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Pattern Recognition of Long-term Ecological Data in Community Changes by Using Artificial Neural Networks: Benthic Macroinvertebrates and Chironomids in a Polluted Stream

Chon, Tae-Soo, Inn Sil Kwak and Young Seuk Park

Department of Biology, Pusan National University, Pusan 609-735, Korea

ABSTRACT: On community data, sampled in regular intervals on a long-term basis, artificial neural networks were implemented to extract information on characterizing patterns of community changes. The Adaptive Resonance Theory and Kohonen Network were both utilized in learning benthic macroinvertebrate communities in the Soktae Stream of the Suyong River collected monthly for three years. Initially, by regarding each monthly collection as a separate sample unit, communities were grouped into similar patterns after training with the networks. Subsequently, changes in communities in a sequence of samplings (e.g., two-month, four-month, etc.) were given as input to the networks. After training, it was possible to recognize new data set in line with the sampling procedure. Through the comparative study on benthic macroinvertebrates with these learning processes, patterns of community changes in chironomids diverged while those of the total benthic macro-invertebrates tended to be more stable.

Key Words: Adaptive Resonance Theory, Artificial neural network, Benthic macroinvertebrates, Chironomids, Kohonen network, Patterning community changes.

INTRODUCTION

Verifying ecological data from long-term surveys is important in ecosystem management. For fulfilling the goal of sustained management of ecosystems, a steady and consistent sampling under a well-defined survey planning is necessary, and this should be followed by an effective analysis. Classification or patterning of collected data is the first step in characterizing the ecological status of target communities on long-term data. Data for ecosystem or community samplings, however, usually consist of multi-variables and are generally difficult to analyze since it is complex, varying in locations and times. Traditionally, multivariate analyses have been used to analyze ecological data, and there have been numerous classifications of communities through conventional multivariate analyses (e.g., Legendre and Legendre 1987, Ludwig and Reynolds 1988, Quin *et al.* 1991). The application of these conventional methods, however, are generally limited to linear data (Ludwig and Reynolds 1988).

In terms of patterning community changes, even fewer studies have been conducted: they were mostly classified in static terms, not in dynamic terms. Legendre *et al.* (1985) and Legendre (1987) discuss classifying communities in temporal domain utilizing ordination and segmentation techniques in multivariate data series. Turchin and Taylor (1992) review time series analysis in analyzing dynamic data for populations. Patterning temporal development of community, however, has been an important topic in ecosystem management in the long-term data. Especially in aquatic ecosystems, communities are vulnerable to various disturbances caused by natural and anthropogenic agents, and subsequently develop in a characteristic manner in response to disturbances as time proceeds (Sladecek 1979, Hellawell 1986). Patterning these changes in communities would be important in monitoring ecological status of the target ecosystem. The long-term survey on the on-time analyses is necessary for characterizing 'changes' in communities. It is helpful for predicting the future development of the community, for monitoring water quality and risk assessment, and for developing strategic tools for the sustained management of aquatic ecosystems.

Recently, artificial neural networks have been noted for their efficacy in patterning nonlinear data. They are information-processing systems that autonomously develop operational capabilities in adaptive response to an information environment (Hecht-Nielsen 1990). The networks have been effectively used for pattern recognition in the various fields of electronics and computer sciences, and have been recently applied to other fields (e.g., Lohninger and Stancl 1992, Melssen *et al.* 1993). In ecology, artificial neural networks have been mainly implemented in classifying groups (e.g., Chon *et al.* 1996, Levine *et al.*, 1996), patterning complex relationships (e.g., Lek *et al.* 1996, Huntingford and Cox 1996, Tuma *et al.* 1996) and predicting population developments (e.g., Elizondo *et al.* 1994, Tan and Smeins 1996). Chon *et al.* (1996) utilizes the Kohonen network to classify community data. There has been a focus on dynamic neural networks for patterning spatio-temporal data in electronics and computer sciences (e.g., Kung 1993, Giles *et al.* 1994). To extrapolate the previous community classification in a static manner (Chon *et al.* 1996), we devised a simple method to pattern the changes in communities by utilizing two unsupervised learning networks in combination (Chon *et al.* 2000). To verify the sustainability in patterning community changes by this method, a comparative study was conducted on the total invertebrates and chironomids. The consistency and variability were observed as sampling interval was increased to recognize new data sets, as well as to assist in biological interpretation on the development of polluted communities.

