High Speed Paper Currency Recognition by Neural Networks

Fumiaki Takeda and Sigeru Omatu

Abstract—**In this paper a new technique is proposed to improve the recognition ability and the transaction speed to classify the Japanese and U.S. paper currency. Two types of data sets, time series data and Fourier power spectra, are used in this study. In both cases, they are directly used as inputs to the neural network. Still more we also refer a new evaluation method of recognition ability.**

Meanwhile, a technique is proposed to reduce the input scale of the neural network without preventing the growth of recognition. This technique uses only a subset of the original data set which is obtained using random masks. The recognition ability of using large data set and a reduced data set are discussed. In addition to that the results of using a reduced data set of the Fourier power spectra and the time series data are compared.

I. Introduction

In conventional paper currency recognition machines, we have developed the recognition algorithm according to the transaction speed and difference of various specifications. For example, we have produced the paper currency recognition machines that can transact from 1 to 10 pieces/s [1], [2]. However, development of the algorithm has been based on the method of trial and error. Namely, engineering designers usually sample the characteristic parameters of conveyed paper currency and examine whether the paper currency can be recognized or not using the sampled characteristic parameters by evaluating large quantities of paper currency. But many researchers have reported that neural networks, (NN's), are suitable for the pattern recognition because of the ability of self-organization, parallel processing, and generalization [3], [4]. Especially, we can reduce work time to find characteristic parameters of the paper currency with our experience and know-how owing to the ability of self-organization. We can hope robustness for defect of data or noise of conveyed paper currency because of the ability of generalization. Still more, we can transact the paper currency recognition with multi-task or multi-CPU owing to the parallel processing. In this paper, we propose a method for Japanese and U.S. paper currency recognition using NN's. Then we show the effectiveness and possibility of the present algorithm on developing period and its recognition ability compared with a conventional manual method by discriminative inequalities that engineering designers are used to apply [1], [2], [5]. Meanwhile, on the ordinary pattern recognition using NN's, the ability of recognition has been evaluated by only maximum value of the output unit [6], [7]. In other words, maximum value mainly has been adopted but its distribution of other output unit values has not been considered. Here, we pay attention to not only maximum value but also the distribution of the output unit values. We newly introduce a measure of reliability as an indicator for the error recognition [1], [2], [5], [6]. We show that the ability of recognition can be evaluated in detail by introducing this measure of reliability. On the other hand, when we try to implement the above NN to the usual commercial products, the NN scale is a serious problem. To solve this, the various methods using FFT have been proposed [2], [8]. But owing to complex pre-processing, they are not preferable for implementation of the commercial products.

In this paper, we propose a new method which condenses input pixels by a simple pre-processing using random masks. The inputs to the NN are not paper currency data or its Fourier power spectra but sums of these data which have been passed through the various random masks. It is shown that we can reduce NN scale using random masks without preventing the growth of the recognition ability.

II. Conventional Recognition Method

Conventionally, engineering designers are used to apply discriminative inequalities to recognize paper currency [1], [2], [5]. In this section, we describe this conventional method and its problems. These discriminative inequalities were determined manually. Namely, to recognize the paper currency, discriminative points are selected from each sensor. The characteristics of each paper currency from a set of discriminative points are extracted by the trial and error. The discriminative inequalities that contain the representative values of the paper currency are then determined. Using this method, paper currency recognition is executed with these discriminative inequalities. Fig. 1 shows a rough sketch of the conventional method to determine the discriminative inequalities. It is constructed by search of discriminative points and determination of thresholds. The former block explains the searching procedure of discriminative points corresponding to pixels which include sufficient information to discriminate the purposive paper currency from the rejected ones. A and B values enclosed by the rectangulars denote the total sums of the mean squared sensor values on the hatched areas A and B, respectively. The aim of the searching procedure is to find preferable A and B such that the distance (A value–B value) between the purposive paper currency and rejected

Manuscript received October 22, 1992; revised December 19, 1993.

F. Takeda is with the Development Center GLORY LTD., Himeji, 670, Japan.

S. Omatu is with the Depart ment of Information Science and Intelligent System, Faculty of Engineering, University of Tokushima, Tokushima, 770, Japan.

IEEE Log Number 9400110.

