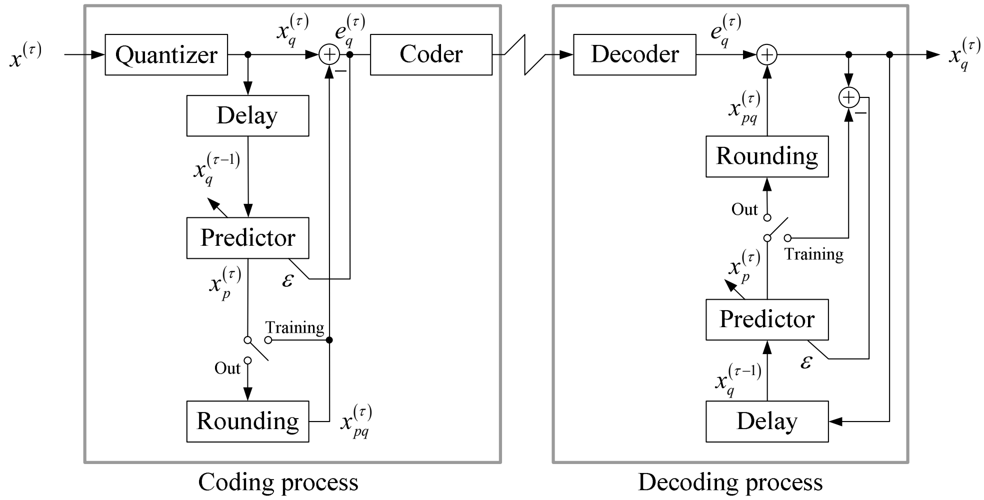


Fig. 5 Independent quantization learning predictive coding

training signal characteristics to a predictive object. Values of model parameters of the predictors are set as initial values before IQLPC is performed. ECNNPs are used for the predictors in this study.

Coding process:

1) A predictor of this process is trained by a quantization series signal x_q at τ as a teacher signal, after x_q at τ-1 was input to it. Values of model parameters of the predictor are tuned by an error signal ε which is a difference between x_q at τ and prediction series signal x_p at τ. This training is iterated to conditions to stop it. The conditions are also used for conditions to stop training for a predictor of the decoding process.
2) A prediction series signal x_p at τ is output from the predictor after the training stopped.
3) A quantized prediction series signal x_{pq} at τ is obtained by rounding the x_p.
4) A quantization error series signal e_q at τ is obtained by subtracting the x_{pq} at τ from the x_q at τ.
5) The e_q at τ is coded with coder, and it is sent to a decoder of the decoding process.

Decoding process:

1) The coded series signal which is sent from the coding process is decoded with a decoder of this process. This decoded series signal is the e_q at τ.
2) The x_q at τ is reconstructed by adding the x_{pq} at τ to the e_q at τ.
3) The x_{pq} at τ is obtained by rounding the x_p
4) The x_p is output from a predictor of this process after training for it stopped.
5) The predictor is trained by the x_q at τ as a teacher signal after x_q at τ-1 was input to it. This training is iterated to conditions to stop it. The conditions are the same as one for a predictor of the coding process.

III. Computer Simulations

A. Method

Evaluation method for generalization capability of an ECNNP and IQLPC is explained. Learning computer simulation for ECG signal prediction is executed using a normal sinus rhythm ECG and the ECNNP constructed of other ID2VNNs of several steps which doubles number of delay elements and filter length based on specification of ID2VNNs of two steps used for improvement of learning capability in last study [6]. 4,000 data from start of a normal sinus rhythm ECG signal of MIT-BIH No.16786 of Fig. 6 are used for training to confirm its generalization capability. This ECG signal is obtained at a sampling frequency of 128 Hz, with quantization bit rate of 12 bit, a significant figure of four-digits, and quantization step size of 0.005 mV.

Initially, an ID2VNN at the first step (ID2VNN$_1$) is trained using combinations of an input signal $x^{(\tau-1)}$ and a teacher signal $y_1^{(\tau)} = x^{(\tau)}$ in the time series pattern of one dimension in space direction, to search its better condition. Here, an ID2VNN of the minimum root mean square error (RMSE) is chosen from among the condition of obtaining the minimum average RMSE, and it is set as ID2VNN$_1$. In addition, output signal of this ID2VNN$_1$ is restored to the teacher signal level, and a signal obtained from difference between the teacher signal and the output signal, and its signal is used for a part of training signals for an ID2VNN at the second step (ID2VNN$_2$).