METHODS

Network process

Initially, all of the community data for one -time sampling were trained by ART (Fig. 1). Weights, b_{ji} (0), were initialized with some small numbers between the output node j and the input node i. Density of an important taxa, x_i, was given to the network. Then, the distance, $d_j(t)$, was calculated for each output node, j, as the following (Pao 1989):

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$$d_j\,(t) = \sqrt{\sum_{i=0}^{n-1}\{b_{ji}\,(t) - x_i\}^2}$$

where n is the number of input nodes

Among the calculated distances, the node j which has the shortest distance, $d_j(t)$, is sele-

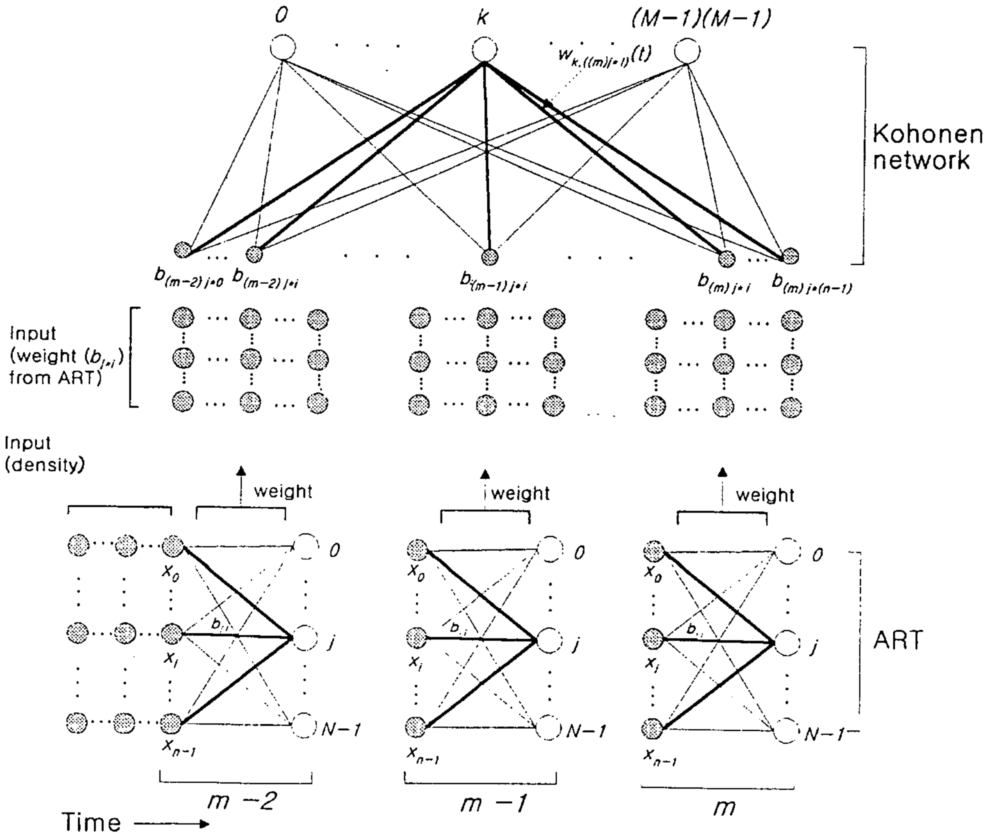

Fig. 1. A flowchart for training community changes with a combined use of two unsupervised learning algorithms, the Adaptive Resonanace Theory (ART) and the Kohonen network (Chon *et al.* 2000).

cted as j^*. If $d_j^*(t)$ is smaller than ρ, which is the threshold parameter in determining vigilance, the input is assigned to the output node j^*, then $b_{j^*i}(t)$ is updated as the following:

$$b_{j^*i}(t+1) = \frac{c}{c+1} b_{j^*i}(t) + \frac{1}{c+1} x_i$$

where c is the number of sample units classified to node j^*. If $d_j^*(t)$ is larger than ρ, the input is assigned to a new output, and its weight $b_{j^*i}(t)$ is assigned as shown below:

$$b_{j^*i}(t+1) = x_i$$

Weights produced by ART preserved conformational characteristics of the input data for each sampling time through training (Zurada 1992). Subsequently, weights trained for one month in ART were combined sequentially to be given to the Kohonen Network as inputs for the sampling times in m-2, m-1, and m, if it was considered as a three-month sampling (Fig. 1). In the Kohonen Network, M^2 neurons were used for output, which could be determined empirically based on the neurons, efficiency of convergence and their sensitivity to the discrimination among patterns. In this case, a two-dimension array of 9 by 9 neurons was used. The weights in the Kohonen Network were represented as $w_{k,(mj^*i)}(t)$. Similar to ART, the weights were randomly assigned with small values. When the input vector was sent through the network, each output neuron, k, computed the total distance, $d_k(t)$, between the input vector and the weights as shown below:

$$d_k(t) = \sum_{m=0}^{T-1} \sum_{i=0}^{n-1} [b_{j^*i}(t) - w_{k,(mj^*i)}(t)]^2$$

The neuron, the weight vector of which has the shortest distance to the input vector, was chosen to be the winning neuron. The winning and its neighboring neurons were allowed to learn by changing the weights, in a manner as to further reduce the distance between the weight and the input vector as follows:

$$w_{k,(mj^*i)}(t+1) = w_{k,(mj^*i)}(t) + \eta(t)(b_{mj^*i} - w_{k,(mj^*i)}(t))Z_{mj^*i}$$

$Z_{(mj^*i)}$ is assigned "1" for the winning and its neighbor neurons while the rest of the neurons are assigned "0". η(t) (e.g. 0.1~0.4) denotes the fractional increment of correction. Detailed algorithm in the Kohonen Network, including the determination of the neighbor neurons, could be referred to Kohonen (1989), Hecht-Nielsen (1990), Zurada (1992) and Chon *et al.* (1996). After the training was completed, newly collected data for community changes could be given to the trained network for recognition. Then, the new data was given to ART and the weights were updated subsequently. The updated weights were then arranged sequentially for a given period, and were given to the trained Kohonen network for recognition. This made it possible to pattern the community changes on the on-time basis as the sampling proceeded.

