# CONSTRUCTION OF STAR CATALOGUE BASED ON SVM

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**ABSTRACT:**

The method of constructing navigation star catalogue always based on Magnitude Filtering Method (MFM). But it did not work well because of two typical disadvantages. On one side it would extract so many stars that there was redundancy in the catalogue. And on the other side it would generate "hole" in some area of celestial sphere. In this article, Support Vector Machine (SVM) was introduced into extracting navigation stars from basic catalogue. After using the new method on SAO catalogue, it was proved that taking SVM as the method of extracting navigation-stars has good prospection.

## 1. PREFACE

Because of its lightness, economy and high precision in confirmation of satellite's attitude, star sensor is becoming mainly instruments for measuring attitude on space probes. The essential of measuring satellite's attitude based on star sensor is confirming the instantaneous orientation of star sensor axes in celestial sphere coordinate system based on starlight vectors, and then ascertaining the attitude of satellite. In above processes the star recognition is the key process. So far, except the recognition method based on neural-network, all kinds of methods promoting by scholars need to consider the construction of star catalogues. At present the popular way of constructing star catalogues is filtering based on star's light, which only reserving the stars lighter than the giving threshold. In some sense, it is only a kind of simple linearity classification method, which cannot ensure that there are plenty of stars in every watch-field because the classification only relay on a giving threshold. In some fields there must be so many stars which makes the recognition redundancy and in some fields there is even none stars which appear a hole. So how to select navigation stars and construct a self-contained and even star catalogues based on the distributing of stars become the basis of star recognition.

## 2. CONSTRUCTION PRINCIPLE OF STAR CATALOGUES

### 2.1 Research Objective

In star catalogue, except for the coordinates in celestial sphere, it includes the anniversary proper motion, anniversary and long-term movement of all the stars. At present, the star catalogues which used widely in space applications are as bellows: SAO, FK4 and Goffin catalogues etc. In the SAO catalogue, it records more than 260,000 stars' information, including position, brightness and spectrum. Specially, the position precision of stars can achieve $10^{-8}$, but brightness precision is only 0.1. Because the position precision is more important than brightness precision in determining attitude of satellite, we select the SAO catalogue as basic catalogue.

In order to construct a self-contained and even star catalogues, it is necessary to find out the distributing rules of all the stars firstly. With the increasing of the threshold, the number of stars appeared in every FOV (Field Of View) increase obviously. Given the threshold of star sensor as 7.0, only when every FOV include more than 4 stars, can the catalogue be self-contained, and there will be more than 16,000 stars in the catalogue. It is difficult for storing the catalogue and matching star pairs effectively. Generically, star sensor can detect stars lighter than 6.0-6.5, so we can design appropriate FOV to make self-contained star catalogue. To assure that there are more than 4 stars in every FOV, the FOV of star sensor should be larger than 14°×14°. According to normally star sensor, which the FOV is 8°×8°, there will be 11% FOVs that cannot complete star recognition, because the numbers of stars in them are lack of 4 [1].

### 2.2 Distributing Rule of Stars

From the discussion above, if we want to determine attitude of satellites based on star sensors, there may be only two choices: using the star sensors which have large FOV or increasing the number of stars that storing in the satellites. But both of the two methods are low efficient. So we have to resolve the problem by different ways. Given the FOV of star sensor is 8°×8°, if in every FOV it must have stars more than some given number (N), so we can determine that in every FOV what their thresholds are, and what the distributing rule of thresholds in the whole celestial sphere is. When N=4 the distributing rule can be shown by figure.1.

From the above figure, the distributing rule of thresholds actually is a spacial irregular plane. If we consider the distributing rule of thresholds as optimized plane that it can devise all stars into two types: navigation stars or non-navigation stars, so the problem of selection of navigation stars can switch to the problem of seeking non-linearity optimized classified plane. It is very difficult for some linearity classified methods, but it is advantage of SVM.

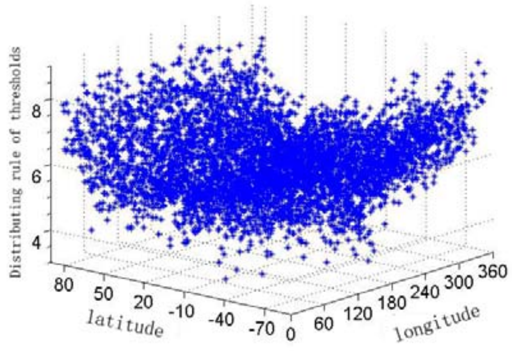


Figure 1. Distributing rule of thresholds (FOV=8°×8°, N=4)