1045-9227/95$04.00 © 1995 IEEE

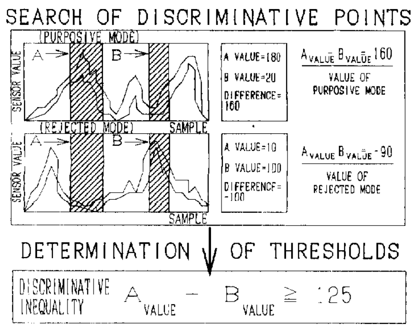


Fig. 1. Determination of discriminative inequalities.

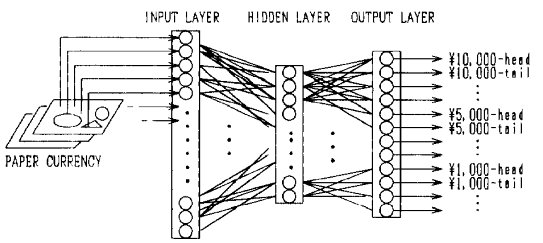


Fig. 2. Configuration of the proposed method with NN.

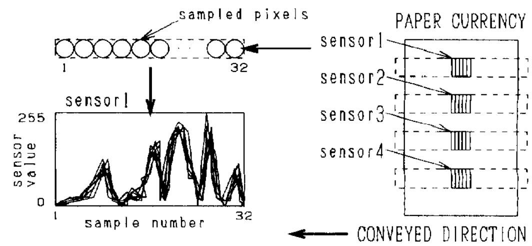


Fig. 3. Paper currency data and its sampling method.

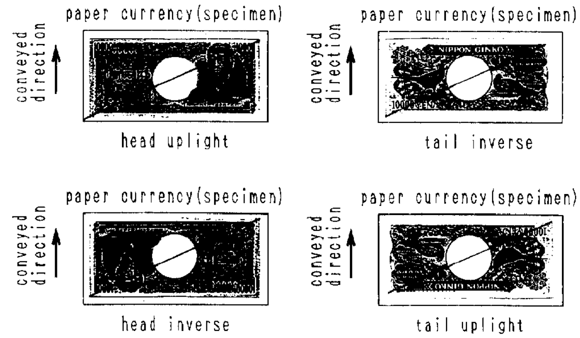


Fig. 4. Conveyed direction of paper currency.

one becomes as large as possible. The latter block is to determine the thresholds of discriminative inequalities. Using this inequalities, we can separate the purposive paper currency from rejected one as shown in Fig. 1 if the threshold is assumed 125 in this case. The discriminative inequalities are given by

$$\begin{aligned} f_i &= f_i(a_1, a_2, \cdots, a_m, b_1, b_2, \cdots, b_n) \\ &\geq \theta_i, \quad , a_j \in A, \quad b_k \in B \\ i &= 1, 2, \cdots, \iota, \\ & j = 1, 2, \cdots, m, k = 1, 2 \cdots, n \end{aligned} \tag{1}$$

where ι is the number of discriminative inequalities, m and n are the numbers of discriminative points, A and B are a set of discriminative points, θ_i is the threshold, and a_j and b_k are discriminative points. Here, m and n depend on i. In the conventional method, engineering designers have determined the number (ι) and parameters (a_j, b_k, θ_i) in discriminative inequalities between the purposive paper currency and the rejected one. However, it is difficult to give a systematic procedure to work of determining discriminative inequalities. This is due to the reason that the conventional method depends on the experience and know-how of engineering designers. So it has taken more than 6 months to obtain the final discriminative inequalities by the conventional method.

III. Recognition Method by Ordinary NN's

The proposed method using the NN's for paper currency recognition is three-layer configuration as shown in Fig. 2. We input paper currency data consisting of 32 samples $\times$ 4 sensors as shown in Fig. 3 or the Fourier power spectra of 17 amplitudes of FFT $\times$ 4 sensors to the NN [2], [5], [8]. The hidden unit number is 64 which have been decided through various experiments considering the over-fitting problem. Output unit number is 12 which correspond to recognition patterns. Namely, we recognize three kinds of Japanese paper currency such as ¥10 000, ¥5000, and ¥1000 and four conveyed directions such as head upright, head inverse, tail inverse, and tail upright as shown in Fig. 4 where the slope line in paper currency denotes specimen. We adopt the back-propagation method [9] for learning and is given by

