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Star pattern recognition method based on neural network

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Abstract **Star sensor is an avionics instrument used to provide the absolute 3-axis attitude of a spacecraft by utilizing star observations. The key function is to recognize the observed stars by comparing them with the reference catalogue. Autonomous star pattern recognition requires that similar patterns can be distinguished from each other with a small training set. Therefore, a new method based on neural network technology is proposed and a recognition system containing parallel backpropagation (BP) multi-subnets is designed. The simulation results show that the method performs much better than traditional algorithms and the proposed system can achieve both higher recognition accuracy and faster recognition speed.**

Keywords: star sensor, star pattern recognition, neural network, BP neural network.

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Star sensor is a sensitive instrument for determination of a spacecraft attitude with high accuracy. The instrument can determine the spacecraft 3-axis attitude through the recognition of observed stars. It measures star magnitude and star coordinates in the spacecraft coordinate frame. The measures are then compared with a reference star catalog to obtain the attitude information of the spacecraft[1,2]. The purpose of star pattern recognition is to identify the corresponding relations between the observed stars and the guide stars stored in hardware. In such process, how to identify the observed stars correctly is the key technique to the success of the attitude determination[3,4].

Most of the existing star recognition algorithms use direct match algorithms that prestore the star feature vectors in a database. During recognition, the measurements are compared with the reference feature vectors in sequence or by using a binary-tree search. The computation time for star recognition with a traditional model-based system is high, and it increases with the increment of the feature patterns number in the database[5]. Star pattern recognition can be considered as a type of pattern recognition, although star recognition is very different from most pattern recognition problems in which the number of star patterns is very large compared with that of training samples. This work proposes a star recognition algorithm using a BP neural network.

The described star recognition system with a neural network offers a highly parallel, real-time solution to the star recognition problem. The neural networks perform statistical, non-algorithmic pattern recognition. They are trained, not programmed, to recognize entire patterns. Thus noise or incomplete data do not inhibit or slow the pattern recognition process. The system is very robust, in which, if a single memory location for each star pattern is corrupted, it is not likely to affect the results of the pattern recognition[6].

1 BP neural network

Artificial neural networks (ANNs) are mathematical models for understanding and predicting complex and chaotic dynamics in complex biological systems. The feedforward BP neural network (Fig. 1) is one of the most popular neural network topologies. The structure of the BP algorithm comprises the input, hidden and output layers. The input nodes transfer the weighted input signals to the nodes in the hidden layer. These are the same as the hidden nodes for the output layer. A connection between the nodes of different layers is represented by the weight w. The iteration is completed when the error in predictions reaches a minimum. A nonlinear transformation, in the form of a sigmoidal transfer function, is applied between the inputs and outputs of nodes. The weight updates are based on the difference between the actual and the desired output of the network[7—11].

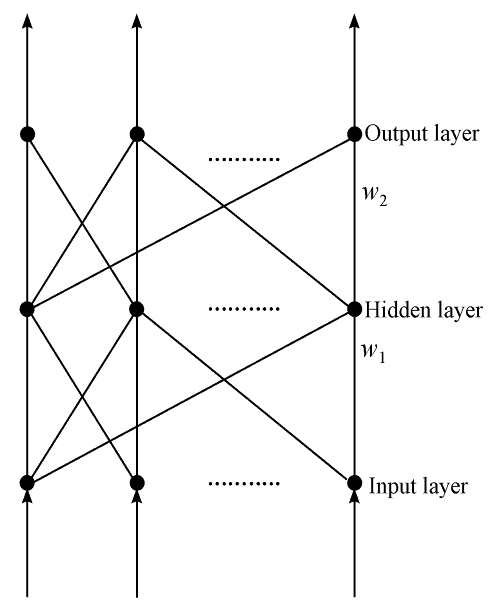

Fig. 1. Model of BP neural network.

2 Star pattern recognition

According to the desired characteristics of the star recognition system itself and the features of a BP network, a recognition system containing parallel BP multi-subnets has been designed and is shown in Fig. 2.

