An Improved Attention Parameter Setting Algorithm Based on Award Learning Mechanism*)

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Abstract The setting of attention parameters plays a role in the performance of synergetic neural network based on PF_{AP} model. This paper first analyzes the attention parameter setting algorithm based on award-penalty learning mechanism. Then, it presents an improved algorithm to overcome its drawbacks. The experimental results demonstrate that the novel algorithm is better than the original one under the same circumstances.

Keywords Synergetic Neural Network(SNN), Attention parameter, Award-penalty learning mechanism

1 INTRODUCTION

The synergetic approach to pattern recognition[1] has been popularly applied in the field of image processing and image recognition since it was first described by Haken in 1980s. Meanwhile, its algorithms, especially the selecting of prototype patterns, the setting of attention parameters and the realizing of spatial invariant pattern recognition, have been deeply studied.

As far as the setting of attention parameters is concerned, Wang, Lever and Pu studied the features of attention parameter and put forward the attention parameter setting algorithm based on award-penalty learning mechanism[2], which was utilized to complete the recognition of optical character. However, this algorithm has the following shortcomings. First, it can not get the optimum. Second, it has several free parameters defined by users. Third, it modifies the attention parameters each time an error recognition happens so that it is time-consuming. Another unbalanced attention parameter training algorithm based on Genetic Algorithm[3] was presented by Wang and used to classify license plates. This approach makes use of Genetic Algorithm to search the solution space globally and converge more quickly than the former but it is more time-consuming. Later, Hogg, Talhami and Rees advanced the SCAPAP algorithm (SCAP[4] with attention parameters)[5] to solve an important problem, the pose classification in the operation of industrial robotics in which the explicit parameter algorithm was presented to determine the parameters functionally equivalent to attention parameters. This scheme can set the parameters in linear time on the condition that there exists a zero-error solution. However, it is not so ideal in reality and under these circumstances its solution is a NP problem.

Considering the shortcomings of the above-mentioned algorithms, an improved algorithm is presented to improve the attention parameter setting algorithm based on award-penalty learning mechanism. The rest of the paper is organized as follows. Section 2 introduces the model of synergetic pattern recognition. Section 3 deals with the improved algorithm. Section 4 gives the experimental results of several algorithms and makes a discussion.

2 THE SYNERGETIC PATTERN RECOGNITION MODEL

The dynamics of pattern recognition can be thought of as the overdamped motion of a particle on a potential hyper-surface. The particle is started at the point corresponding to the test image and the pattern is classified when it reaches a potential minimum corresponding to one of the prototypes.

In synergetic pattern recognition, the M prototype v_k and test image q are represented as raster-scanned column vectors which have been normalized to have zero mean and unit length. Assume the column vectors have N dimensions. To guarantee the linear independency of the M prototypes, it is required

$$M \leqslant N \tag{1}$$

The dynamic equation of pattern recognition is given by

$$\dot{\xi}_k=\lambda_k\xi_k-\sum_{k'\neq k}B_{kk'}\xi_{k'}^2\xi_k-C\Big(\sum_{k'}\xi_{k'}^2\Big)\xi_k \tag{2}$$

where $\lambda=[\lambda_1\cdots\lambda_M]$ is a vector of constant labeled attention parameter. Only when $\lambda_k>0$, q can be categorized as the corresponding class k. ξ_k, the order parameter is given by

$$\xi_k=v_k^+q \tag{3}$$

v_k^+ is the adjoint vector of v_k, satisfying

$$v_k^+v_{k'}=\delta_{kk'}=\begin{cases}0 & k\neq k'\\ 1 & k=k'\end{cases} \tag{4}$$

and $B_{kk'}$ and C are constants.

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This model is called pattern-formation model labeled PF and Haken[2] has proved that PF has the following properties:

- all the prototypes are possible final states;
- there are no other possible final states, that is, the system will not learn any 'spurious' memories.

These two features prove that it is rational to construct SNN with PF model.

Let $B_{kk'}=C, \lambda_k>0$, equation (2) is transformed into

$$\dot{\xi}_k=f_k(\xi,\lambda)=\xi_k(\lambda_k+C\xi_k^2-2C\sum_{k'}\xi_{k'}^2) \qquad (5)$$

The above formula is called PF_{AP} model, where AP stands by "Attention Parameter".