$$\begin{aligned} \Delta W_{j,i}(t) &= -\varepsilon d_j o_i + \alpha \Delta W_{j,i}(t-1) + \beta \Delta W_{j,i}(t-2) \\ d_k &= (o_k - y_k) f' \quad (\mathrm{net}_k), \mathrm{net}_k \\ &= \sum_j W_{k,j}(t) o_j \quad \text{for output layer} \\ d_j &= \left(\sum_k W_{k,j}(t) d_k \right) f'(\mathrm{net}_j) \\ \mathrm{net_j} &= \sum_i W,_j, i(t) o_i \text{ for hidden layer} \end{aligned} \tag{2}$$

where $W_{j,i}(t)$ is weight from unit i to j, $\Delta W_{j,i}(t)$ is the change of weight $\Delta W_{j,i}(t)$, d is the generalized error, o is the output value, t is the sample, ε is the positive learning coefficient, α is the proportional coefficient of inertia term, β is the proportional coefficient of oscillation term. Here, β term has the role of escaping from a local minimum [9]. We regard that learning is converged when the sum of squared error between output unit values and desired values for each pattern becomes less than a threshold value of 0.001. The data is obtained by a high speed conveyed paper currency recognition machine [1], [2], [5] as shown in Fig. 5 and they are sampled from real products. This figure shows each sensor

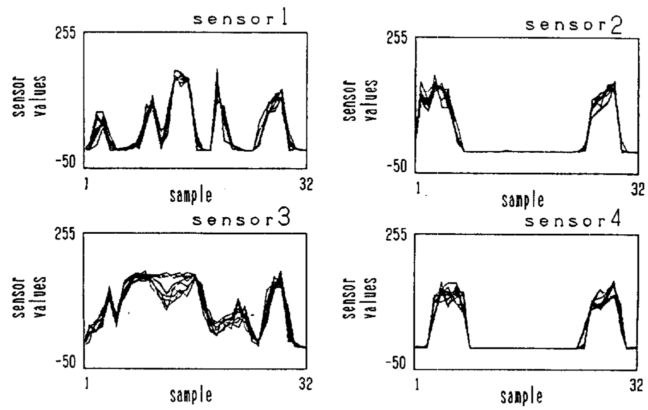


Fig. 5. Sensor data for ¥10 000 head upright.

data for ¥10 000 head upright for 10 pieces. The data set used are as follows:

1) Learning data; the kinds of paper currency are ¥1000, ¥5000, and ¥10 000. Each paper currency is not worn out and have not the defected corner. Number of each paper currency is 10 pieces.
2) Testing data; the number of each paper currency is 100 pieces, each of which is worn out and has the defected corner.

Henceforth, we represent the sensing data in a time series form. First, we adopt pass ratio ES_1 [6] as a recognition index and is given by (see (3) at bottom of page).

For comparison of recognition ability, we consider three methods. Namely, method (i) is the conventional method using discriminative inequalities, method (ii) is NN method with time series data, and method (iii) is NN method with Fourier power spectra. ES_1 for each method is 100% in this experiment. Still more, we need less than one month to determine the configuration of the NN and their parameters. This shows that the methods (ii) and (iii) are more superior than the method (i) on developing period.

IV. Scale Reduction of NN's by Random Masks

We show the effectiveness of NN's for paper currency recognition in Section III. However, the NN scale is one of the important design factors when we apply NN's to development of paper currency recognition machines. Generally, it is difficult to implement this type of NN's to usual paper currency recognition machines owing to its large NN scale. To solve this problem, the various methods which condense input pixels with FFT or other transformation have been proposed [10], [11]. But complex pre-processing is required for current paper currency recognition machines. Therefore, they are not preferable for implementation.

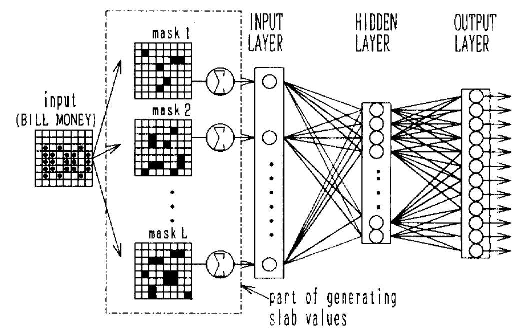


Fig. 6. Configuration of the scale reduction method by random masks.

We propose a method which condenses input pixels with simple pre-processing. Namely, we adopt a slab-like architecture [10]–[12]. In the present method, we use a slab value that is sum of pixels as the input to the NN. However, it may generate the same slab values even if the inputs are different. To solve this problem, we cover some parts of the input by using random masks. Then we apply this method to paper currency recognition.

