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ASSESSMENT OF ENVIRONMENTAL VARIABLES USING ARTIFICIAL NEURAL NETWORK

Yuhei Matsubara, Hideaki Noda and Wataru Shiraki
Tottori University
4–101, Koyama, Tottori–shi, 680, JAPAN

INTRODUCTION

The knowledge on how the biomass reacts the environmental factors is very vital for the assessment of the marine environmental change induced by the construction of the coastal structures. In general, however, it is very difficult to reach the whole understanding the role of the biological and physical variables, therefore such assessment has been depending on experienced inspections of biologists, ecologists and engineers.

Nakamura (1991) presented a logical chain judgements method which would lead sound decisions on the selection of proper variables in a given environment as "Environmental Analysis Logic (EAL)". If there is a sufficient on–site environmental data and Nakamura's EAL leads one to introduce specific variables to attain expected goals for biomass production and control in a given environment. But Nakamura's EAL depends on the experienced personal judgement for the evaluation of the environments, it is very laborious and time–consuming process in case of a large numbers of environmental variables.

In recent years the network of artificial neurons has received considerable attention in the field of pattern recognitions and the identification and control of dynamic systems. Especially the neural approach to computation has emerged to tackle problems for which conventional computations have proven ineffective. Such problems arises when a computer is asked to interface with the real world which cannot be modeled with concise mathematical expressions.

The general characteristics of neural networks including morphological features are similar to biological neural networks, and the basic rule to computation are common in both networks. This leads to computer that can tackle such problems very effectively. The purpose of this paper is to investigate the possibility of using a computational data processing technique, an artificial neural network (ANN), for analyzing the relationship between various environmental variables and the changes. Our goal is first to propose a specialized training scheme of the network based on backpropagated errors. Secondary, we try to present the applicability of the proposed algorithm to EAL by using a environmental data for the reed zone preservation project in Biwa lake of Japan.

Human brain and ANN

Neurons are nerve cells, and neural networks are interconnection among of these cells. The network of artificial neurons, usually called as an artificial neural network (ANN), is a data processing system consisting of a number of simple, highly interconnected processing elements in architecture inspired the structure of human brains.

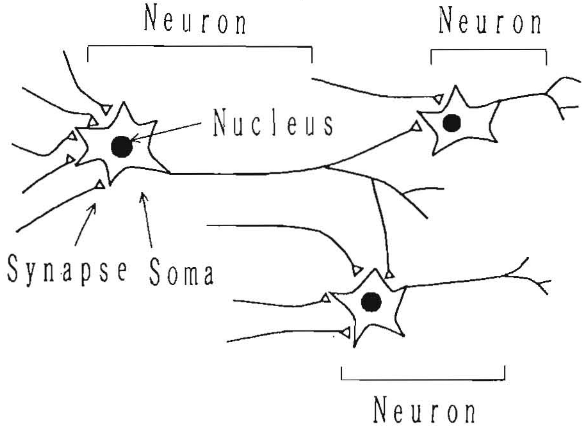

Figure 1 Network of real neurons

Figure 1 shows a diagram of a real neural network which consists of somas, axons, dendrites and synapses. Soma is a cell body, and axons are long transmission-linelike structures. Dendrites are branching structure where signals are picked up, and the synapses are the physical connection at the tail end of the axon. When a signal arrives at a synapse, it elicits the neurotransmitter from a soma through an axon, which builds up until its summation exceeds a certain threshold. When this happens, an signal is elicited and transmitted to the neighboring cells.

Figure 2 demonstrates a mathematical abstraction of a neuron, where x_i (i=1,2,3 ...) equals the inputs transmitted to the receiving neurons, W_{ji} represents weighing function which is the strength of association between neurons. A neuron receives signals as a train of pulses through the synapses and then performs a weighted algebraic summation of the inputs as follows.

$$X = \sum_{i}^{n} W_{ji} \, x_i \qquad (1)$$

The sum of the weighted signals constitutes an activation function , and sigmoidal functions are introduced in general for the activation function to evaluate the threshold condition.