Next, an ID2VNN$_2$ is trained using combinations of input signals $x_{21}^{(\tau-1)}$ and $x^{(\tau-1)}$ in the time series pattern of two dimensions in space direction and a teacher signal $y_2^{(\tau)} = x_{21}^{(\tau)}$ in the time series pattern of one dimension in space direction, to search its better condition. A signal to which gain tuning to adjust the maximum absolute value of error signal to 1 is performed, are used for $x_{A2}^{(\tau-1)}$ and $y_{A2}^{(\tau)}$. Here, computer simulations for the training are executed as $Ae_{\mathrm{in}2} = A_2$ and $a_{21} = 1 / 3.275$. Here, an ID2VNN of the minimum RMSE is chosen from among the condition of obtaining the minimum average RMSE, and it is set as ID2VNN$_2$. In addition, output signals of the ID2VNN$_1$ and this ID2VNN$_2$ are restored to a teacher signal level to the ECNNP, and an error signal obtained from their signals and the teacher signal to the ECNNP is used for a part of training signals for an ID2VNN at the third step (ID2VNN$_3$).

ID2VNNs from the third step are decided one by one as well as means of deciding ID2VNN$_2$. The decision for NNs is finished, when prediction error obtained from output signal of the ECNNP obtained from sum of output signals from

$ID2VNN_1$ to ID2VNN at the final step which are restored to the teacher signal level to the ECNNP and the teacher signal to the ECNNP, frees completely. Their training are executed with presenting a pair of input signal and a teacher signal once, after the initial data of 2,080 unit time are input. This process is defined as one training cycle, and this is iterated. Three times of training to search better parameters of ID2VNNs are executed by computer simulations, and averages of RMSEs obtained from results by them are compared. Conditions for learning computer simulation are shown in Table I. Initial values of the prediction coefficients are decided by exponential smoothing, and the other initial values are decided by pseudo-random numbers at the training process a time. The generalization capability is evaluated by inputting 1.875 seconds and 240 data of unlearning signal in Fig. 8 consecutive in Fig. 6 after ECG signal data in Fig. 6 are initially input to ECNNP obtained from the above-mentioned search.

Next, evaluation method for IQLPC is explained. There are training cycle, output error, etc., and combinations of them in conditions to stop training for ECNNPs. The training cycle is used for the condition in this study. An ECNNP using ID2VNNs of two steps is trained using combinations of an input signal $x^{(\tau-1)}$ and a teacher signal $y^{(\tau)} = x^{(\tau)}$ in the time series pattern of one dimension in space direction. An ECG signal used for computer simulations is shown in Fig. 7 and 8. This also is a normal sinus rhythm ECG signal of MIT-BIH No.16786. This quantization step size is the same as one of IQLPC. Values of model parameters of an $ID2VNN_1$ and an $ID2VNN_2$ have been obtained beforehand using ECG in Fig. 7 as a training signal by last study [6]. Specifications of these ID2VNNs are shown in Table II. Signal data of the ECG from top to 300 are used for initial input to the ID2VNNs. And, the ID2VNNs are trained using the ECG signal from 0 to 15 seconds.

Initially, Training cycles for the $ID2VNN_2$ are from zero to five every datum concerning $ID2VNN_1$ of the training cycles which is obtained the minimum absolute values of the maximum prediction error amplitude. A learning reinforcement coefficient of the $ID2VNN_2$ is the same as one when it is decided. These trainings are executed one time under each condition.

Here, the means to reduce values of an error series signal is proposed. It is to apply which an absolute value of difference of two values with the same sign is smaller than one of two values with different sign. This means is applied to the ECNNP. Concretely, signs of a teacher signal and an output of NN at each step in the ECNNP are made the same. Prediction error of the ECNNP is reduced with this means. This is shown in (19) and (20).

