An Improved Star Identification Method Based on Neural Network

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Abstract—In order to increase the star identification speed and recognition rate of star sensor, an improved rapid star identification method based on neural network (NN) is presented. The proposed method is composed of three levels, including the coarse classification of navigation stars, star pattern recognition based on NN and the final validation of recognition results. The angular distance of characteristic triangle is employed for coarse classification to active the subnets for star pattern recognition. Then the star pattern obtained by the grid method for the main star is sent to the corresponding subnets for the star pattern identification. At last, the identification results of the active subnets are validated to obtain the only recognition result. The experimental results show that, compared with traditional triangle identification method, the proposed method has higher accurate recognition rate, lower redundancy and better robustness.

Keywords—Star Sensor, Neural Network, Star Identification;

Navigation Star database

I. INTRODUCTION

As an important part of celestial navigation system, star sensor provides the attitude reference information of carrier with high precision via the star pattern recognition and the data post-processing. Therefore, it is necessary to study a rapid and high recognition rate star recognition algorithm theoretically and practically.

Numerous alternative star recognition methods have been proposed recently. These star recognition algorithms mainly include triangle algorithm, grid algorithm and NN-based algorithm, and so on. Among these algorithms, triangle algorithm is relative easy by using angular distances for match identification. Because of the low character dimension of triangle, which is the basic identification element of triangle algorithm, its defects are redundant match, poor robustness to noise and so on. Grid algorithm is robust to noise, but it is time-consuming because of searching navigation star pattern database with high character dimension. As NN has such strong capability of nonlinear mapping, parallel operation, information distributed storage, fault tolerance and adaptive learn, it is wildly employed for star pattern recognition [4~6].

Reference [4] extracted feature of star map by grid algorithm and then applied BP(Back Propagation) network to the classification of navigation stars. Reference [5] extracted the navigation pattern of all stars' convex polygons from star map, then took its angular distance and vertex angle as recognition vector which is recognized by BP NN. Reference [6] extracted navigation pattern by the triangulation cutting method, then particle swarm algorithm is used to train BP network, and the trained BP network is applied to star identification.

Star identification method based on NN has the following characteristics. The pattern feature embodies the connect intensity of weights between neurons. Weight matrix replaces pattern library. The final identification results can be directly obtained without searching the navigation star database. Therefore, the computer resources and computation time are reduced greatly.

Reference [4] proposed a two-level structure star identification method based on NN. However, the coarse classification of the first level couldn't divide navigation stars into categories with moderate samples well. During the feature construction of second level, only the presence of navigation star was considered and the detail feature such as the navigation star number in grids was neglected, which finally affected the correct recognition rate. Meanwhile, the subnet identification results were not validated.

Therefore, an improved star identification method with a three-level structure based on NN is proposed. In this method, the feature extracted from the characteristic triangle is employed for coarse classification in the first level. Then more detailed characteristics obtained from grid are employed in the second level. Also taken the influence of noise on the coarse classification result into consideration, the activated subnets could be more than one. The identification results of active subnets were validated in the third level.

II. ALGRITHM DESCRIPTION

Star identification is actually a process of pattern recognition. According to the characteristic, neural network algorithm is applied to star identification in this paper. In order to identifying each navigation star in navigation star database, input and output samples should be constructed and sent to the recognition network for training. Since there is huge number of navigation star, if only one BPNN is employed to identify all navigation stars, the complex network structure will cause long training time, even training failure. Hence, it's hard to obtain high correct recognition rate.

