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自组织特性图形的检测理论与应用

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摘　要　人工神经网络模型已研究多年，已使得在信息处理领域中具有类似人的性能，本文将 Kohonen 自组织特征映射的学习规则进行了修改，以降低拓扑邻域边界上的模糊性，而后，用它的联想存贮功能可以实现输入统计过程的特征存贮，以达到检测的目的。本文也讨论了多维检测的数学机理，作为它的一个结果，可以得出高精度的检测性能。

关键词　神经网络，Neural Net，目检检测，Target Detection

分类号　TN911.23　TP18

国防科技大学学报
JOURNAL OF NATIONAL UNIVERSITY OF DEFENSE TECHNOLOGY
第16卷第1期 1994年3月 Vol. 16 No. 1

The Detection Theory of Self-Organizing Feature Map and Its Application*

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Abstract Artificial neural net models have been studied for years in the hope of achieving human like performance in the field of information processing. In the paper the learning rule of Kohonen self-organizition feature map is modified in order to decrease the fuzziness on the edges of topological neighbours. Then with its associative memory function, we can realize the memory of the features of the input stochastic process, conseqently the detection can be performed. We also describe the mathematical mechanisms of multi-dimentional detcction, as its result high-accuracy performance can be derived.

Key words neural net, target detection

1 The Optimized Learning Rule based on Kohonen Self-Organizing Feature Map

It's no doubt all kinds of artificial neural net come from the research results of the neural physiology. An impormant organizing principle of sensory path-ways in the brain is that the placement of neurons is orderly and often reflects some physical characteristics of the external stimulus being sensed. Further more, although much of the low-level organization is genetically pre-determined, it is likely that some of the organization at higher levels are created through sensory experience. Kohonen presents his algorithm to produce what he calls self-organizing feature map similar to those occurs in the brain.

Fig 1-1. shows a two-dimentional Kohonen self-organizing system with N input nodes to M output nodes Here's his rules:

1) Similarity Matching:

$$\| X(t) - W_c(t) \| = \mathrm{Min}\{ \| X(t) - W_i(t) \| \}$$

2) Updating

* Received June 15, 1993

$$W_i(t+1) = W_i(t) + \alpha(t) \cdot [X(t) - W_i(t)] \qquad \text{for } i \in NE(t) \cdot$$
$$W_i(t+1) = W_i(t) \qquad \text{other}$$

$NE(t)$ is the set of nodes considered to be in the neighborhood of node c at timet. The neighborhood starts large and slowly decreases in size over time. The term $\alpha(t)$ is a gain term that decreases in time.

According to the rules, training samples are presented one by one at the input and the learning process is repeated until the gain term is reduced to zero. The weights between the input and output nodes converge. The fixed weights will coincide with the centers of gravity of the input space with respect to weighting function of probability distribution of the input vectors.

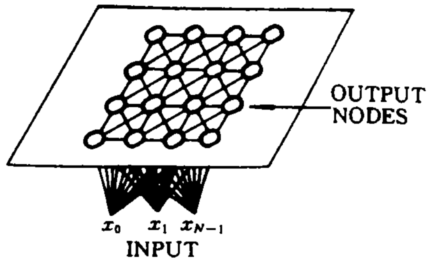

Fig 1-1

The initial stage of the training procedure is important for specifying cluster. Now let's consider the mathematical process of this stage. It's can be tested that the adaptation equation

$$d[W_i(t)]/d(t) = \alpha(t) \cdot [X(t) - W_i(t)]$$

has the solution:

$$W_i(t) = \mathrm{EXP}(-\alpha(t) \cdot t) \cdot [W_i(0) + \alpha(t) \cdot \int_0^t \mathrm{EXP}[\alpha(\tau) \cdot \tau] \cdot x(\tau) d(\tau)]$$