TABLE I
CONDITIONS FOR LEARNING COMPUTER SIMULATIONS

Items \ Steps			The 1st	From the 2nd
Learning rule			Learning rule for Volterra Neuron Network	
Initial values	Connection weights		−0.1 – 0.1	
	Thresholds		−0.1 – 0.1	
	Prediction coefficients	σ_1	0.7×0.3^p	
		σ_2	$0.7 \times 0.3^p \times 0.7 \times 0.3^q$	
Number of elements in middle layer			4	10
Filter length			137	127
Number of taps			283	
Learning reinforcements	Gradient-based method	Range	10^{-6} – 1	
		Interval	10 times	
	Momentum		0	
Output coefficient			1	
Number of training cycles			1,000	
Processing times			3	

TABLE II
SPECIFICATION OF INPUT-DELAY SECOND-ORDER VOLTERRA NEURON NETWORKS IN THE ERROR-CONVERGENCE NEURON NETWORK PREDICTOR

Items \ Steps	The 1st	The 2nd
Number of elements in middle layer	4	10
Filter length	69	64
Number of taps	142	142

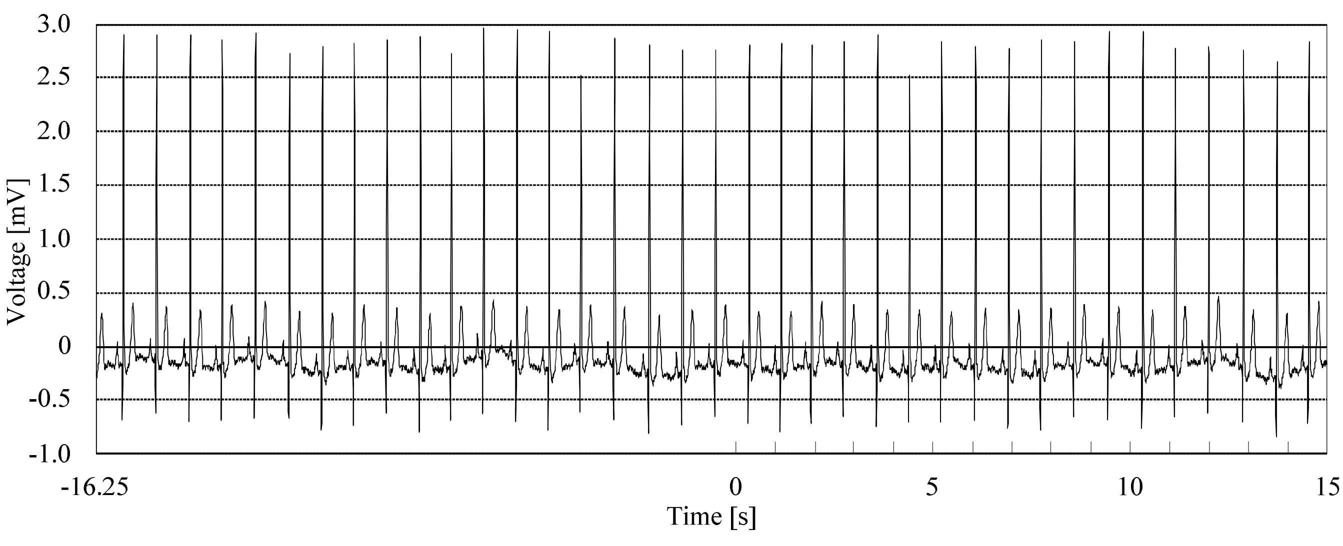


Fig. 6 Electrocardiogram signal for the training to confirm the generalization capability