### 3. SUPPORT VECTOR MACHINE

The Vapnik-Chervonenkis Dimension (VC) theory and structure risk least theory of Statistics Learning Theory (STL) is the theoretical basis of SVM. It can find furthest compromise between complexity of models and capability of learning and the best generalization capability according to limited sample information. Relative to classical statistics theory and non-linearity theory, SVM has the advantages in resolving pattern recognition issues as bellow:

1. It need not to statistic infinitude samples because it seek the best systemic results based on finitude samples;
2. SVM will transform to a quadratic optimization problem finally, and theoretically, find the final optimized resolution. And it can avoid plunging local extremum in Neural Network.
3. SVM can transform the eigenvectors into high dimension feature space by kernel function, and construct the linearity classified function substituting for non-linearity classified function in original area. The special particularity resolves the disaster of VC dimension subtly and it can assure that the machine learning has better capability of generalization.

SVM is developed from linearity optimized classified plane, shown as figure 2. The solid point and the hollow point denote two types of samples, and **H** is the right line that divided two types correctly. $H_1$ and $H_2$ are the lines paralleled with H, so the distance between $H_1$ and $H_2$ is the Margin between the two types.

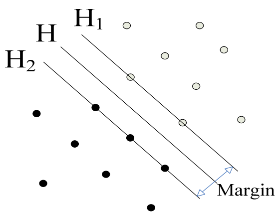


Figure 2. Optimized classified plane

To linearity divisible samples:

$$(x_i, \tau), i = 1, 2, \cdots n, x \in R^d \quad (1)$$

$\tau = \pm 1$, the different types. The general linearity classifier in D dimension is:

$$g(\mathbf{x}) = <\boldsymbol{\omega}, \mathbf{x}> + b$$

And the plane equation is:

$$g(\mathbf{x}) = 0 \quad (2)$$

The practical classifier equation is:

$$g(\mathbf{w}, \mathbf{x}, b) = \mathrm{sgn}(<\boldsymbol{\omega}, \mathbf{x}> + b)$$

And $\mathrm{sgn}(\,)$ is sign function.

In order to assure that the margin between the two types is $2/\|\boldsymbol{\omega}\|$, the classifier function should be generalized, and to every samples, $|g(\mathbf{x})| \geq 1$. So seeking the optimized classifier plane or getting the maximum margin is getting the least $\|\boldsymbol{\omega}\|$ (or $\|\boldsymbol{\omega}\|^2$). Only this way can the classifier have the most generalization capability. And if the classifier can divide all samples correctly, it must satisfy the bellow equation:

$$\tau[(<\boldsymbol{\omega}, x_i> + b] \geq 1, i = 1, 2 \cdots, n \quad (3)$$

Except the above restriction, if the classifier can make the least VC dimension $h(h \leq \frac{1}{2}\|\boldsymbol{\omega}\|^2)$ of $g(\mathbf{x})$, so we call it the optimized classifier[2]. The process of seeking the optimized classifier can show as the bellow Lagrange equation:

$$\begin{cases} \min_{\mathbf{w},b}(\frac{1}{2}\|\boldsymbol{\omega}\|^2) \\ s.t. \quad \tau[(<\boldsymbol{\omega}, x_i> + b] \geq 1, i = 1, 2 \cdots, n \end{cases} \quad (4)$$

Using Lagrange optimized method can transform Equation(4) to its allelism equation, and the equation has only one result. So the final optimized classifier is:

$$g(\mathbf{w}, \mathbf{x}, b) = \mathrm{sgn}(<\boldsymbol{\omega}, \mathbf{x}> + b) = \mathrm{sgn}(\sum_{i=1}^{n} \lambda_i \tau < x_i, x > + b) \quad (5)$$

$\lambda_i \geq 0$ is the Lagrange coefficients.

The training samples $x_i$ for equation(3) in hyper planes $H_1$、$H_2$, are the most close points to the classified plane in the two types of samples. Because $H_1$、$H_2$ looks like supporting the optimized classified plane, so we can call $x_i$ support vector(SV). In Equation(5), corresponding non-SV, $\lambda_i = 0$, it only need to sum up SV $x_i$ . The alphabet b is the classified threshold.