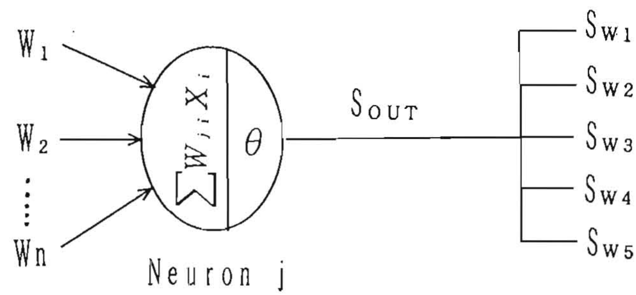

Figure 2 mathematical abstraction of a neuron

A sigmoidal function is expressed by

$$S_0 = 1 \;/\; (1 + \exp(- (X - \theta) / T)) \qquad (2)$$

where S_0 is the output of the activation function, θ is the temperature coefficient and T is the gradient coefficients. θ and T are important parameters which controls the

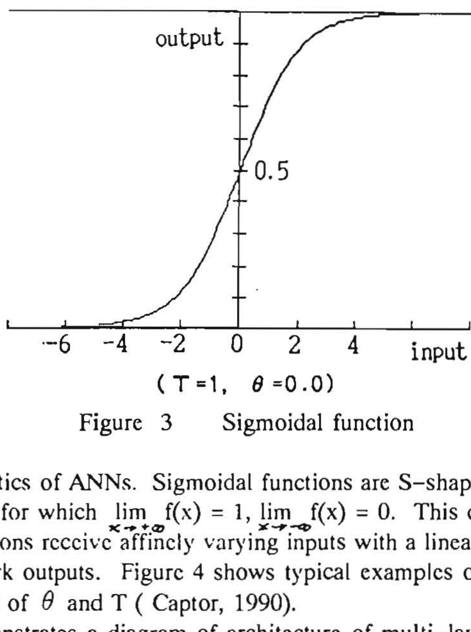

Figure 3 Sigmoidal function

learning characteristics of ANNs. Sigmoidal functions are S-shaped function, as shown in Figure 3, those for which $\lim_{x \to +\infty} f(x) = 1$, $\lim_{x \to -\infty} f(x) = 0$. This describes the situation when identical neurons receive affinely varying inputs with a linear combination of their outputs as a network outputs. Figure 4 shows typical examples of sigmoidal functions with various values of θ and T (Captor, 1990).

Figure 5 demonstrates a diagram of architecture of multi-layered neural networks used in this study. The first layer, the input level, is a raw of transducers that receive the input signals from the external stimulus. The second level is the hidden layer that propagate the output from the first level forward through layers to the final layer, the