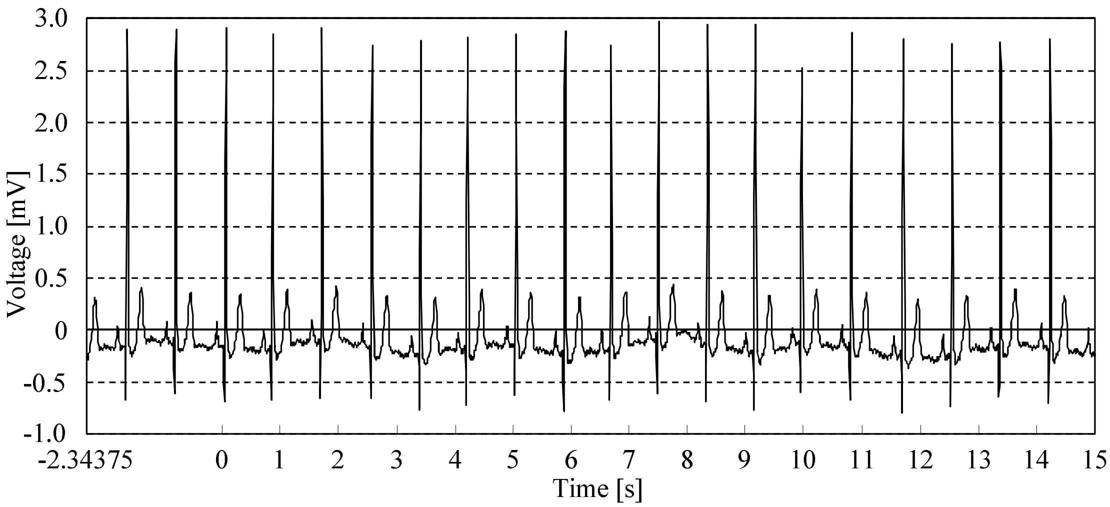


Fig. 7 Electrocardiogram signal for the training to evaluate independent quantization learning predictive coding

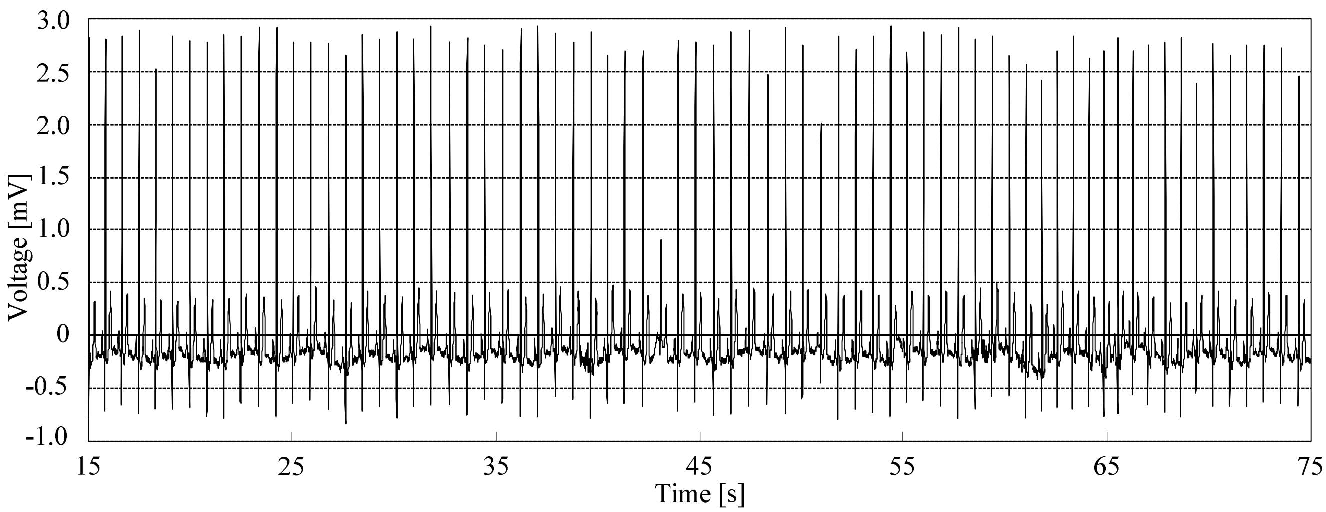


Fig. 8 Electrocardiogram signal to decide conditions to stop training for input-delay second-order Volterra neuron networks in the error-convergence neuron network predictor

$$\begin{cases} \mathrm{sgn}\left(y_i^{(\tau)} + b_i\right) = \mathrm{sgn}\left(z_i^{(\tau)} + b_i\right) \\ y_{i+1}^{(\tau)} = y_i^{(\tau)} - z_i^{(\tau)} \end{cases} \quad \left(1 \le i \le n\right) \tag{19}$$

$$\begin{cases} \mathrm{sgn}\left(y_i^{(\tau)} + b_i\right) \ne \mathrm{sgn}\left(z_i^{(\tau)} + b_i\right) \\ y_{i+1}^{(\tau)} = y_i^{(\tau)} + z_i^{(\tau)} + 2b_i \end{cases} \quad \left(1 \le i \le n\right) \tag{20}$$

where b_i is a bias of the teacher signal and an output signal of NN at the i^{th} step in the ECNNP. This means is applied to only ID2VNN$_2$, and the bias is zero in computer simulations.