Therefore, a three-level structure star identification method was designed as shown in figure 1. The tasks of the three-level structure were respectively the coarse classification of navigation stars, fine identification by NNs and recognition results validation. The general process of algorithm is given as follows:

- According to the distribution of navigation stars in FOV (Field of view), the navigation star nearest to the center of FOV is selected as the main star. Then the angular distance at the opposite sides of the characteristic triangle constructed for main star is extracted as a feature to realize the coarse classification. The result of coarse classification determines the activated subnets in the second level.
- The grid-based pattern of current star map is constructed for current main star and sent to corresponding activated subnets for fine identification.
- The identification results of activated subnets are validated for final recognition result. Two adjacent angular distance of the candidate navigation stars obtained from activated subnets is compared with that of main star in characteristic triangle to judge the accuracy of recognition results and get the ultimate recognition result.

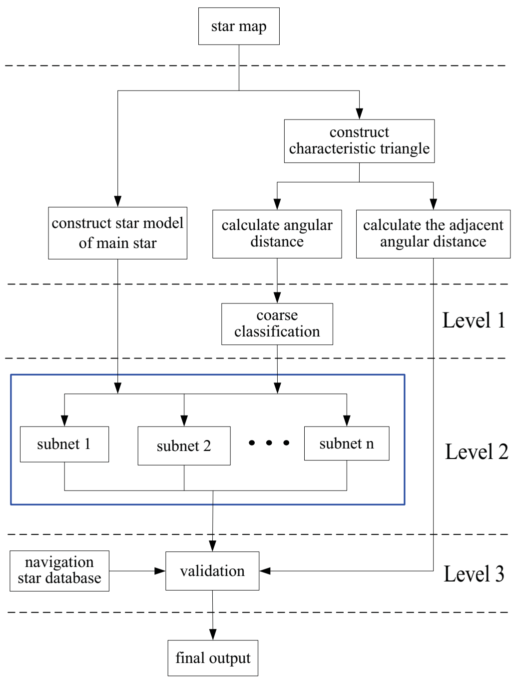


Figure 1. Structure of star identification algorithm based on NN

III. ALGORITHM IMPLEMENTATION

A. Classification of navigation star

In the process of star identification, navigation stars listed in navigation star catalog cover the entire sky and make star sensor have enough stars to identify in any FOV. And the navigation star database should not be too large to save the storage capacity and recognition time. In the actual applications, visual magnitude threshold is usually set to let the limited number of navigation stars to form the navigation star catalog. Then, the input-output samples for each star listed in navigation star catalog are constructed for NN training.

In this paper, the highest visual magnitude availably detected by the star sensor is set to 6.0. Then 5056 stars selected from the SAO star catalog are composed of the navigation star catalog, including the information of stellar magnitude, number, right ascension and declination. Thus there are 5056 samples totally.

To limit the scale of NN, 5056 stars are divided into different sub-classes by the coarse classification. Then the corresponding subnet at the second level realizes the input-output mapping of all stars that belong to each sub-class respectively. And every sub-class includes approximately equal number of stars to make all subnets with the similar scale.

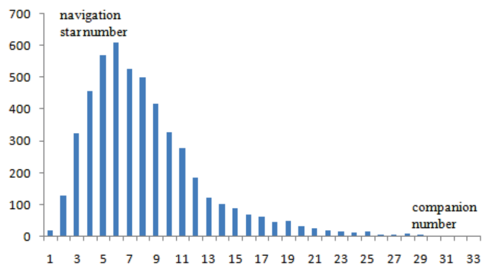
- Determination of the radius of circular region

In this paper, navigation stars are classified by their opposite side angular distance of the main star in characteristic triangle in the first level. Each navigation star together with two companions close to it are used to construct characteristic triangle, where the companion is defined as the star whose distance to the studied navigation star is no more than a predefined radius of circle *R*.