If samples cannot classify in given input space, it should be mapped to a high dimension space by kernel function[2], thereby, in the transform space the samples can be classified by optimized classified plane. The classifier function getting from SVM is similar with from neural network. The output of SVM is the linearity combination of middle layer nodes, and every middle layer node is dot metrix of an input sample and a support vector. The process of classifying by SVM is showed as Figure. 3:

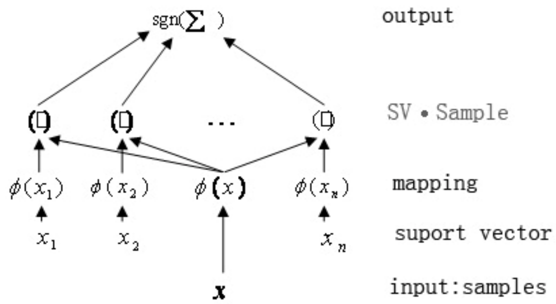


Figure3. Operation of SVM

## 4. NAVIGATION STARS SELECTION BASED ON SVM

Navigation stars selection based on SVM include some steps as Table.1 shown:

Table.1 Navigation stars selection based on SVM

| | |
|---|---|
| Step 1 | Support VMT=8.0，initialize basic catalogue based on MFM； |
| Step 2 | Select samples in the whole celestial sphere according to a given sample interval $FOV_{Interval}$； |
| Step 3 | Select the stars in every sample FOVs $FOV_s^i$ ($FOV_s^i < FOV$)，getting $S_{star}{}^i$； |
| Step 4 | Arrange the stars in $S_{star}{}^i$ from bright to dark based on their brightness (Vmag)，only reserve n(n>3) stars from the beginning of list； |
| Step 5 | Consider 3 of the most brightness stars in $S_{star}{}^i$ as navigation stars, and label with “1” ;the other stars labeled with “0”,as non-navigation stars; |
| Step 6 | Record every stars in $S_{star}{}^i$ as a sample； |
| Step 7 | Whether done with the samples?<br>YES：getting Samples, to Step 8； NO：to Step 3； |
| Step 8 | training SVM with samples |
| Step 9 | Classify all stars in the catalogue with trained SVM; if the output is “1”,select the stars as navigation stars; record the other stars as non-navigation stars. |

Because SVM is iterative optimization process, so it is necessary to verify continually what the right SVM parameters is and select samples for training SVMs again and again until the catalogue can support navigation applications perfectly.

## 5. TEST AND ANALYSIS

Taking SAO catalogue as basic catalogue, we designed some tests for verifying the method mentioned in this paper. Firstly, given threshold VMT=8.0, we got a temporary catalogue include 46,136 stars by filtering basic catalogue with MFM. Then, given $FOV_S^i$=3°×3°, sampled the temporary catalogue randomly by $FOV_S^i$ for getting training samples data.

Then the samples data were separated into two parts, one part was used as training samples for confirming SVM parameters, the other part was used as inspection samples for testing the performance of SVM and optimizing SVM parameters according to classified results. At last, all stars in the temporary catalogue were classified by trained SVM, and then we got navigation-stars catalogue for determining attitude of satellites. The classification was executed 1,000 times randomly and the experiment results can be shown by Table 2. FOV is given field of view when extracted training samples from temporary catalogue.

| Method | Capability of catalogue | Density of navigation-stars in FOV | | | |
|---|---|---|---|---|---|
| | | 0 | <3 | <5 | >=5 |
| MFM8.0 | 46136 | - | - | - | - |
| SVM8.0 | 9117 | 0 | 0 | 46 | 954 |
| MFM7.0 | 15914 | 0 | 0 | 0 | 1000 |
| MFM6.5 | 9023 | 0 | 4 | 37 | 959 |
| SVM6.5 （FOV=3） | 6936 | 0 | 1 | 29 | 970 |
| SVM6.5 （FOV=6） | 7685 | 0 | 0 | 43 | 957 |

Table.2 Experiment results

From Table.2, we can find that the capability of catalogue based on SVM is obvious smaller than that based on MFM and the density of FOVs has notable change. For example, when VMT=6.5, the capability of catalogue based on MFM is 9,023 and the probability of stars fewer than 3 in FOVS is 0.4 %. But the capability and probability of catalogue based on SVM is 6,936 and 0.1%. When adopted MFM, in order to avoid empty hole of field, the VMT must be 7.0 and the capability is 15,914.

And when adopted SVM, the capability of catalogue is only 7,685 and VMT<=6.5. So it can be easily concluded that the method based on SVM have highly flexibility.

## 6. CONCLUSIONS

1. When taking the extraction of navigation-stars as classification of stars, the author confirmed catalogue based on SVM, a machine learning tool. And compared with MFM, SVM can get catalogue with smaller capability. This is benefit to alleviate storage requirement on satellites.
2. The training samples and SVM parameters can affect extraction of navigation-stars. In this paper, after training the parameters of SVM by given samples, with RBF kernel function, punishment coefficient C=40 and threshold =0.001, the SVM is verified to be the most effective method. In order to improve the performance of SVM, the coefficients of SVM need to rectify based on the training data continuously.

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