At last, a bias is added to the quantization error series signal obtained under the best condition to eliminate minus sign of its quantization level, and it is more compressed by CAB which is a compressed archive format. Here, only size of the processed quantization error series signal is evaluated. Data sizes of their programs and parameters of ID2VNNs are negligible, if data size of a quantization original series signal is very large, because its percentage of total data size is small. Compression ratio is used for the evaluation for compression. The compression ratio is shown in (21).

Compression ratio

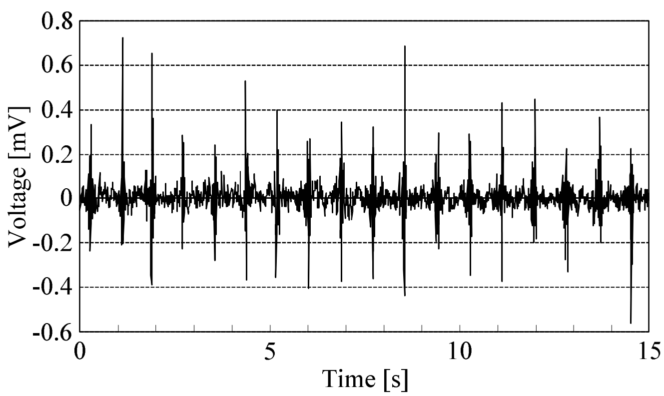
$$= \frac{\text{Data size of a quantization original series signal}}{\text{Data size of a coded series signal}} \tag{21}$$

B. Results

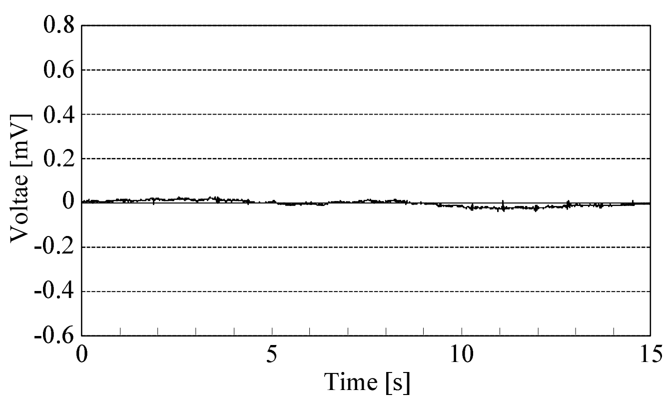
Initially, results for generalization capability of the ECNNP are shown. Output error of the ECNNP free when an ID2VNN at the fourth step was decided when NNs of the ECNNP was decided from the first step one by one with training ID2VNN, and complete learning was achieved. Error signals for ID2VNNs at steps from the second to the fourth in the ECNNP are shown in Fig. 9. From these figures, amplitudes of the error signals becoming small can be confirmed as the number of NN steps increases, and output error of the ECNNP converging is shown. Averages of RMSEs to learning reinforcements of ID2VNNs at steps from the first to the fourth are shown in

TABLE III
AVERAGES OF ABSOLUTE VALUES OF PREDICTION ERROR TO INPUT-DELAY SECOND-ORDER VOLTERRA NEURON NETWORK AT EACH STEP IN ERROR-CONVERGENCE NEURON NETWORK PREDICTOR BY INPUTTING UNLEARNING SIGNAL DATA

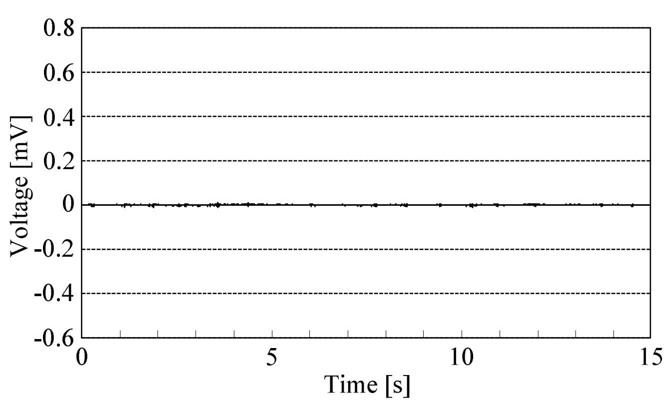
Items of data \ Number of Stetps	1	2	3	4
Averages of Absolute Values of Prediction Error [mV]	0.2915	0.2880	0.2871	0.2870
Percentage [%]	100	98.79	98.49	98.46