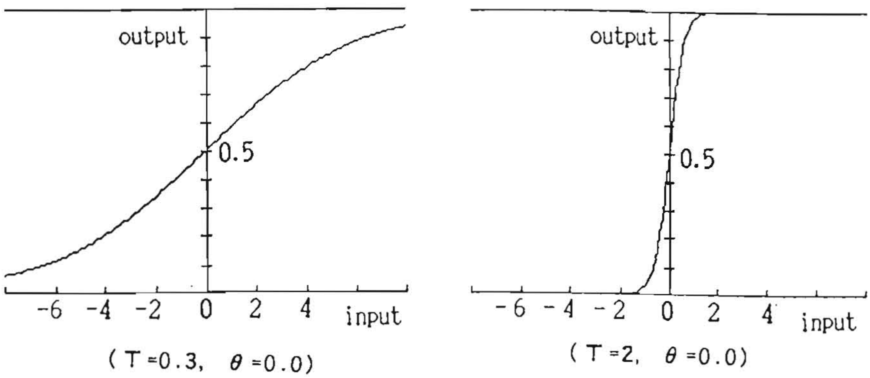

Figure 4 Sigmoidal function

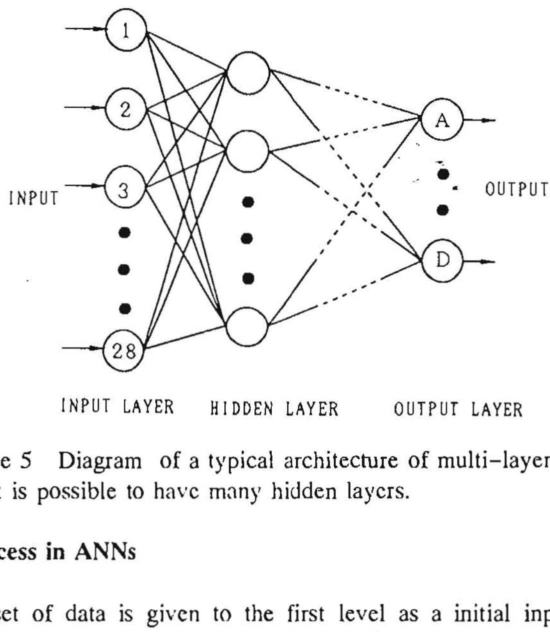

Figure 5 Diagram of a typical architecture of multi-layered ANNs

output level. It is possible to have many hidden layers.

Learning process in ANNs

when a set of data is given to the first level as a initial input, those data are transmitted forward through several layers of processing elements to the final output layer. The weighted connections in each layer play an important role in these architecture. The output thus generated is compared with the desired output. The error, difference between those two sets of outputs, is calculated by the mean square errors as follows

$$E = \left(\sum_{i} (Y_i - t_i)^2 / n \right)^{1/2} \qquad (3)$$

where E is the mean square error, Y_i is actual output of ANNs, t_i is the desired output and n is the number of processing elements. If the error excess the certain critical value, then the same input is presented to ANNs. The resulting output would more closely match the desired output. When the learning of five thousands times was done, ANNs was regarded as a converged condition.

Application to EAL by ANNs

As an application of the environmental analysis logic procedure by using ANNs, a set of research data obtained in reed zone preservation project in Biwa lake, Shiga prefecture in Japan was introduced (Committee of red zone preservation in Biwa lake, 1978). The aim of the project was to enlarge the reed zone in the Biwa lake since the reed is a well known useful plant for improvement of the water quality. Many of the physical on-site data were selected as initial input to ANNs. Figure 6 shows the observed areas in Biwa lake. In Field observations physical and topographical data of reed zone, and waves and winds data were collected in forty nine areas. Table 1 presents the relationship between the reed zone and physical condition. Each reed zone was classified into three classes, from rank A to C, graded by specific ways as shown in Table 2.