Field data

The benthic macroinvertebrate communities were collected monthly in the Soktae stream in the Suyong river from March 1992 to April 1995 (Fig. 2). A wide range of organic pollution was observed at the study sites from oligosaprobity to polysaprobity. Community compositions varied correspondingly to the biological index, TBI (Trent Biotic Index: Woodiwiss 1964) and BOD (Fig. 2). Additional ecological information for benthic macroinvertebrates in the Suyong river is also reported elsewhere (Kang *et al.* 1995, Yoon and Chon 1999).

The total number of species collected at the sample sites was 132. Species were grouped into seven selected taxa (Gastropoda, Oligochaeta,

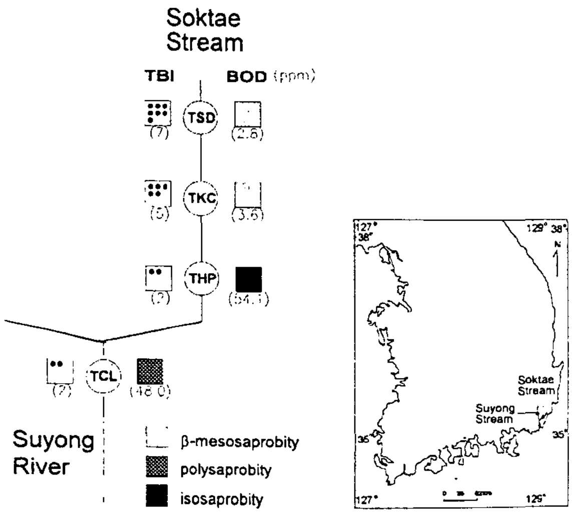

Fig. 2. The sample sites for collecting benthic macroinvertebrates in the Soktae stream, Suyong River in Korea from March 1992 to April 1995. TSD, TKC, THP and TCL represent the names of sample sites, Sadeungkol, Kochon, Hapansong and Chungli, respectively (modified from Chon *et al.* 1996).

Trichoptera, Ephemeroptera, Odonata, Diptera (except Chironomidae), and Chironomidae) in order to represent the overall ecological status of the sampling sites, as well as to eliminate noise effects due to species that rarely appear at low densities. Chironomids, consisting of many species and known independently to represent water quality (Chon *et al.* 1996), were compared with the total benthic macroinvertebrates. Among the 48 species of collected chironomids, the following four most abundant and characteristic species were selected: *Chironomus flaviplumus, Orthocladius suspensus, Cricotopus* sp. 1, *Orthocladius* sp. 2. *Chironomus flaviplumus* and *Orthocladius* sp. 2 are known to be collected at highly polluted sites of poly-saprobity, while *Orthocladius suspensus,* and *Cricotopus* sp. 1 are observed at the polluted sites of α-mesosaprobity (Chon *et al.* 1996). Fig. 3 shows the community dynamics of the two groups. Densities (number of individuals per m^2) in each selected taxa during the study period were provided as inputs for training with the ART as previously explained. Collected data from March, 1992 to February, 1994 was given as inputs for training in the total invertebrates. Due to the time required for classification and specimen handling, samplings in a shorter period of from March, 1992 to August 1993 were used for training in chironomids. Community data of the rest months after February, 1994 were used for recognition in the total invertebrates, while samplings for six months after August, 1993 were used for recognition in chironomids. For the convenience of calculation time at PC level, as well as for feasibility in predicting water quality in a short term in the field, a period of four months was selected as the training period in representing the community changes.

TRAINING AND RECOGNITION

Patterning one-month samples

The input data, regarding each monthly collection as a separate sample unit, was provided to the networks to produce the final map after the training by the Kohonen network. Patterns of communities of the total benthic macroinvertebrates on the map reflected impacts from the pollution (Fig. 4a). Being separated from the other less-polluted sites, a large number of communities collected from highly polluted sites of TCL and THP (see Fig. 1) formed a large group on Neuron (1: x axis, 5: y axis) (Group A). At these sample sites, Oligochaetes dominated by *Limnodrilus hoffmeisteri* and chironomids mainly consisting of *Chironomus flaviplumus* were highly