3 AN IMPROVED ATTENTION PARAMETER SETTING ALGORITHM BASED ON AWARD LEARNING MECHANISM

According to equation (5), enlarging λ_k increases the probability that a certain test image is recognized as the category k. On the basis of this feature, Wang, Lever and Pu presented the attention parameter setting algorithm based on award-penalty learning mechanism which modified the attention parameters when the result was false. This approach is time-consuming because it classifies each training samples in each iteration and then modifies the corresponding attention parameters. What is worse, if different category samples are mutually classified by mistake, for instance, q_1 belongs to the first class but it is recognized the second class by mistake. On the contrary, q_2 belongs to the second class but it is recognized the first class. Under such circumstances, it is certain that we can not get the attention parameters λ_1 and λ_2 which make q_1 and q_2 correctly classified. However, this algorithm alters the corresponding attention parameters each time a sample is error classified. Therefore, it causes them repeatedly modified and even oscillation. To overcome this drawback, an improved algorithm is presented. This scheme first classifies all training samples in each iteration, then calculates the category i whose recognition rate is the lowest and later modifies the corresponding attention parameter λ_i based on award mechanism according to the following formula,

$$\lambda_i \Leftarrow \lambda_i+\delta \qquad (6)$$

where δ, a small parameter given by users, represents the award degree.

The flow chart of the novel algorithm is detailed as follows,

①Set the original values of the attention parameters, training goal, δ and iteration step;

②Classify all training samples in the SNN, if the goal is satisfied or the iteration is completed, terminate the algorithm, otherwise goto step ③;

③Calculate the category i whose recognition rate is the lowest, modify λ_i based on equation (6) and then goto step ②.

Compared with the original algorithm, this improved one shows better search performance and greater speed.

4 EXPERIMENTAL RESULTS AND DISCUSSIONS

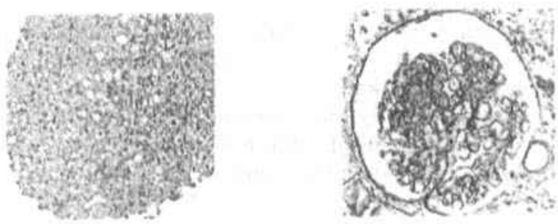

Figure 1 the prototype pattern

Here we take the classification of hepatitis pathology and kidney globule true color images as an example. The prototype pattern is shown in figure (1) and the training samples are composed of 13 hepatitis pathology and 11 kidney globule images collected from reality. The experimental results of different attention parameter setting algorithms are given as follows.

①The attention parameter setting algorithm based on award-penalty learning mechanism

Figure 2 demonstrates the training process of this algorithm, where $\lambda_1=\lambda_2=1, \delta=0.01$. It takes about 20 minutes, the result is $\lambda_1=2.43, \lambda_2=2.45$, and the recognition rate is 66.6667%.

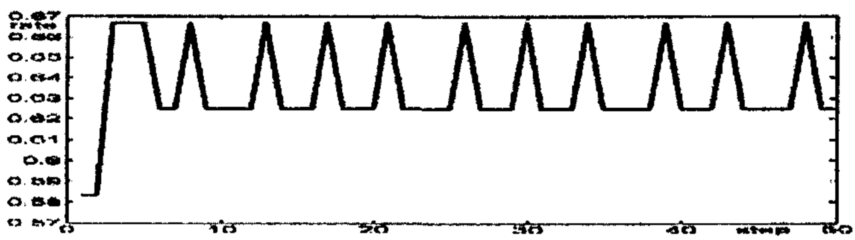

Figure 2 the training process of the attention parameter setting algorithm based on award-penalty learning mechanism

②The unbalanced attention parameter training algorithm based on Genetic Algorithm

Figure 3 shows the training process of this algorithm, where B=C=1, the attention parameters are encoded in real number and $\lambda_k \in [2,4]$. It takes about 3.5 hours, the result is $\lambda_1=2.3814, \lambda_2=2.$

2779 ,and the recognition rate is 70. 8333%.