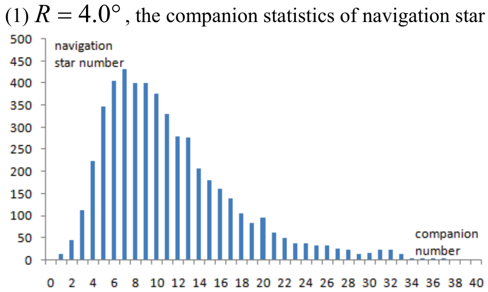
As the navigation stars whose magnitude are less than 6.0 were investigated in this paper. The companion number of each navigation star within the given circle radius was counted. When R is 4.0° , there are 21 navigation stars whose companion number is 0, and 129 navigation stars whose companion number is 1. When R is 5.0° , there are 3 navigation stars whose companion number is 0, and 15 navigation stars whose companion number is 1. When R is 6.0° , it ensures all navigation stars that the companion number is more than 2.

The statistics of companion number for navigation stars is shown in Figure 2. Horizontal axis represents the companion number of navigation star, while the vertical axis indicates the number of navigation star with the same companion number.

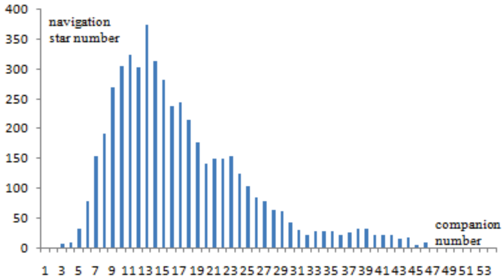
Therefore, the radius of circle R is set to 6.0° in the paper.



(1) $R = 4.0°$, the companion statistics of navigation star



(2) $R = 5.0°$, the companion statistics of navigation star



(3) $R = 6.0°$, the companion statistics of navigation star

Figure 2. The companion statistics of navigation star

- Sample classification method

After determining the circle radius R, the characteristic triangle needs to be constructed for each navigation star.

Firstly, every navigation star listed in the navigation star catalog is selected as the main star O. Then, given a predefined circle radius $br < R$ and $pr = R$, for the navigation stars which angular distance d to the main star are $br \le d \le pr$, the star which is nearest to the main star is chosen as neighbor star A and the star which is the second near to the main star is chosen as the neighbor star B. Finally, the characteristic triangle is composed by the main star, the neighbor star A and B, which is shown as figure 3.

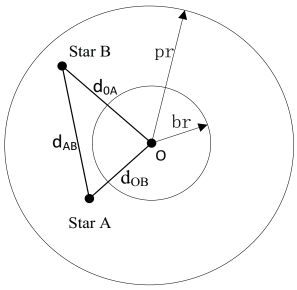


Figure 3. The construction of characteristic triangle

The navigation stars are classified according to the angular distance d_{AB} between two neighbor stars of its characteristic triangle. In order to make all subnets with the similar scale, the unequal interval of d_{AB} is adopted to divide all navigation stars in catalog into different sub-classes with approximate equal number of navigation stars. Also considering the requirement of the recognition rate and storage, the number of sub-class should not be too large. Thereby, while br is set to $1.5°$, 55 sub-classes are formed in this paper. The sample number of each sub-class is shown as Figure 4.

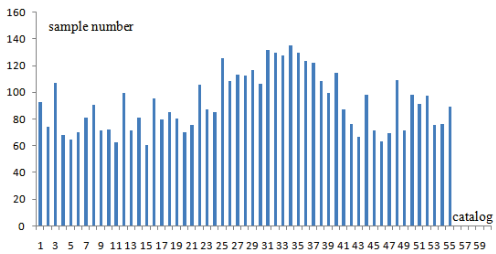


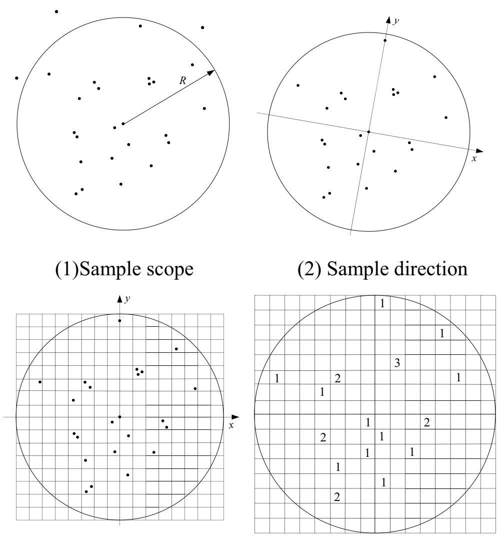
Figure 4. The sample number of subclass

B. *Neural network identification*

- The construction of the input sample

The key of NN-based identification in the second level is to construct the input-output samples for NN training with the universality and uniqueness as far as possible. Here, the input sample is constructed according to the grid method.