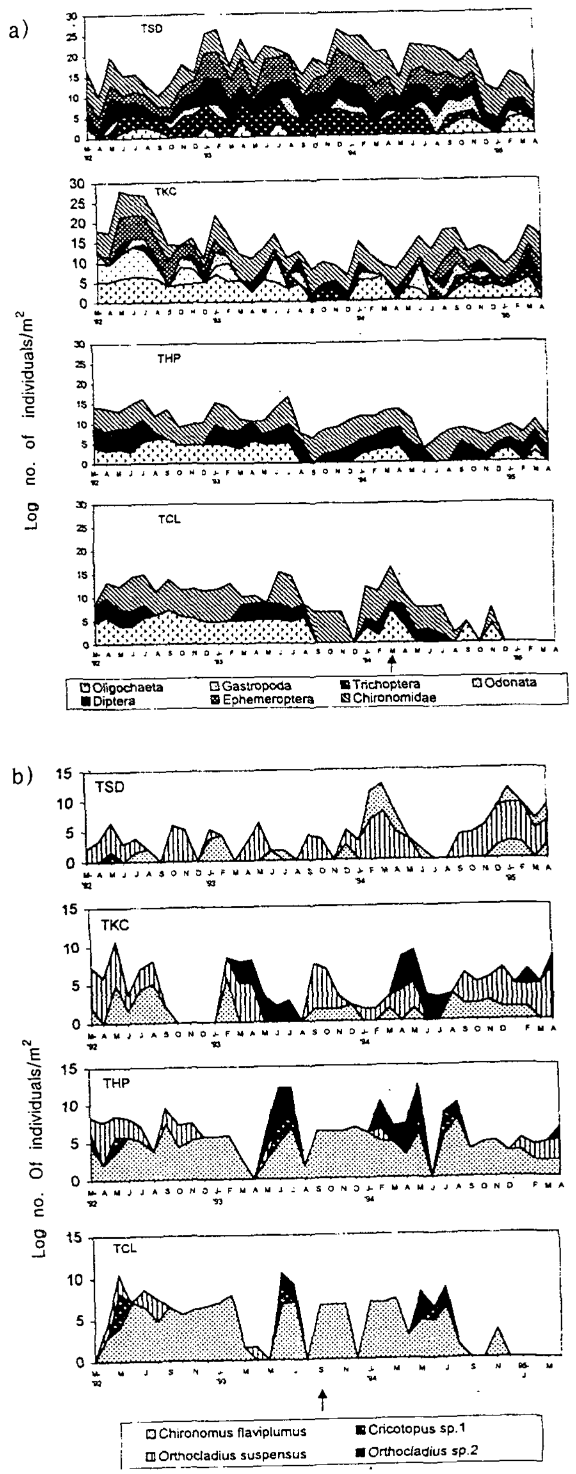

Fig. 3. Monthly changes in densities (log number of individuals per m^2) in selected taxa of benthic macroinvertebrates (a) and chironomids (b), which were collected in the Soktae stream, Suyong River in Korea from March 1992 to April 1995. Arrow represents the time when recognition was started.

abundant. These two species are considered to be indicators for organic pollution (Brinkhurst 1974, Andersson *et al.* 1978, Yoon and Chon 1996, 1999).

A large number of samples, mostly from a relatively clean site of TSD, formed another large group on Neuron (8,1) (Group B). In this group, densities tended to be evenly high in all taxa, reflecting high diversity in communities. The other small groups were formed on Neuron (2,0) (Group C) and Neuron (0,8) (Group D). Group C represented the communities in low densities, mainly collected from TSD and TKC. In this case, densities were generally low due to environmental disturbance of flooding. Group D patterned communities from an intermediately polluted site TKC, where diversity was in an intermediate level and neither chironomids nor oligochaetes were present.

The mapping of chironomid communities was somewhat similar to that of the selected benthic macroinvertebrates (Fig. 4b). Groups A and B

a)

	0	1	2	3	4	5	6	7	8
0	L3-12 L4-10*		C D2-3 D2-6 D2-7 D2-8 D2-9 D3-4 D3-7 C2-8 C4-10* C5-3* P4-12* P5-1* L4-8* L4-9* L4-11*		P2-10	C3-5 C3-7 C4-5*		D3-9 C3-12 C4-4* P4-6* P4-9* P4-10* P4-11* P5-2* P5-4* L4-5* L4-6*	C2-12 C3-8
1				C2-9 C5-1		C4-12* C5-2*		C3-11	B D2-5 D2-10 D2-11 D2-12 D3-1 D3-2 D3-3 D3-6 D3-8 D3-10 D3-11 D3-12 D4-1 D4-2 D4-3* D4-4* D4-6* D4-7* D4-8* C4-7* C4-8* C4-9* C4-11* C5-4*
2	P3-8				D2-4				C3-10
3	L2-3 L2-4 L3-3 L3-4 L4-4*	P4-2 P4-7*				P3-9			D4-5* C3-9
4			P3-11					D3-5	
5	L3-5	A D4-12* C3-4 C4-1 P2-3 P2-4 P2-5 P2-6 Pw-7 P3-1 P3-2 P3-3 P3-6 P3-7 P4-1 P4-3* P4-4* P4-5* L2-5 L2-6 L2-7 L3-6 L3-7 L4-2 L4-3*	L3-9	P3-10 L4-7*					
6	P3-4 L3-8	L3-10	L3-11						
7	D5-3* C4-3* P2-8	D5-1* P3-12	P3-5	L4-1			P2-11		L3-1
8	D D4-9* D4-10* D4-11* D5-2* D5-4* C2-3 C2-4 C2-5 C2-6 C2-7 C2-10 C2-11 C3-1 C3-2 C4-2 P5-3*	C3-6 C4-6		P2-12	P2-9 L2-8 L2-9 L2-10	C3-3 L2-11		L2-12	L4-8* L3-2