(a) The second step



(b) The third step



(b) The fourth step

Fig. 9 Training error signal for input-delay second-order Volterra neuron networks from the second step to the fourth step

TABLE IV
RESULTS OF COMPRESSIONS

Items of data \ Compression method	None	IQLPC
Average bit rate	12.0	7.00
Bytes of series signal data	11,520	6,720
Compression ratio	1.00	1.71
Items of data \ Compression method	**CAB**	**IQLPC + CAB**
Average bit rate	6.95	5.95
Bytes of series signal data	6,676	5,712
Compression ratio	1.73	2.02

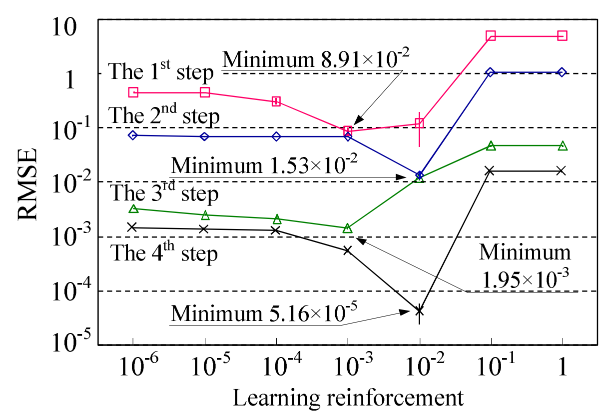


Fig. 10 Averages of root mean square errors input-delay second-order Volterra neuron networks from the first step to the fourth step to learning reinforcements

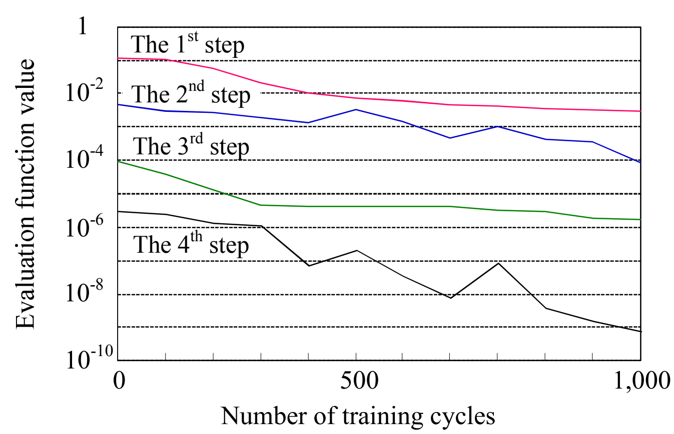


Fig. 11 Averages of average evaluation values a unit time to the number of training cycles of input-delay second-order Volterra neuron networks achieved the minimum average value of root mean square errors from the first step to the fourth step

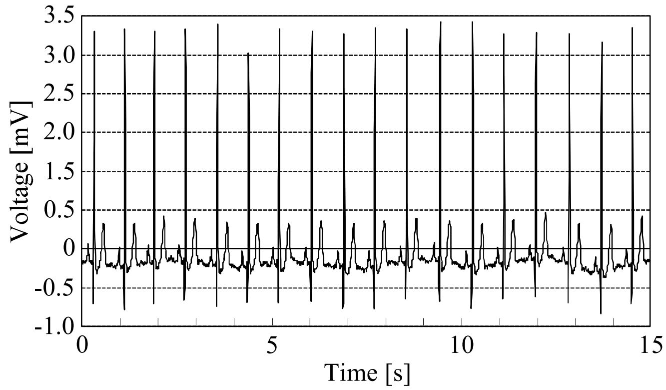


Fig. 12 An output signal of the error-convergence neuron network predictor after the training