Firstly, taken a navigation star as the circle center, a circle with the radius of R is taken as the sampling range as shown in Figure 5(1). The information of all navigation stars inside is used to form input sample. Then a rectangular coordinate system which origin is at the circle center is built. Its positive direction of y axis points to the navigation star which is the farthest from the origin as shown in Figure 5(2). After that, the rectangular coordinate system is meshed with the grid number of D on each side. Actually, there is more than one navigation star in some grids, as shown in Figure 5(3). If only the presence of stars in each grid is considered to form star pattern, the exact feature such as the star number is lost. This may decreases the recognition rate. Therefore, both the presence and the number of navigation star are considered to construct the input sample. Then each grid is filled with the corresponding star number, as shown in Figure 5(4). Accordingly, a two-dimensional matrix is employed to describe this grid-type feature as an input sample. It is noteworthy that the navigation star at the origin should not be considered in the input sample.



(1)Sample scope (2) Sample direction

(3)Grid division (4) Sample matrix

Figure 5. The construction of input sample

Obviously, if R is too small or D is too large, it is difficult to ensure the uniqueness of samples. If R is too large or D is too small, the dimension of input sample increases, which makes the subnet structure be very complex and increases the difficulty of network training. Consequently, parameters R and D have great influence on the performance of star recognition algorithm. In section 4, the parameter R and D are given according to the simulation results.

- The construction of output sample

Compared with the input sample, the output sample is easier to be constructed. All stars in navigation star catalog have been previously divided into 55 sub-classes. And in each sub-classes, a index is given to the navigation star which has a only number in the navigation star catalog. According to the index of navigation star in the subclass, the corresponding right ascension and declination can be directly found from the navigation star catalog. The output sample of each navigation star is represented by a binary number according to its index in the corresponding sub-class.

In this paper, the sample number of each sub-class is not more than 256, so the output sample can be encoded by an 8-bit binary.

- The training of identification network

According to the input-output samples prepared by the abovementioned method, the number of input neuron and output neuron for each subnet can be determined as 256 and 8, respectively. As to determine the number of hidden layer and hidden layer neurons, it is found from the simulation result that one-hidden-layer NN is enough for the star pattern recognition.

Compared with hidden layers, to determine the number of hidden layer neurons is much more complex. By far, there is no good way to determine the number of hidden layer neurons theoretically. Therefore, it is found by the experience that the number of hidden layer neurons between 20 and 30 may solve the problem of star identification. The hidden layer neurons number of each subnet is chosen according to the specific identification effect. Here, for the convenience of programming, the number of hidden layer neurons is selected as 25.

Since the basic BP training algorithm converges relative slowly, the gradient descent training method which combines the momentum and adaptive learning is adopted in this paper. Then it reduces the NN training times greatly. The training time of basic BP algorithm is about 10 times shorter than that of the latter method.

After training, the weight and threshold for each subnet are saved in the navigation star database for the application of star map recognition later.

It is known that many kinds of noises influence accuracy of angular distance of the characteristic triangle, which is generated for a real star map sensed by star sensor. Then miss classification at the first level may occur. Then one wrong subnet may be activated and cause the miss recognition at the second level.

Therefore, in order to reduce the fault recognition rate, according to angular distance d_{AB} and its uncertainty range, several corresponding subnets are activated. All the identification results output from these activated subnets are candidates of the final recognized navigation star. Then the correctness of all navigation star candidates is validated at the third level.