when the condition $|t \cdot d\alpha(t)/d(t)| \ll |\alpha(t)|$ and $d\alpha(t)/dt \geqslant 0$ are met, if $\alpha(t) = 1 - t/N$. (N represent the whole training times). Then the above conditions are satisfied. Ignoring the small random values of weights, we get:

$$W_i(t) = (1 - t/N)$$
$$\cdot \sum_{\tau=1}^{t} \mathrm{EXP}[(\tau - t)(1 - (\tau + t)/N)] \cdot X(\tau)$$
$$\approx \sum_{\tau=1}^{t} \mathrm{EXP}(\tau - t) \cdot X(\tau) \qquad t \ll N,\ i \in NE(t)$$
$$W_i(1) \approx X(1)$$
$$W_i(2) \approx \mathrm{EXP}(-1) \cdot X(1) + \mathrm{EXP}(0) \cdot X(2)$$
$$W_i(3) \approx \mathrm{EXP}(-2) \cdot X(1) + \mathrm{EXP}(-1) \cdot X(2) + X(3)$$
$$= \mathrm{EXP}(-1) \cdot W_i(2) + X(3)$$
$$W_i(t) \approx \mathrm{EXP}(-1) \cdot W_i(t-1) + X(t)$$

We see on the initial stage, the weights tend to the gravity center of the input space by an exponencially weighted moving average of $X(t)$. However, the weights to all nodes in the larger neighbourhood will get the same evolution according to the above formula by each iteration. Thus the fuzziness on the edges of topological neighbours which response to different kinds of input pattern may produced. We modify the updating rule:

$$W_t(t+1) = W_t(t) + \alpha(t) \cdot \mathrm{EXP}[-\sqrt{|i-c|/2}] \cdot [X(t) - W_t(t)] \qquad \text{for} i \in \mathrm{NE}(t)$$

$$W_t(t+1) = W_t(t) \qquad \text{other}$$

$|i-c|$ represents the distance between the output node i and its topological center c.

Here the weights is then proportionately modified according to how far away from the topological center, so that the fuzziness on the edges of different neighbours is decreased. Improved clustering ability thus can be got.

Adaptation stops after training. Output nodes will be ordered in a natural manner. The weights are organized such that topologically close nodes are sensitive to inputs that are physically similar. Detection would be fulfilled under the supervision of the response region on the feature map when the detection sample is presented at the input.

2 The Estimation of the NN Detection Performance

As for detection problem, we have only two response regions on the feture map corresponding to the two cases of having target or not. According to the similarity matching rule, the cluster is specified by the Euclidean distance. That is to say the threshold seems likely to be the mid-point of two centers of the probability distribution of input samples.

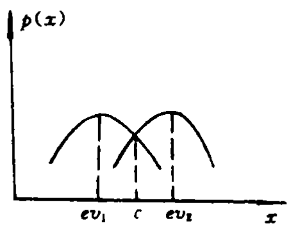

Fig 2-1

Seeing Fig. 2-1. To simplify our analyses, we suppose:

Firstly, the elements of input vector is independent of each other i. e. ignoring their correlations in time.

Secondly, the shapes of the probility distribution of the two cases are approximately the same.

Thirdly, the trained neural net is equilibrium for both case.

Thereby NN has two centers (i. e. ev1, ev2) which are symmetric about the threshold C. It's easy to get:

$$P_f + P_d = 1$$

$$(P_f + P_d)^M = C_M^0 \cdot P_f^M + \cdots C_M^{M/2-1} \cdot P_f^{M/2+1} \cdot P_d^{M/2-1} + C_M^{M/2} \cdot P_f^{M/2} \cdot P_d^{M/2} + C_M^{M/2+1} \cdot P_f^{M/2-1} \cdot P_d^{M/2+1} + \cdots C_M^M \cdot P_d^M$$

We apply 1/2 criterion to make the decision:

$$P_{ff} = C_M^0 \cdot P_f^M + \cdots C_M^{M/2-1} \cdot P_f^{M/2+1} \cdot P_d^{M/2-1} + P_f \cdot C_M^{M/2} \cdot P_f^{M/2} \cdot P_d^{M/2}$$

$$P_{dd} = C_M^M \cdot P_d^M + \cdots + C_M^{M/2+1} \cdot P_f^{M/2-1}$$

$$\cdot P_d^{M/2+1} + P_d \cdot C_M^{M/2} \cdot P_f^{M/2} \cdot P_d^{M/2}$$

Here, P_f, P_d represent respectively the false alarm rate and the detecting rate of one-dimentional testing.