Fig. 4. One-month mapping of the benthic macroinvertebrate communities, collected from the Soktae Stream, Suyong River when trained by artificial neural networks. The names of sample sites are abbreviated with the following: D:TSD, C:TKC, P:THP, L:TCL. Letter-number combination represents the sample site, the year and the month of when a sample was collected, respectively. For example, L2-5 means the sample collected at TCL in May, 1992. The name of sample sites with asterisk mark represents that the community was recognized by the trained networks. a) Pattern of the one-month in the total macroinvertebrates in the Soktae Stream.

b)

	0	1	2	3	4	5	6	7	8
0	B D2-9 D2-12 D3-3 D3-8 D3-11* C2-10 C2-11 C2-12 C3-1 C3-8 P2-7 P3-4 L2-3 L3-5 L3-8						A D2-8 D3-2 D3-6 C2-9 C3-12 P2-8 P2-12 P3-1 P3-2 P3-3 P3-8 P3-9* P3-10* P4-1* L2-6 L2-9 L2-10 L2-11 L2-12 L3-1 L3-2 L3-3 L3-9* L3-10* L3-11* L3-12* L4-1* L4-2*		
1									
2								D2-7 D3-1 D3-12* C2-6 C3-11* L2-4	P2-9
3	C D2-3 D2-4 D2-6 D3-4 D3-9* D3-10* D4-1* C4-1* C4-2* L3-4								
4					P2-3 P2-5		D2-5		C2-3 C3-9* C3-10* P2-4
5	D2-10 D2-11 D3-5 C2-4							C2-5	
6						L2-5			
7			D3-7 C3-5 C3-6			P3-7 L3-6			D C2-7 C2-8 C3-2 P2-6 P2-10 P2-11 L2-7 L2-8
8			D4-2* C3-3 C3-4		P3-5		P3-6 P4-2*		

Fig. 4. (Contionued) b) Pattern of the one-month in chironomids in the Soktae Stream.

appeared in the mapping of chironomids on Neuron (6,0) and Neuron (0,0), respectively. Groups C and D were also formed on Neuron (0,3) and Neuron (8,7), respectively. However, many communities except Group A scattered to other neurons in the mapping of chironomids.

Patterning community changes

In the two-month mapping, the main features found in the one-month mapping were also observed. The total benthic macroinvertebrates showed similar characteristics as the results observed from the one-month sampling (Fig. 5a), which is the following: grouping was mainly based on the pollution impacts and patterns generally persisted in the longer-time mappings. Group A, to which a large number of samples from polluted sites of TCL and THP belonged in the one-month mapping, appeared in the two -month mapping on the Neuron (2,3). Group B, representing communities from a relatively clean site from TSD, and Group D, consisting of communities mainly from TKC, were formed on the Neuron (7,0) and Neuron (4,6), respectively. In Group D, however, about half of communities which originally belonged to Group D in the one-month mapping, remained in the two-month mapping. It did not form as large of a group as the one shown in the one-month mapping. Group C was disintegrated and was not identifiable. This disappearance of Group C indicated that the low densities in communities in the one-month sampling may not be a consistent character istic in the community organizations while Groups A and B were persistent in the two-month mapping. The longer observations of Groups A and B continuously showed similar results as shown in the four-month mapping, while the other groups were not observable (Fig. 6a).

The chironomid communities tended to diverge more in the longer-period mappings than in the one-month mapping. Group A was still formed in the two-month mapping on Neuron (7,4) (Fig 5b). Communities belonging to Group A were divided into the two Neurons, (6,2) and (7,3) in the four-month mapping, but they were very close on the map, indicating that these groups generally formed similar patterns. In a)