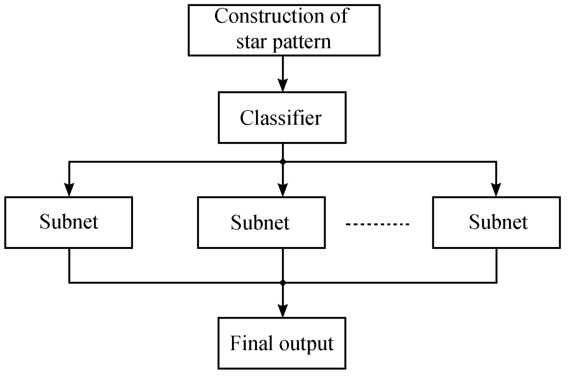

Fig. 2. Module figure of recognition system.

(i) Selection of the guide stars and the star sensor FOV. The average number of the guide stars in the FOV and the brightness of the stars are crucial to the recognition accuracy. Guide stars should cover the whole sky and in every image the sensor acquires there should be a sufficient number of recognizable guide stars. To meet such a requirement, the FOV of $8° \times 8°$ and the star brightness threshold of visual magnitude 6.0 are adopted since the standard can provide relatively accurate attitude information with a manageable number of guide stars.

(ii) Construction of samples. The actual star recognition from a CCD image is performed by extracting a combination of features from the observed star positions and magnitudes for each selected star. The determination of the type of chosen features is based on a statistical analysis of a star catalogue to yield a uniform pattern distribution of distinctive features. All the guide stars and the observed stars are constructed as samples. Such samples are actually patterns, since patterns are often obtained depending on the base stars and the stars in their adjacent areas. The brightest star within a certain radius from the base star determines the sample direction. The size of circle radius depends on the size of the FOV and is taken as 4°. The sample with the ascertained direction is divided into grids, and the length of each grid is 0.5°.

The construction process of a sample is shown in Figs. 3—6. All the conceivable patterns for about 4000 guide stars are stored in the database, and each of the star patterns is uniquely encoded with 13 binary digits. When a CCD image is taken, each base star in the picture will be constructed as a sample in the form described above and is then looked up in the database.

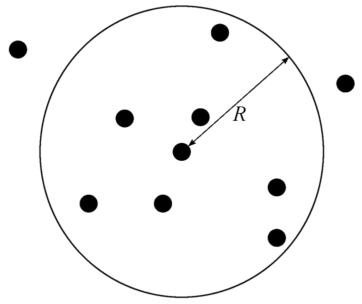

Fig. 3. Determination of the sample scope.

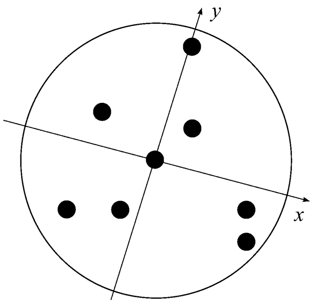

Fig. 4. Determination of the sample direction.

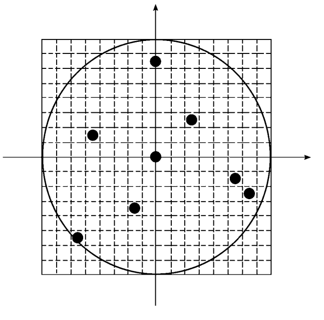

Fig. 5. Grid dividing.

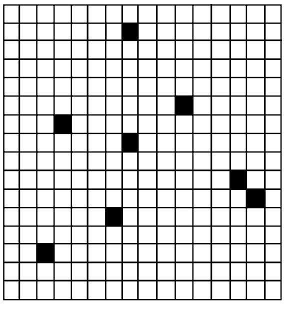

Fig. 6. Obtainment of sample matrix.

(iii) Design of classifier. The number of samples is too large to be trained with a single neural network. Therefore the network is divided into a set of parallel subnets that can be trained more efficiently.

The function of a classifier is to organize the samples and determine their corresponding subnets. In conventional systems, the samples are allocated to subnets according to their properties. If samples are assigned to subnets according to their celestial areas, the system will not know which subnet should train the sample. Therefore, all subnets will be initialized to look for the sample. This directionless searching requires extensive calculations and needs a relatively long time and thus reduces the recognition efficiency. Additionally, it may occur that similar samples are classified into different subnets and more than one subnet may claim a recognition result due to the limited discrimination ability of the subnet. Such procedures will simply lead to failure.