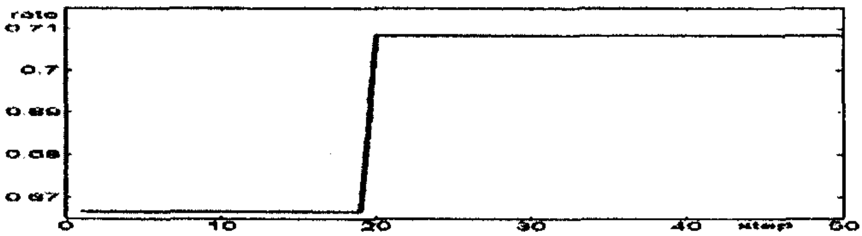

Figure 3 the training process of the unbalanced attention parameter training algorithm based on Genetic Algorithm

③The improved algorithm

Its training process is demonstrated in figure 4, where $\lambda_1 = \lambda_2 = 1, \delta = 0.01$. It takes about 20 minutes, the result is $\lambda_1 = 1.04, \lambda_2 = 1$, and the recognition rate is 70. 8333%.

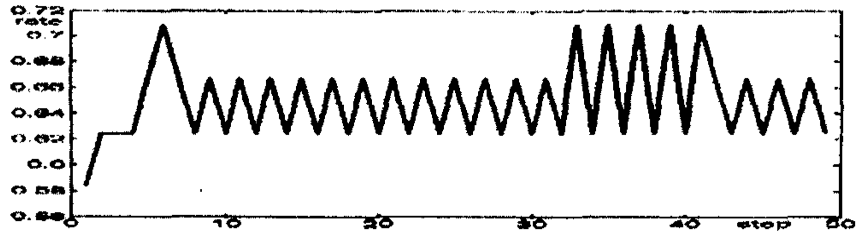

Figure 4 the training process of the improved algorithm

The above experimental results show that the novel algorithm is better than the original one under the same circumstance and less time-consuming than the unbalanced attention parameter training algorithm based on Genetic Algorithm.

References

1 H. Haken. Synergetic Computers and Cognition, Vol. 50 of Springer Series Synergetics. Springer, Berlin(1991)

2 F.-Y. Wang, P. J. A. Fever, B. Pu. A Robotic Vision System for Object Identification and Manipulation Using Synergetic Pattern Recognition. Robot. Comput. Integrated Manufacturing, 1993, 10 (6): 445~459

3 Wang Hai Long, Qi Feihu, Zhang jinfeng. A Genetic-Synergetic Learning Algorithm Under Unbalanced Attention Parameters. Journal of Electronics, 2000, 28(11): 15~17

4 Wagner T, Bobel F G. Testing Synergetic Algorithms with Industrial Classification Problems. Neural Networks, 1994, 17(8): 1313~1321

5 Trevor Hogg, Habib Talhami, David Rees. An Improved Synergetic Algorithm for Image Classification. Pattern Recognition, 1998, 31(12): 1893~1903

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全局尺度因子，剩下15个自由度。而每个摄像机中心有3个元素，至多提供3个自由度。所以至少需要5个摄像机。

总结及展望 我们给出了对于 m 摄像机装置 ($m \geq 5$)，从射影重构恢复到欧氏重构的一种简单的线性算法，这里需要添加的额外信息仅仅是摄像机中心的相对位置已知。并且证明了这种最小配置是5个一般位置的摄像机。这种方法的优点是摄像机可以自由旋转和改变内参数，并且算法是线性的。

今后的工作中，我们将进一步研究这种算法的鲁棒性和稳定性以及退化情形。

参考文献

1 Faugeras O. What can been seen in three dimensions with an uncalibrated stereo rig? G. Sandini. Proc. ECCV'92. Santa Margherita Ligure, Italy: Springer-Verlag, 1992. 563~578

2 Hartley R I. Stereo from uncalibrated cameras, E. Grimson Proc. CVPR'92. Urbana-Champaign, Illinois: IEEE Computer Society. 1992. 761~764

3 Frangois G. Hierarchical visual perception with calibration: [Report of research]. INRIA, France. No: 3002, 1996

4 Hartley R I, Zisserman A. Multiple View Geometry in Computer Vision. Cambridge University press, 2000

5 Shashua A. Omni-rig Sensors: What Can be Done With a Non-rigid Vision Platform? Proc. of the Workshop on Applications of Computer Vision (WACV), Princeton, 1998

6 Zomet A, Wolf L, Shashua A. Omni-rig: Linear Self-recalibration of a rig with Varying Internal and External Parameters, ICCV'2001 Vancouver, Canada, July, 2001