C. Recognition Results Validation

As previously mentioned, during constructing the characteristic triangle, the angular distance between the main star and its two neighboring stars can be obtained. Such information is employed for the validation of identification results.

Assumed that the two adjacent angular distances of the characteristic triangle for the main star in studied star map are d_{OA} and d_{OB}, and for the ith recognized candidates are d_{1i} and d_{2i}. Only the candidate satisfied the following equation is the final recognition result.

$$\sqrt{(d_{OA}-d_{1i})^2+(d_{OB}-d_{2i})^2}<\theta_{th} \tag{1}$$

Where, θ_{th} is the given threshold, the default value can be set as the mean square deviation of system error.

If there is no candidate satisfies the above equation, it means the recognition fails.

D. The construction of navigation star database

Navigation star database is the foundation of the star recognition algorithm. According to the proposed method, the database consists of the navigation star catalog, the weight table of recognition network, the index table of subnet output and the table of characteristic triangle for each navigation star listed in the navigation star catalog.

Navigation star table includes navigation stars which are selected from fundamental star catalog, such as SAO, according to the visual magnitude of star sensor can be sensed. It contains the information of star number, magnitude, right ascension and declination.

The information all identification subnets, including network weights and thresholds, are stored in the weight table of recognition network.

The index table of subnet output contains navigation star number and its index in the subnets. Three angular distances of characteristic triangle for each navigation star and the corresponding star number are stored in the table of characteristic triangle.

IV. The Star Recognition Algorithm Based on NN

The steps to apply NN-based star recognition algorithm to identify a star map are given as follows:

Step 1: Constructing the characteristic triangle. According to the navigation stars distribution in star map, a star which is nearest to the center of FOV is chosen as the main star. Then the star in the range of radius r ($br \le r \le pr$), which is nearest to the main star, is chosen as neighbor star A, while the secondary near star is chosen as neighbor star B. Then the angular distance d_{OA}, d_{OB}, d_{AB} of the characteristic triangle are calculated.

Step 2: Input sample generation. According to the method previously mentioned, a corresponding star pattern for each main star is constructed and it is the input sample which will be sent to the second level.

Step 3: Coarse classification of navigation star. According to d_{AB} and its uncertain range obtained from the given star map, the corresponding BP subnets are activated

Step 4: NN identification. The input sample generated in step 2 is sent to the candidate BP subnets. According to the output of BP subsets, the index of navigation star candidates in the navigation star table can be determined to get their information of right ascension and declination.

Step 5: Recognition results validation. Two adjacent angular distance of all navigation star candidates and d_{OA}, d_{OB} obtained in step 1 are substituted into equation (1). If (1) is satisfied, then current match of candidate is successful. Otherwise, this match is failed.

V. Simulation Result and Analysis

A. The simulation parameters

In this paper, the parameters of optical system are set for the simulation as follows.

The FOV is $20° \times 20°$. The resolution is $1024° \times 1024°$ pixels. The pixel size is $15 \times 15 \mu m$. The focus is 43.555mm. The maximum visual magnitude detected by star sensor is 6.0.

Accordingly, the fundamental star database includes the information of 5056 stars which are selected from SAO star table. The capacity of navigation star table, weights table of recognition network, table of subnet index and table of characteristic triangle are respectively 194KB, 3.28MB, 1KB and 261KB. The total capacity of navigation star database is 3.73 MB.

B. Parameters R and D on the effect of recognition rate

In the construction of input sample, parameters R and D impact the input dimension of subnet and star pattern of subnets, also affect the complexity of network structure and the recognition rate.

Here, the influence of parameters R and D on the recognition rate is obtained by the simulation analysis. The recognition rate of different parameters R and D shown in table 1 were obtained without the noise influence.