	0	1	2	3	4	5	6	7	8
0	P2-8 L2-8 L4-9* L4-10* L4-11*		C3-4 C4-4* P4-9*		C3-9 P3-9 P4-7*		D2-4	B D2-11 D2-12 D3-1 D3-2 D3-3 D3-4 D3-5 D3-6 D3-7 D3-8 D3-10 D3-11 D3-12 D4-1 D4-2 D4-3* D4-4* D4-5* D4-6* D4-7* D4-8* C3-8 C3-11 C4-8* C4-9* C4-11* C5-3* C5-4*	D2-5 D2-10
1			L3-12	P4-12*	P4-11*		D2-7 D2-8 D2-9 C3-5 C4-5* C5-2*	C3-12	C3-10
2			P3-8 L4-4*	L3-8			L4-1		D2-6 D3-9 D4-9* D4-12* C4-10* C4-12* P4-10*
3		L2-4 L3-4	A D5-1* P2-4 P2-5 P2-6 P2-7 P3-1 P3-2 P3-3 P3-7 P4-1 P4-2 P4-3* P4-4* P4-5* P5-2* L2-5 L2-6 L2-7 L3-6 L3-7 L4-2 L4-3* L4-5* L4-6* L4-7*		P3-10				
4			P3-6	L3-9		C4-1			P3-11 P3=12 L4-8*
5					P5-3*	D4-11*			
6			P2-9 L2-9		D D4-2* D5-3* D5-4* C2-5 C2-6 C2-7 C2-8 C2-9 C2-10 C3-6 C4-6* C5-1	C3-1 C4-2			
7			P2-11 P2-12 L2-11						
8			P4-8* L2-12 L3-1	C2-4 C3-2 C3-3 C3-7 C4-3* C4-7	P2-10 L2-10	L3-11			D4-10* C2-11 C2-12 P5-4*

Fig. 5. Two month mapping of benthic macroinvertebrate communities, collected in the Soktae stream, Suyong River when trained by artificial neural networks (The name of sample sites listed in the map was explained in Fig 4.). a) Pattern of the two-month in the total macroinvertebrates in Soktae Stream.

contrast, the communities that belonged to Groups B, C and D in the one-month mapping scattered on the map and were not identifiable. Especially, the disintegration of Groups C and D are significant, since chironomids were generally found in high densities in these groups, which indicates that the community changes in chironomids are highly diverging.

Some communities that diverged from Group A formed a new group on Neuron (0,6) in the two-month mapping of chironomids (Fig. 5b: Group E). This group generally represented a recovery from the flood. This new grouping was not found in the mapping of the total community. This trend, the formation of a new Group E, persisted until the four-month mapping on Neuron (0,3) (Fig. 6b).

Recognition

The process of recognition was begun by feeding the new input data into the trained networks in the total and chironomid communities. The communities collected after February, 1994 for the total invertebrates, and those collected after August, 1993 for the chironomids (see Fig. 3), were provided as new data sets, respectively. The recognition results appeared on the trained mapping. Communities recognized b)

	0	1	2	3	4	5	6	7	8
0	C2-11 C2-12 C3-1								P2-8
1						D3-11 L3-5			
2			P3-5			D2-9 D3-3 C2-10 P3-4			L3-9*
3		P3-7 P3-8 L2-6 L3-7	P3-6 P4-2 L2-5 L3-6			P3-9			
4	L3-8				D3-1 D3-12* L2-4			A P3-1 P3-2 P3-3 P3-10* P3-11* P3-12* P4-1* L2-10 L2-11 L2-12 L3-1 L3-2 L3-3 L3-10* L3-11* L3-12* L4-1* L4-2*	
5	C2-9 P2-6 P2-7 P2-10 L2-7		D3-7						
6	E D2-8 D3-2 C2-7 C2-8 C3-2 C3-12* P2-9 P2-11 P2-12 L2-8 L2-9				D3-4 D3-9*			C4-1* L3-4	
7	D2-7			D2-4 D3-10 C4-2					
8	D3-6 D2-12 C2-6 C3-11* P2-5		D3-8 C3-4 C3-5 C3-6 C3-7 C3-8		D2-6 D2-11 C2-4 C2-5 C3-9* C3-10*		D2-10		D2-5 D3-5 D4-1* D4-2* C3-3 P2-4

Fig. 5. (Contionued) b) Pattern of the two-month in chironomids in Soktae Stream.

by the networks were so indicated with the "*" mark (Figs. 4-6). The recognized groups generally shared similar characteristics with the patterned groups, both in the total and chironomid communities. In the one-month and longer-period mappings a large number of new communities collected from TSD were patterned to Group B. Also, communities that were collected from the polluted site, THP, and some of communities from TCL, were grouped into Group A. Communities from the intermediate polluted site, TKC, were generally unstable; if they formed groups, they belonged mostly to Groups B and D, and some communities tended not to belong to any patterned groups. This recognition trend appeared in the longer-period mappings also. These unstabilities appeared more strongly in chironomids.

In the one-month mapping of the total communities (Fig. 4a), however, a group of new communities of THP and TCL were unexpectedly recognized to a Neuron (7,0). On Neuron (7,0), a sample from TSD (D3-9, Fig. 4a) was originally patterned. This exceptional recognition was in fact due to similarity in community abundance between the trained and recognized data. Although the sample "D3-9" was collected from the relatively clean site TSD, communities were exceptionally concentrated on Diptera and Chironomidae with low diversities. Recognized data from THP and TCL also highly consisted of Diptera and Chironomidae.