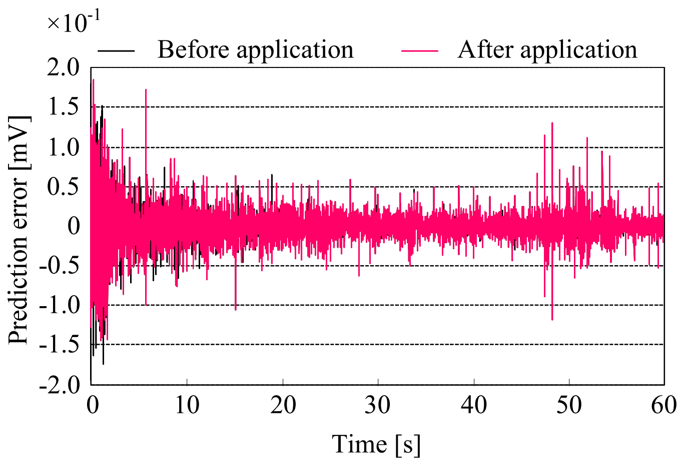


Fig. 14 Prediction error series signals by independent quantization learning predictive coding

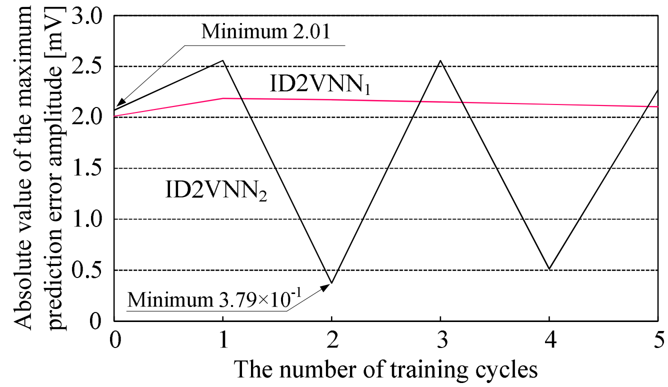


Fig. 13 Absolute values of the maximum prediction error amplitude to conditions of the number of training cycles for input-delay second-order Volterra neuron networks in the error-convergence neuron network predictor

Fig. 10. Also from this figure, the minimum average of RMSEs at each step decreasing in exponential by about 1/10 a step can be confirmed as the number of NN steps increases, and the output error of the ECNNP converging is shown. Averages of average evaluation value a unit time datum to the number of training cycles of ID2VNN that achieved the minimum average of RMSEs concerning ID2VNNs at steps from the first to the fourth, are shown in Fig. 11. From this figure, an error of ID2VNN at up step when their training were finished, is succeeded as an error when ID2VNN at down step beginning to train, and their training progressing well can be confirmed as the number of NN steps increases. An output signal of ECNNP after the training is shown in Fig. 12. This is completely corresponding to the teacher signal. From the above-mentioned result, a complete learning being able to be obtained by increasing the number of NN steps even the training for the ECNNP of only 1,000 cycles, is shown.

Next, results of generalization output of ECNNP obtained by inputting unlearning data to the ECNNP after the training are shown in Table III. From this table, an average of absolute values of prediction errors after 1.875 second decreases as the number of NN steps increases, that is, improvement of its generalization capability can be confirmed. Therefore, the effectiveness of the compensating effect of the error with NNs at down step in the ECNNP when its generalization was used can be confirmed. Next, results for IQLPC are shown. Fig. 13 shows absolute values of the maximum prediction error amplitude to conditions of the number of training cycles for the $ID2VNN_1$ and the $ID2VNN_2$. The following can be confirmed from this figure. The absolute value of the maximum prediction error amplitude of the $ID2VNN_1$ is the smallest when the number of training cycles is zero. Moreover, when this $ID2VNN_1$ is used, the absolute value of the maximum prediction error amplitude of the $ID2VNN_2$ is the smallest when the number of training cycles is two.

Fig. 14 shows a result of giving the means to reduce values of an error series signal to the $ID2VNN_2$ obtained from the best combinations of these the number of training cycles. The following can be confirmed from this figure. The absolute value of the maximum prediction error amplitude of the $ID2VNN_2$, that is, the absolute value of the maximum prediction error amplitude of the ECNNP is 3.29×10^{-1} mV. It is reduced by 13.2% than before applying the means. The prediction error is large at the beginning. It increases again in the middle of the prediction, though it gradually becomes small with the time passage.