Here, we determine the masking pixels in the following way. We generate random values $[-1, 1]$ using random functions where the total number of random values is equal to input pixels. We cover the pixels which correspond to the number of random values whose values are minus values. The configuration of the proposed NN with random masks is shown in Fig. 6. In this figure, some parts of input are covered with various masks in pre-processing. The sum of the pixels which are not masked becomes one slab value, which is used as an input value for the NN. Namely, both numbers of the mask kinds and slab values are the same. The configuration of the proposed NN is three layers and each layer has 16, 16, and 12 units, respectively.

$$ES_1 = \frac{\text{(the number of correctly recognized paper currency)}}{\text{(total number of evaluated paper currency)}} \times 100. \tag{3}$$

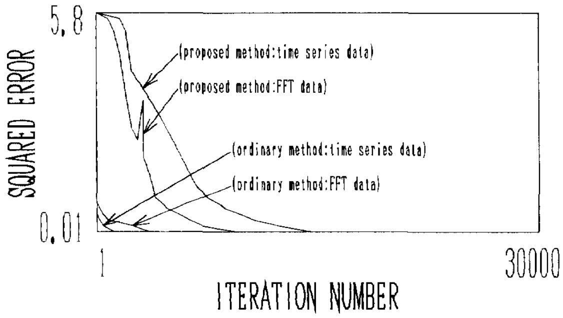


Fig. 7. Learning curves for time series data and FFT data.

TABLE I
COMPARISON OF THE NN SCALE BETWEEN PROPOSED METHOD AND ORDINARY ONE

Time Series Data	
Proposed Method:	16x16 + 16x12 = 448
Ordinary Method:	128x64 + 64x12 = 8,960
Fourier Power Spectra	
Proposed Method:	16x16 + 16x12 = 448
Ordinary Method:	68x64 + 64x12 = 5,120

We experiment in the following two cases. One is to use the time series data as an input to the proposed NN. Another is to use the Fourier power spectra to the proposed one. Fig. 7 shows the learning curves for the proposed method where "FFT data" means Fourier power spectra. Pass ratios ES_1 for both data are 100%. For comparison of the NN scale, we adopt the methods (ii) and (iii) that have been already described in Section III. In these methods (ii) and (iii), henceforth, we call the methods (ii) and (iii) the ordinary method. From this figure, the proposed method needs more time to converge than the ordinary one. However, we do not need on-line learning in paper currency recognition machines because of the products specification. We define the NN scale by the weight number. Table I shows comparison of the NN scales between the proposed method and the ordinary one. In these experiments, we can reduce the NN scale less than 1/10 compared with the ordinary method. Therefore, we find that the proposed method is effective to paper currency recognition and does not make worse recognition ability.

V. ANOTHER VERIFICATION FOR SCALE REDUCTION BY RANDOM MASKS

We verify an effect of the scale reduction by random masks using another paper currency recognition machine as shown in Fig. 8. The sensor system in the recognition machine can sample 216×30 pixels from paper currency. The sampled data has 1 byte gray level. Paper currency is conveyed in the parallel direction of its short part and its conveyed speed is 10 pieces/s. This experimental system can sample paper currency data by recognition machine on-line. Learning is executed off-line. Once we can obtain the suitable weights, this system recognizes paper currency using them on-line and its transaction speed is more than 3 pieces/s. The data set used here are as follows:

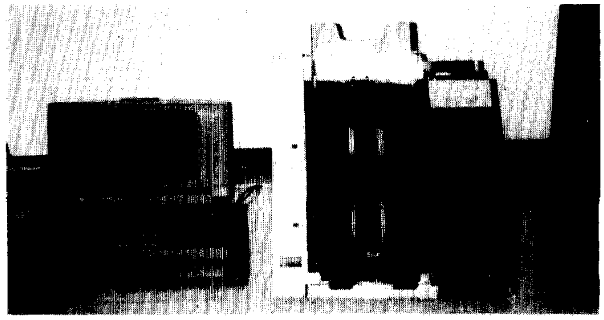


Fig. 8. An experimental system using the scale reduction method by random masks.