After a survey on the classifying criterions and styles of different neural networks, the BP network is adopted as the classifier. Before the classifier is applied, it must be trained. During training, all the samples constructed with the guide stars are organized by the classifier initially. Next, the classified samples are trained to obtain the weight matrix of each subnet separately. Subsequently, the classifier is ready for work. In operation, an acquired input sample from the CCD image is judged preliminarily by the classifier to determine which subnets are appropriate for it. Then it will be sent to the corresponding subnets. Because the weights are fixed, the network can recognize it very well. In order to increase the efficiency, the capacity of each subnet should be balanced. That is, the classifier should allocate the samples to the subnets as evenly as possible so each subnet contains roughly the same amount of samples.

(ⅳ) Training of the network. It is often necessary to determine an optimal number of hidden nodes when using a BP network to solve a given problem. Thus, we attempted to gradually reduce the number of hidden nodes from 50 to 10. With a comparison of training times and deviations between the actual and the desired outputs, 20 to 30 hidden nodes are determined as the optimal number. The results are shown in Table 1. Therefore, the final network size for recognition is 256-(20 or 30)-13.

Table 1 Influence of the hidden nodes number on training

Number of nodes	Times of training	Final average error	Evaluation
10	400000	0.4431	local minimum
20	400000	0.0644	usable
30	450000	0.0973	usable
40	700000	0.1328	more complicated
50	1500000	0.2332	too complicated

3 Conclusion

A novel method with a BP neural network for star pattern recognition is proposed. In our research, we compared a star recognition system using a BP neural network with a traditional triangle algorithm. Testing with no noise added to the system yielded a recognition accuracy of 97.5%. When additional noise (in magnitude and separation) was added to the 1000 randomly generated images of the FOV, a recognition accuracy of 83.1% was observed, compared with the 80% obtained by the triangle algorithm. The simulation tests showed that the average recognition time required by the triangle algorithm was over 2 s, while the BP algorithm only needed approximately 1 s. The results are shown in Figs.7 and 8.

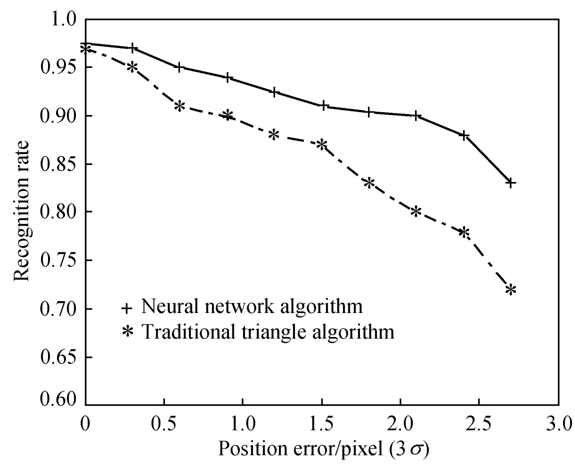

Fig. 7. Comparison of recognition rate between BP algorithm and triangle algorithm.

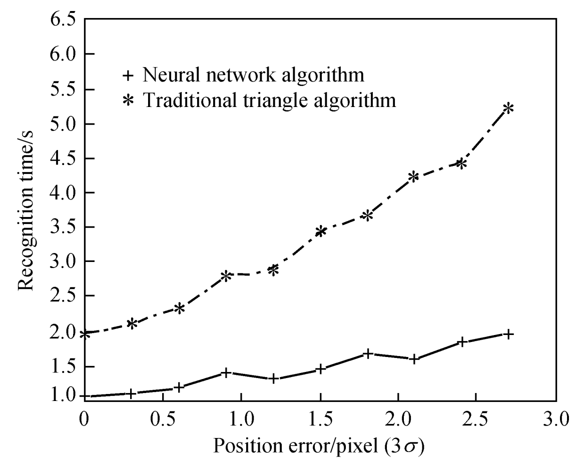

Fig. 8. Comparison of recognition time between BP algorithm and triangle algorithm.

The application of neural network technology in star recognition for spacecraft applications shows great propect in reducing spacecraft development and operation costs. The system is simple and robust, providing advantages over conventional attitude determination techniques for star sensors[6]. Compared with direct match algorithms, the system can obtain both higher recognition accuracy and faster recognition speed. With the proposed algorithm, the influence of magnitude errors can also be minimized. Therefore, the proposed system shows great promise for autonomous star recognition[2].

In addition, using the neural network, our method incorporates weights and interrelated intensities of neurons to memorize the topological structure characteristics of graphics. Thus it can be applied for not only star recognition but also recognition of expanding source and area source images such as topographic maps and city traffic maps, etc.

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