The comparative results of the compression ratio by each compression method are shown in Table IV. The following can be confirmed from this table. IQLPC and CAB have an almost equal compression capability. The method of giving double compression by IQLPC and CAB is the highest compression ratio. It shows that the original data size can be compressed less than 50 %. Moreover, the compression ratio of this method is improved more than only CAB by 16.8 %.

II. Discussion

Initially, the generalization capability of the ECNNP is discussed. Complete learning of the ECNNP being able to be achieved is proved by increasing the number of NN steps, even if the number of training cycles is a few. This can be caught in case of the results which effects of increasing its output accuracy and training speed can be expected enough by increasing the number of NN steps also concerning ECNNP as described in last paper [11]. Increasing learning accuracy to teacher signal of NN interferes to its generalization capability in a typical theory concerning the generalization capability. However it not necessarily happening is shown in this result. This cause is that the effectiveness of the compensating effect of error with NNs at down step exists when also generalizing, as well as when learning. The compensating effect of error when also generalizing can be obtained, when an average function concerning relations of input signals and teacher signals which are obtained by training and functions concerning relations of input signals and output signals, are similar. That is, the effectiveness having been obtained is considered from results of simulations to confirm the generalization capability, because the above-mentioned condition to obtain the compensating effect of error is include in the unlearning signal of 1.875 seconds just behind the learning signal, for this normal sinus rhythm ECG. In addition, the improvement of the generalization capability can be expected by devising the ECNNP, the NN, and the input output signal, etc.

Next, IQLPC is discussed. Lossless compression to the original series signal obtained with the same quantization step size as the quantization of IQLPC of a compression ratio that was higher than one of CAB, could be achieved with changing predictive coding to IQLPC, using an ECNNP for its predictor, introducing the means of reducing values of an error series signal, and double compression using CAB. However, examine it more is the stop conditions of training for the ECNNP. The number of training cycles, prediction error, those combinations, and the condition corresponding to the error signal for training, etc. are thought as a stop condition of training. In this study, being able to improve the generalization capability of the ECNNP is considered with examining a condition that the data compression ratio becomes the largest in the various stop conditions of training, because it is a confirmation of only the number of training cycles. Moreover, using the combination of IQLPC and other methods of data compression, etc. are considered as a method to more improve the data compression ratio. For example, they are designs of the original compression method matched to prediction error signal feature and the means that changes its compression order. These should also confirm the effectiveness of data compression.

Finally, the application of means to reduce values of an error series signal is discussed. There is a possibility of improving training speed by applying the means to an output of NNs in training. Moreover, if a sign output NN is prepared, and the sign of a teacher signal to an output NN is trained to it, there is a possibility that the accuracy of the generalization output of an output NN can be improved by giving the sign of an output signal of the output NN with the sign output NN.

III. Conclusion

Results of confirmation concerning the compensating effect of error with NNs at down step in an ECNNP by using unlearning normal sinus rhythm ECG signal composed of 240 data of 1.875 seconds, its effectiveness could be confirm as well as when concerning the learning capability, because absolute averages of its prediction error decreased with increasing the number of NN steps, and improvement of the generalization capability was shown, for generalization capability of the ECNNP constructed of ID2VNNs of four steps after the complete learning concerning normal sinus rhythm ECG signal prediction by 1,000 cycles of training. This result can be considered that increasing learning accuracy to teacher signal of NN interfering to its generalization capability in a typical theory concerning the generalization capability not necessarily happening is shown.

Next, Results of examining typical predictive coding as a method with which prediction accuracy can be improved, even if generalization capability of an ECNNP is poor, 1) IQLPC to reduce prediction error as training a predictor, 2) means of matching the sign of an output signal of an NN to the sign of teacher signal to it and reducing error, and 3) double compression by IQLPC and CAB, were designed. A Result of compressing 7,680 data of an unlearning normal sinus rhythm ECG signal of 60 s, using the ECNNP constructed of ID2VNNs of two steps for the predictor of IQLPC, as their computer simulations, IQLPC was shown to obtain the same degree of compression ratio as CAB. In addition, compression ratio 2.02 was obtained with double compression using IQLPC and CAB. This double compression improved more than only CAB by 16.8 %.

Future works are the improvement of the generalization capability of the ECNNP, the examinations of the training stop condition of the ECNNP which compression ratio can be the largest and the method to improve compression ratio, and the verification of applications of the means to reduce error.

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