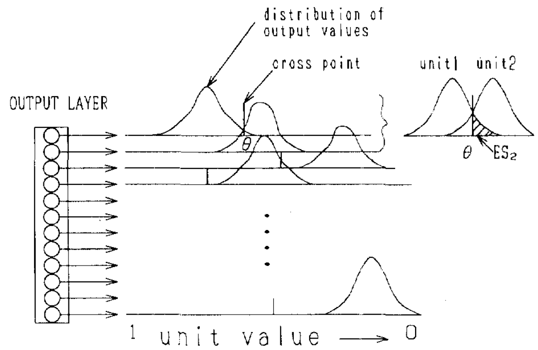


Fig. 9. Distribution of NN output values.

1) Learning data; the kinds of paper currency are \$1, \$5, \$10, \$20, \$50, and \$100. Each paper currency is not worn out and does not have the defected corner. The number of each paper currency is 10 pieces.
2) Testing data; the number of each paper currency is 2000 pieces, each of which is worn out and has the defected corner.

When we evaluate the recognition ability using ES_1, it becomes more than 92% for each paper currency kind.

VI. EVALUATION METHOD OF RELIABILITY

A. Standard of Reliability Evaluation

We newly introduce a standard of reliability evaluation [1], [2], [5], [6] as an index for the recognition ability. Generally speaking, the pattern classification by NN is based on the winner-take-all. However, considering output unit values, we can regard the difference between maximum value and other values of output units as a reliability measure. Furthermore, using several data for the same kind of paper currency, the output unit values are fluctuating and obey stochastic distribution. Error probability appears when the distribution of purposive mode (unit 1) and that of rejected one (unit 2) crosses each other as shown in Fig. 9.

We define upper probability as a standard of reliability evaluation and describe it as ES_2 [1], [2], [5], [6]. But the distribution of output unit values is asymmetry in [0, 1]. However, if we assume that this obeys Gaussian distribution

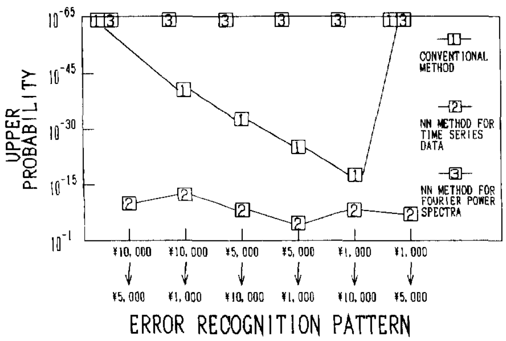


Fig. 10. Comparison of reliability.

N(μ: average value, σ: standard deviation), then ES_2 can be given by

$$ES_2 = \int_{\theta}^{\infty} \frac{1}{(2\pi)^{\frac{1}{2}}\sigma_p} \exp\left(-\frac{(x_p - \bar{x}_p)^2}{2\sigma_p^2}\right) dx \qquad (4)$$

where x_p is the output unit value of purposive mode, $\bar{x}_p$ is the mean value of x_p, σ_ρ is the standard deviation of purposive mode, θ is the x coordinate of cross point between the distribution of purposive mode and that of rejected one. We can regard that the recognition reliability is high when ES_2 is small.

B. Comparison of Reliability

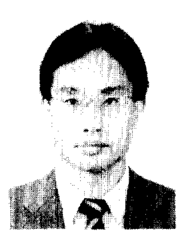
Fig. 10 shows the comparison of reliability using ES_2 for Japanese paper currency. We choose the worst ES_2 (the largest ES_2) as the reliability value for each error recognition pattern. From Fig. 10, the reliability of the method (ii) is lower than that of the method (i). It is supposed that the discriminative points of the method (i) are independent of conveying paper currency with the experience and know-how. So ES_2 by the method (i) is not influenced so much by conveying paper currency [1] [2]. But ES_2 by the method (iii) is much higher than that of the methods (i) and (ii). Because we can reduce the influence of fluctuation of conveyed paper currency using Fourier power spectra [2]. Still more, there is no difference of recognition ability among the methods (i), (ii), and (iii) if ES_1 is used. However, we can find the difference among them if we use ES_2. Thus, ES_2 is effective for paper currency recognition.

VII. Conclusion

In this paper, we have applied the NN to paper currency recognition and showed the effectiveness compared with a conventional manual method. Furthermore, we have proposed a structure reduction method of the NN using random masks and showed its effectiveness for time series data and its Fourier power spectra. Finally, we also introduced the new evaluation method for reliability and showed its effectiveness using real data. We expect that the present method will promote compactness, high speed transaction, and low cost of paper currency recognition machines.