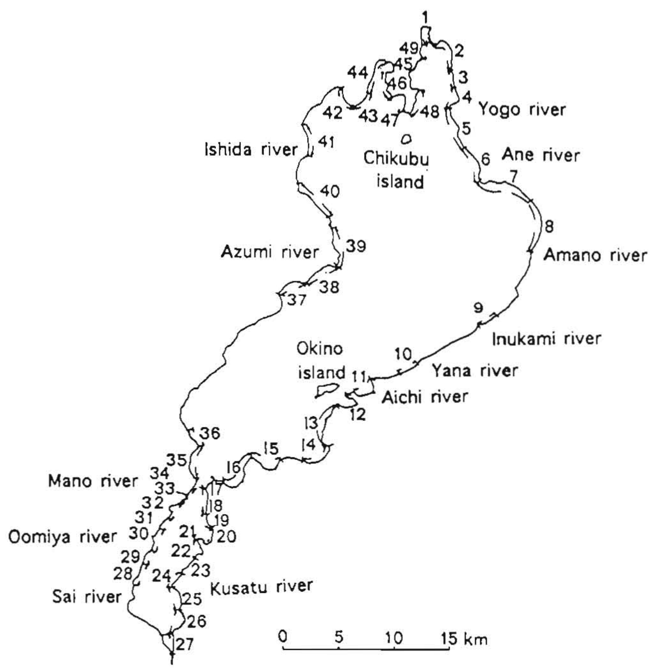

Figure 6 Survey area of reed zone

Table 1 Relation of reed zone and physical condition

No.	y	x_i					
		h (m)	I_i	I_f	B	h_b (m)	E
5	A	1	1/120	1/100	S	1.30	5.38
19	A	0.8	1/70	1/150	M,S	0.80	4.56
20	A	0.5	1/40	1/80	M	0.73	14.05
22	A	0.9	1/50	1/100	M	0.90	16.85
24	A	0.7	1/50	1/50	M,S	0.66	18.97
25	A	1	1/50	1/100	S	1.10	1.51
26	A	1	1/50	1/80	M,S	1.10	17.37
35	A	1.3	1/50	1/50	S	1.07	1.92
40	A	1	1/100	1/100	S	1.37	0.96
2	C	0.5	1/10	1/10	St,G	0.58	3.19
3	C	0.5	1/10	1/10	St,G	0.62	1.26
4	C	0.5	1/10	1/10	G,M,S	0.71	16.85
8	C	0.5	1/10	1/50	S	1.44	24.38
12	C	1	1/10	1/10	S,St	0.53	12.94
13	C	2	1/10	1/20	S	1.14	78.28
15	C	0.7	1/20	1/100	S	1.26	51.6
16	C	1	1/20	1/60	S,G	1.05	54.32
17	C	0.2	1/10	1/30	S	0.59	12.94
18	C	0.5	1/20	1/30	S	0.59	3.17
29	C	1	1/10	1/50	S,M	0.66	1.197

y : ranking by Table 1 h : maximum depth of reed zone
I_i: slope of reed zone I_f: front slope of reed zone
h_b: breaking depth of wave E :energy of wave (unit : 232kw/m/day)
B : kind of bed material (s : sand, M : mud, G : gravel, St : stone)

Table 2 Ranking of Reed Zone (y)

condition ranking	A (good)	B (normal)	C (poor)
area (m^2)	>40000	40000 - 2000	2000>
width (m)	>20	20 - 1	1>
density of reed	◎	○	△
growth of reed	◎	○	△

Results

Table 3 indicates the results of the estimation of ANNs with various type of the architecture. In the application of ANNs three types of multi-layered models; three layers, four layers and five layers model, were examined. In each ANNs model the number of the processing elements were changed as shown in Table 3. The field data obtained in twenty nine stations were chosen and given to ANNs as the initial input for EAL, then the five thousands learning steps were repeated. After the learning of the network, ANNs evaluated the rank of the reed zone for another set of data which were obtained at 6 observation areas. For the verification of the estimation by ANNs, the correctness of the estimation was evaluated by

Evaluation Accuracy (%) = (number of the zones estimated correctly) / 6

The results of the accuracy of estimation are also presented in Table 3.

Table 3 Results of the evaluation by ANNs

MODEL No.	NUMBER OF LAYERS	ARCHTECTURE	ERRORS	CONVERSION	ACCURACY (%)
3	3	28－25－4	0. 030	△	33. 3
4	3	28－15－4	0. 034	△	33. 3
5	3	28－ 5－4	0. 030	△	33. 3
6	4	28－25－25－4	0. 027	△	33. 3
7	4	28－15－15－4	0. 039	△	33. 3
8	4	28－ 5－ 5－4	0. 054	○	0
9	5	28－25－25－25－4	0. 049	○	66. 7
10	5	28－15－15－15－4	0. 057	○	100
11	5	28－ 5－ 5－ 5－4	0. 054	○	100

In case of three and four layers' ANNs models, the estimation correctness are 33.3 per cent except the result of model 7. Also the state of the conversion of each model are not so good. On the other hands, the five layers ' ANNs are rather good estimator and those of correctness are above 66.7 per cent. Especially in case of model 10 and 11 sufficient results were obtained. It should be noticeable that even if the architecture of the network is rather simpler, as shown in model 11, the estimation level is perfect and ANNs reached to the conversion in small repetition time.

Conclusions

We have demonstrated how ANNs can be used to solve the problems of environmental evaluation and classification. In this study a successfully trained ANNs was established, then can be guaranteed of finding the global correct solution and its usefulness was verified. Using this neural network system, inexperienced engineers can find out the optimum sets of the environmental variables to be adopted in the assessment. Furthermore a well learned ANNs can be used to find the most important input variables that strongly influence the environmental change. Finally the method by using ANNs proposed here has been found to be very powerful for environmental assessment as a new rational approach of evaluation of impacts.

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