DISCUSSION AND CONCLUSIONS

With the combined use of the two unsupervised neural networks, it was possible to pattern the temporal variations in community data. Feasibility of neural network in the feature extraction on temporal data was demonstrated in this comparative study on community changes, indicating that artificial neural networks could be used for comprehensive understanding of community dynamics in a reduced dimension.

This study also showed some possible pattern recognition on the on-time basis in the long-time survey of an ecological data. As previously shown, after training with the previous data sets, a new data set could be easily fed into the trained network to be able to determine the a)

	0	1	2	3	4	5	6	7	8
0	B D2-11 D2-12 D3-1 D3-2 D3-3 D3-4 D3-5 D3-6 D3-7 D3-8 D3-9 D3-10 D3-11 D3-12 D4-1 D4-2 D4-3* D4-4* D4-5* D4-6* D4-7* D4-8* D4-9* D4-10* C3-10* C3-11* D4-10* C4-11* C4-12* C5-4*	D2-6		P4-9*	P3-11		P3-10 L2-11	A P2-6 P2-7 P2-8 P3-2 P3-3 P3-4 P3-5 P3-6 P3-7 P3-9 P4-4* P4-5* P4-6* P4-7* P4-12* L2-6 L2-7 L2-8 L3-6 L3-7 L3-8 L4-3* L4-5* L4-7* L4-11*	P2-9 P2-10 L2-10 L3-9 L4-9* L4-10
1	C3-12	D2-7 P4-2	P4-1 P4-10*				P4-8* L3-10	P5-1* L4-6*	L3-5
2	C4-1 L4-8*	P4-11*			P3-12			P4-3* P5-2*	P3-8 L3-4 L4-4*
3	C4-2						L3-11		P3-1 L3-3
4	D2-8 D2-9 C5-2*	D2-10		L4-1					P2-11 L2-11
5	C5-1* P5-3*					L3-2	L3-1		
6	C3-6 C4-6*	C3-8 C4-8* C5-3*				D5-2*			P2-11 L2-11
7			C4-7*				D5-3* D5-4* C2-6 C2-7 C2-8 C2-9 C2-10 C2-11 C4-9*	D4-12 D5-1* C4-3*	
8	C3-5 C3-9 C4-5*		C3-7		L3-12		D4-11* C3-1 C3-2	C3-4 C4-4* L4-2	C2-12 C3-3 P5-4*

b)

	0	1	2	3	4	5	6	7	8
0	C3-1		D3-11*			C2-12	L3-4		P3-5
1									L3-5
2	D2-6 D2-7	D2-12 C3-11*	D3-6				A P3-3 P3-4 P3-12* L4-1* P4-2* L2-12 L3-1 L3-2 L3-3 L3-12* L4-1* L4-2*		
3	E D2-8 D3-1 D3-12* D4-1* C2-6 C2-7 C2-8 C3-12* C4-1* C4-2* P2-6				C3-6 C3-7 C3-8		C2-11	A P3-1 P3-2 P3-11* L2-10 L2-11 L3-11*	
4	D3-2		D3-7 C3-5				C3-2		
5	D2-9 D3-3 P2-7								D3-4
6			D3-8				D3-9 C3-9		D2-10
7	C2-10 P2-8		P3-8 L3-8		P3-7 L2-6 L3-7				D3-5
8	P2-12 P3-10* L2-9 L3-10*	P2-9 P3-9* L2-8 L3-9*	C2-9 P2-10 P2-11 L2-7		P3-6 L3-6		D3-10* C3-10*		D2-11 D4-2* C3-3 C3-4

Fig. 6. Four month mapping of benthic macroinvertebrate communities collected in the Soktae Stream, Suyong River when trained by artificial neural networks. a) Pattern of the four-month in the total macroinvertebrates in the Soktae Stream. b) Pattern of the four-month in chironomids in the Soktae Stream.

pattern of the in-coming data. The training process could be effectively conducted whenever data were sufficiently accumulated or field ecologists decided to do so. These advantages in pattern recognition by artificial neural networks could be effectively used for the long-term ecological survey where the assessment on the community development was necessary in line with the sampling procedure. Through the traditional clustering analyses, the classification of communities may be conducted, however pattern recognition is generally not possible.

The mapping by the trained network reflected environmental effects when sampling sites were exposed to pollutants. This confirmed the results of groupings by artificial neural networks from a previous study (Chon *et al.* 1996), where communities were patterned according to the level of their response to pollution effect as the levels of disturbances were high.

It was observed in this study, that Group A, which represented the communities from highly polluted sites, persisted in the total and chironomid communities, as well as in the one-month and the longer-period mappings. This indicated that benthic macroinvertebrates maintain a strong persistent characteristic pattern in community changes at polluted sites. This could be an effective information in assessing water quality as well as to the interpretation of ecological status of stream ecosystems. In Group A, the *Chironomus flaviplumus* in Chironomidae was consistently dominant and therefore this was the basis for its consistency that was observed both in the total benthic invertebrates and in the chironomids (Fig. 4).