References

[1] F. Takeda, S. Omatu, and T. Inoue, "An expert system for determining the discriminative functions for bill money recognition," *Trans. Info. Process. Soc. Japan*, vol. 33, no. 7, pp. 980–9 90, 1992, in Japanese.
[2] F. Takeda, S. Omatu, T. Inoue, S. Onami, and K. Konishi, "High speed conveyed bill money recognition with neural network," *Trans. Inst. Elect. Eng. Japan*, vol. 112-C, no. 4, pp. 101–110, 1992, in Japanese.
[3] Sonehara, "An application of neural network to image data," *Trans. Inst. Syst., Control and Info. Eng.*, vol. 35, no. 1, pp. 11–18, 1991, in Japanese.
[4] S. Amari, *The Present and the Future of Neural Network*. Kyoritsu Press, 1990, in Japanese.
[5] F. Takeda, S. Omatu, T. Inoue, and S. Onami, "High speed conveyed bill money recognition with neural network," in *Proc. IMACS/SCINE Int. Symp. Robotics, Mechatronics and Manufact. Syst.* Kobe, Japan, 1992, vol. 1, pp. 16–20.
[6] N. Suzuki, Y. Yasuoka, and T. Shimura, *Probability and Statistics Seminar*. Kyoritsu Press, 1979, in Japanese.
[7] M. Nagao, *Pattern Information Processing*. Corona Press, 1986, in Japanese.
[8] F. Takeda, S. Omatu, T. Inoue, and S. Onami, "Bill money recognition using neural network with FFT as pre-processor," *Trans. Inst. Syst., Control and Info. Eng.*, vol. 5, no. 7, pp. 265–2 73, 1992, in Japanese.
[9] S. Nagata, M. Sekiguchi, and K. Asakawa, "mobile robot control by a structured hierarchical neural network," *IEEE Control Syst. Mag.*, vol. 10, no. 2, pp. 69–76, 1990.
[10] M. Fukumi, S. Omatu, F. Takeda, and T. Kosaka, "Rotation-invariant neural pattern recognition system with application to coin recognition," *IEEE Trans. Neural Net,*, vol. 3, pp. 272–279, 1992.
[11] B. Widrow, R. G. Winter, and R. A. Baxter, "Layered neural nets for pattern recognition," *IEEE Trans. Acoust., Speech Sig. Process.*, vol. ASSP-36, pp. 1109–1118, 1988.
[12] F. Takeda and S. Omatu, "Bank note recognition system using neural network with random masks," in *Proc. World Cong. Neural Net.*, Portland, OR, 1993, vol. 1, pp. 241–244.



Fumiaki Takeda received the B. E. and M. E. degrees in mechanical engineering from the Nayoga Institute of Technology, Aichi, Japan, in 1982 and 1984, respectively. He received the Ph. D. degree in the Facult y of Engineering, University of Tokushima, Japan in 1994.

From 1984 to 1986, he was with Toyota Central Research and Development and in 1986 he joined GLORY Ltd., Himeji, Japan. Since then, he has been engaged in research and development work on a recognition system for paper currency. His research interests include neural networks, expert system, and genetic algorithms as applied to paper currency recognition.

Sigeru Omatu received the B. E. degree in mechanical engineering from the University of Ehime, Japan in 1969, and the M. E. and Ph. D. degrees in electronics engineering from the University of Osaka Prefecture , Japan, in 1971 and 1974, respectively.

From 1974 to 1975 he was a Research Associate, then a Lecturer (1975–1980), an Associate Professor (1980–1988), and finally a Professor at the University of Tokushima, Japan. From November 1980 to February 1981 and from June to September 1986, he was a Visiting Associate on Chemical Engineering at the California Institute of Technology, Pasadena. From November 1984 to October 1985 he was a Visiting Researcher at the International Institute for Applied Systems Analysis, Austria. His current interests center on neural networks and distributed parameter system theory.

Dr. Omatu received the Excellent Young Researcher Award from the Society of Instrument and Control Engineers of Japan in 1972 and a Best Paper Award from the Institute of Electrical Engineers of Japan in 1991. He is an Associate Editor of the *International Journal of Modeling and Simulation*, the *IMA Journal of Mathematical Control and Information*, and of the IEEE Transactions on Neural Networks. He is a co-author of *Distributed Parameter Systems: Theory and Application* (Oxford University Press).