TABLE I. THE INFLUENCE OF PARAMETERS R AND D ON THE RECOGNITION RATE

R	D	recognition rate
4.0°	0.5°	97.6%
5.0°	0.5°	98.1%
6.0°	0.5°	98.3%
6.0°	0.75°	98.7%
6.0°	1.0°	97.8%

According to table 1, (1) when D is fixed, with the increase of R, the recognition rate increases continuously. Here, the recognition rate increases from 97.6% to 98.3%. However, as R increases, the dimension of input sample is also increased, which makes network structure more complex and the storage capacity of navigation star database larger. (2) When R is fixed, with the increase of D, the recognition rate increases at first and then decreases. However, with the increase of D, the dimension of input sample reduces. But when D increases to a certain extent, the minutiae feature will be lost. It causes reduction of recognition rate.

Therefore, while designing the algorithm, the influence of parameters R and D to the recognition algorithm performance should be comprehensively considered, and the two parameters should be reasonably determined to insure the algorithm performance. In this paper, R is set to 6.0° and D is set to 0.75°, thus the dimension of input sample is 256.

C. Noise on the Influence of the Recognition Rate

As for the simulation experiment, 1000 optical axis directions were generated randomly. Then star maps of each optical axis direction were simulated by Monte Carlo method.

During the process of star map simulation, we considered many factors such as noise caused by the CCD star point imaging error and visual magnitude error location. When visual magnitude error was modeled as Gaussian white noise for gray with N(0,3).

Traditional triangle algorithm and improved NN-based star map recognition algorithm were used to identification respectively. The recognition results are shown in Figure 6:

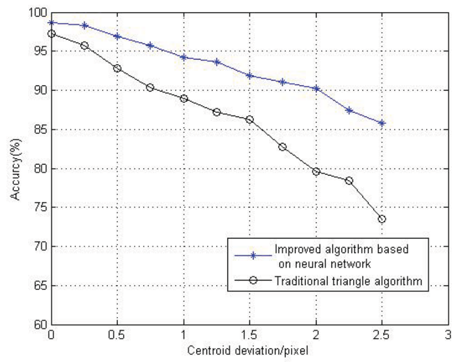


Figure 6. Performance comparison of two methods

As shown in figure 6, compared with the traditional triangle algorithm, improved star identification algorithm based on NN has a higher recognition rate. And, its recognition rate decreases slowly while the noise increases, which indicates that the improved algorithm is more robust.

D. Algorithm Efficiency

All the algorithm was realized on an Intel dual-core 2.40GHz PC, and programmed by using VC ++6.0.

Under the same simulation conditions, the average recognition time of traditional triangle algorithm for a star map is 1.23ms. While the average recognition time of improved star identification algorithm based on NN is 5.18ms. If the time of input sample and characteristic triangle construction were not considered, the average recognition time of improved algorithm is just 0.45ms.

Obviously, the recognition time of improved algorithm is a little longer. Most of time was spent on the construction of characteristic triangle and input sample. So in order to improve the efficiency of algorithm, the processing time of the construction of characteristic triangle and input sample should be reduced.

VI. CONCLUSIONS

An improved star identification algorithm based on NN is presented in this paper. This method combines advantages of both tradition triangle algorithm which uses the angular distance to match and grid method which is robust to noise. Also, it overcomes the shortcomings of both traditional triangle algorithm and grid method, the traditional triangle algorithm easily generates redundant match and weak robustness to noise, while the grid method is time consuming.

Conclusions can be draw from the simulation results as follows: compared with the traditional triangle algorithm, the improved star identification algorithm based on NN has higher recognition rate, and more robustness to noise.

Although the proposed algorithm improved the recognition rate, recognition speed and robustness, but the dimension of input sample was still large, the complexity of recognition network structure should be reduced to make it more reasonable. Meanwhile, the BP network algorithm is easily limited to local minima, so the training method should be improved to optimize the network weights and improve the performance of star pattern recognition algorithm.

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