It was noted that the number of communities belonging to Group B was lower in the mapping of chironomids (Fig. 4b) than in that of the total communities (Fig. 4a). This may be due to the limited selection of species in chironomids for patterning. As previously mentioned, 4 species were selected in chironomids, representing the α-mesosaprobity and the poly-saprobity. However, the species which could represent clean or relatively clean state such as in TSD, could not be selected in chironimids, due to the scarcity in specimen collections. In the total community, Epemeroptera, Odonata and other Diptera were included in contrast. This proposes an improvement in collection of chironomids in this comparative study for patterning community changes. In order to use chironomids as patterning community and to span the whole spectrum of water quality, it might be desirable to add sample collections where chironomid species indicating clean water would be abundant.

In Group B of the one-month mapping, although species from clean sites were not included, chironomid communities were more characteristic to represent environmental disturbances. Communities were selectively grouped from TSD and TKC in July and August when flooding occurred, or during the period from December to February when the temperature was very low. In Group D, chironomid communities also homogeneously represented the community characteristics of the one-month mapping more than in the total communities. In these samples, *Chironomus flaviplumus* and *Orthocladius suspensus* appeared at the same time in a characteristic manner except in some communities of TSD. These facts indicated that the chironomid community patterning could serve as an alternative in comprehensive understanding of water quality.

In the one-month mapping (Fig. 4b), a chironomid, *Orthocladius suspensus*, played a key role in characterizing Group C in the mapping of chironomids. This species indicated the water quality of α-mesosaprobity and frequently appeared in the samples from the intermediately polluted site, TKC, and at other samples from TSD. The disintegration of Groups C in the longer-period mappings was characteristic in chironomids while these groups persisted in the total communities (Fig. 5 and Fig. 6). In Group C, community abundance was generally low at all taxa in the one-month mapping. In the two-month or the longer-period samplings, high density was subsequently observed in the following months in chironomids while low densities were maintained at the other taxa. This caused the divergence of the Group C in chironomids.

With a similar reasoning, Group D also diverged in the mapping of the longer-period in chironomid communities. In Group D, Chironomidae, Gastropoda and Odonata were generally abundant in the total communities. However, community abundance was diversified the most in chironomids in the following months. This divergence may be due to different life cycles of abundant chironomids. Many reviews indicated that the life cycles of the different species of chironomids are dependent upon temperature (e.g., Huryn 1990, Commins 1979, Graham and Burns 1983, Edward 1986). Since the summer water temperature in Korea generally exceeds 14℃, above which the development of chironomid nymphs may be accelerated to a certain point (Storey 1987), the period of a complete life cycle would be shortened in different temperatures in different species. In this study, chironomids that were in immature stage were sampled in representing community size.

Some communities that diverged from Group A formed a new group, E, with other communities on Neuron (0,6) in the two-month mapping of chironomids. These communities represented a recovery from flooding. In the first month, densities were generally low due to flooding while in the following month chironomids were in high densities. This new grouping was not found in the mapping of the total community, which suggests that chironomids may be appropriate *in patterning community* changes during recoveries after flooding. Chironomids are known to be sensitive to flooding as well as to recover quickly after flooding (Storey 1987, Saether 1979).

As previously mentioned new\9 input data generally shared with similar characteristics to the patterned groups in recognition. This verified artificial neural networks could effectively extracted information of community data. In the one-month mapping of the total communities as previously mentioned, however, a group of communities of THP and TCL were unexpectedly recognized to a Neuron (7,0), where a sample from TSD was originally patterned (Fig. 4a). This shows that a longer period may be required for training. If the training period is extended to that of recognition, the community composition concentrated on Diptera and Chironomidae would in fact become a new pattern representing communities from the polluted sites based on these recognition results. The training process in the extended period could be readily conducted as previously mentioned. In group A, which is a large group representing polluted sites, oligochaets were additionally abundant. The community difference in benthic macroinvertebrates in ecological aspect will be discussed elsewhere in detail.

As mentioned in Chon *et al.* (1996), a problem of objectivity existed in the neural networks since the network was based on random effects and iteractive calculations: each configuration after convergence may have been different with different trainings. In this case, neurons representing the same group appeared differently in different training periods. This is a problem for comparing community patterns of different sampling periods. In the future, it would be desirable to improve artificial neural networks for more comprehensive understanding of data for community changes.

As a summary, the combined use of unsupervised artificial neural networks was effective in patterning community changes. This method could be utilized for assessing ecological status of aquatic ecosystem in concurrence with long term survey. Through the comparative study on benthic macroinvertebrates with the learning processes, patterns of commnity changes in chironomids were shown to be diverging and more sensitive to the impacts of internal or external factors, while those of benthic macroinvertebrates in total appeared to be more persistent.

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