P_{ff}. P_{dd} represent respectively the false alarm rate and the detecting rate of m-dimentional testing.

As for term $C_M^{M/2} \cdot P_f^{M/2} \cdot P_d^{M/2}$, considering the false alarm rate, we weight it by P_f.

For example, if $M=12$, $P_f=0.1$, then we get $P_{ff}=10^{-4}$, so high accuracy performance is expected through such multi-dimentional joint decision by NN.

To support our analyses, we design a group of simulation experiments, of which the same numbers of training samples are independently produced and are symmetrically distributed about a threshold according to some probability density function, refering to Fig. 2-1. Table 2-1 gives the simulation results. Fig. 2-2 illustrates the probability distributions of the weights of two response regions on the trained feature map respectivly. Our analyses seem to be reasonable. Because of the symmetric distribution of the training samples and their equal opportunities to be learned, the false decision rate for each case is approximatly the same, thus is approximate to their average values shown in the table. The performance is therefore relatively stable. This way suggests what we called equal-risk criterion. The reason for the better results than the estimations is because of the fuzzy decision mainly corresponding to $C_M^{M/2} \cdot P_f^{M/2} \cdot P_d^{M/2}$ as $P_f \ll 1$. Better performance are expected as the fuzziness on the edges of topological neighbours is decreased. Therefore further optimization of the algorithm still has practical significances. Here the essential conclusion is that high-accuracy performance can be achieved by NN detection, also the detection is nonparametric because of the self-organizing learning process.

3 Application of NN Detection in Rader MTD System

As one application, we construct NN detection unit in Radar MTD system in the place of the general cell averaging CFAR. Fig. 3-1 shows such a digital moving target spectrum processing unit. Before the detection can be applied, the knowledge of the environment must be learned. Here $K+1$ points DFT correspond to $K+1$ filters, the number of the pulse accumulation is M, and N neighbouring range cells are considered to belong to the same environment. Seeing Fig. 3-2, if we slip one sample point each time, $M-K$ outputs will be got through each filter for every range cell. We made them a sample vector of $M-K$ dimention. We collect our sample set on N neighbouring range cells, then we get the sample set X_{ij} $(i=1,\cdots,N, j=1,\cdots,M)$. Except for zero channel, the outputs of which we keep the clutter map detection, the other K filters will give K groups of such a sample set that offer the samples of K frenqency-ranges. We construct the reference samples by adding constant vectors to the sample vectors so as to cause the weights connecting to the nodes outside the clutter region tend to distribute meaningly.

We present the sample sets and its references ones to train K Kohonen feature maps at the same time. We just need to keep the distances of the two cases of training samples to keep CFAR.

We illustrate the channel one's (i. e. f_1) detection performance under sea clutter enviroment in Fig. 3-3. Here $M=20$, $K=8$, $N=32$, the NN has 13 input nodes and 28 output nodes in lines. As a comparison, we also give the result of the generalized sign-threshold-detection with the same numbers of pulse accumulation which is also a non-parametric method. Obviously the performance of NN detection has 5db or so improvement under the 10^{-6} false alarm rate, and is more sensitive to SNR.

Table 2-1

	Dim.	T	Pee(ES) $* 10^{-4}$	Pee(NN) $* 10^{-4}$
Gaussian distribution	$M=6$	0.7	634	500
		0.8	406	317
		0.9	250	188
		1.0	148	106
		1.1	84	53
	$M=9$	0.7	430	359
		0.8	250	200
		0.9	138	100
		1.0	72	46
		1.1	36	20
	$M=12$	0.6	396	336
		0.7	204	158
		0.8	97	65
		0.9	43	29
		1.0	18	10
Rayleigh Distribution	$M=12$	0.25	1095	1561
		0.35	559	798
		0.45	260	381
		0.55	115	123
		0.65	43	43

Pee(ES) is the estimation of false decision rate
Pee(MM) is the average false decision rate on NN
T is the half distance between the centers of two cases.

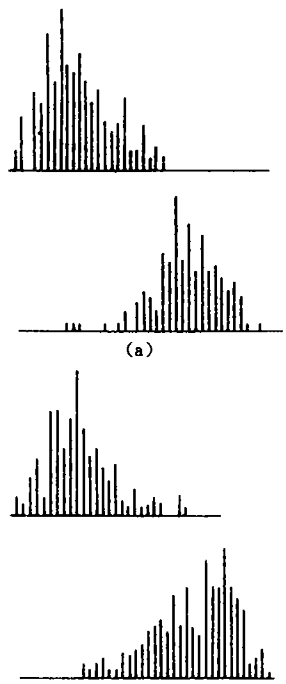

Fig. 2-2
The probability distribution of the weights of two response areas on the trained feature map. (a) The Gaussina case and it's symmetric one (b) the Rayleigh case and it's symmetric one

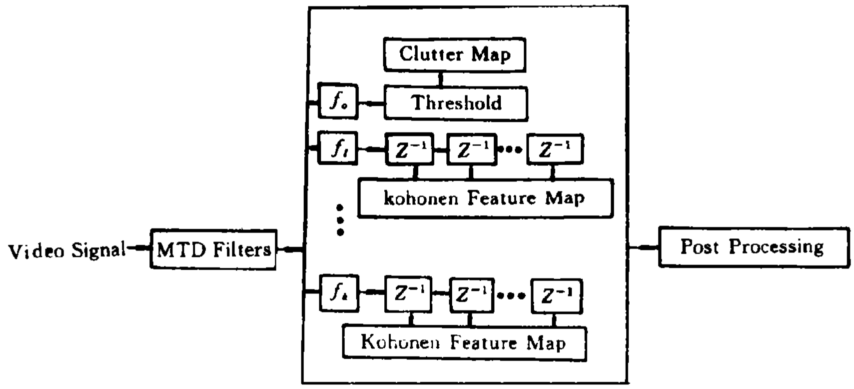

Fig. 3-1 NN Detection Unit

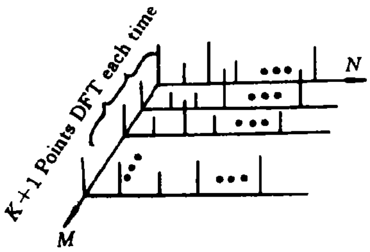

Fig. 3-2

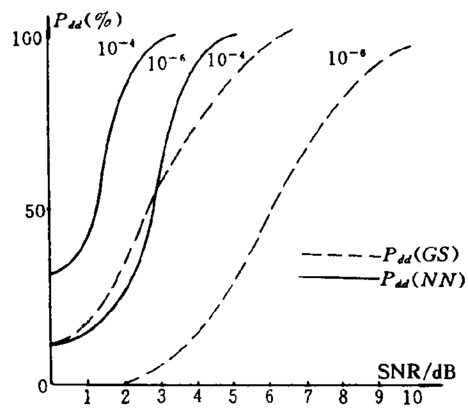

Fig. 3-3

4 Conclusion

The high-accuracy performance is achieved through the multi-dimentional joint decisiion by NN on the bases of equal-risk training condition. In addition, the NN detection is nonparametric because of the self-organizing learning process.

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