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A novel method for subdivided locating of star image in star identification

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ABSTRACT

A novel method is put forward in subdividing locating of star image in this paper, which is based on super resolution image reconstruction that can generate high resolution image with more information contained by using one or more low resolution images. There are methods of super resolution reconstruction and camera calibration introduced in order to simulations results, and researching the angular distances obtained systematically. By comparing the angular distances with real angular distances in star database, the results show that angular distance achieved from super resolution reconstruction star map is closer to real value, with the precision 21.70% improved than that from original star map.

1. Introduction

With the development of navigation technology, the requirement of spacecraft attitude determination accuracy is higher and higher [2]. As the sensor with highest precision, star sensor can obtain accuracy of attitude in angular second, which make it play an important role in modern navigation. The key of spacecraft attitude determination is the star pattern recognition, and its working principle is as follows. First, star sensor shoots starry sky within field of view, preprocessing the star map by denoising and star extracting, and then calculating the angular distance between two observed stars according to centroid coordinates of star image extracted, the corresponding navigation stars can be found from the navigation star database by triangle matching algorithm. The absolute attitude of spacecraft can be determined on the basis of the identified navigation stars finally.

As mentioned previously, gaining the angular distance between two observed stars in star map is the premise for triangle matching. It would be massive redundant matching afterwards if the error of angular distance is larger, affecting matching efficiency and accuracy seriously, even lead to false matching, which is fatal to spacecraft navigation. Therefore, the significance of angular accuracy is presented, and the very accurate centroid coordinate is required when extracting the star image. Aiming to the limit of image resolution, certain effect is achieved based on the study of sub-pixel algorithm. Among them there are centroid method, square weighted method, threshold centroid method etc. These algorithms, however, are completely dependent on the image resolution, and the precision would reach the bottleneck when suffering low image resolution, centroid accuracy requiring exceedingly and even CCD high-cost. The use of new methods to get more information of images for super-resolution image reconstruction will emerge as the times require [1].

Super resolution reconstruction has been extensively applied in the fields of medicine, military, remote sensing etc. In order to improve the resolving power of the original image by introducing new information, super resolution reconstruction from multiple images is focused on studying [3,4], in which the key technology of image registration is required considering. In space navigation, however, due to the requirement of real-time attitude output, it is impossible to operate the super resolution reconstruction by using multiple images. Therefore, this paper focuses on the study of single image super resolution. The main algorithms of super resolution include interpolation method [5], projection onto convex sets (POCS) [6,7] and maximum a posterior [8] (MAP) etc. The super resolution reconstruction of star map is achieved by using the theory of sparse representation with dictionary learning in this paper. Firstly, acquiring the over complete dictionary through learning via original star map, and then obtaining sparse representation of star map according to the dictionary, extracting the centroid coordinate of original image and super resolution image respectively afterwards with square weighted centroid method, finally calculating the angular distance between any corresponding two stars. The two angular distances were compared with

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the real value, from which whether the novel method better is verified.

2. Method of super resolution reconstruction

The general thought of sparse representation is to select the information structure that contains being expressed signals as far as possible. Sparse decomposition of signals is to express the signal by choosing some atoms which are best in linear combination from over complete dictionaries. In fact it is a kind of process of approaching. It is assumed that $y \in R^n$ is the original signal, $\boldsymbol{D}$ is assemblage of the n-dimensional unit length vector d_r with the amount of L, namely:

$$\boldsymbol{D} = \left\{ d_i \in R^n \middle| \, ||d_i|| = 1, \quad 1 \le i \le L \right\} \tag{1}$$

where the matrix $\boldsymbol{D}$ is the over complete dictionary, and d_i is one of the atoms of the $\boldsymbol{D}$. For super resolution reconstruction [9] of image, it is necessary to work with both two dictionaries, namely $\boldsymbol{D}_h$ for high resolution patches and $\boldsymbol{D}_l$ for low resolution ones. The sparse representation of each low resolution image patch l_i is available through the methods of previous section, and $\boldsymbol{D}_l$ and $\boldsymbol{D}_h$ share the same sparse representation, then the high resolution patch h can be represented as a sparse liner combination with the product of high resolution dictionary $\boldsymbol{D}_h$ and the coefficients x of sparse representation [10], namely, $h = \boldsymbol{D}_h x$. Therefore, solving the problem of sparse representation of low resolution image l can be calculated by the formula (2), and replace the ℓ_0 norm with ℓ_1 norm according to Basis Pursuit algorithm [11] put forward by Donoho:

$$\arg\min ||x||_1 \quad \text{s.t.} \quad ||F\boldsymbol{D}_l x - Fl||_2^2 \le \varepsilon \tag{2}$$

where F is feature extraction operator. It only processes for a single image patch respectively, while operates the super resolution reconstruction of the whole image, the matching problem between adjacent image blocks must be taken into account. By making use of one-pass method [12], an optimized formula is obtained:

$$\arg\min ||x||_1 \quad \text{s.t.} \quad ||F\boldsymbol{D}_l x - Fl||_2^2 \le \varepsilon_1, \, ||G\boldsymbol{D}_h x - w||_2^2 \le \varepsilon_2 \tag{3}$$

where G is the matrix extracting the overlap region between the current target patch and the image reconstructed high resolution previously, and w is the estimated value of the image reconstructed high resolution previously on the overlap. Then the formula can be rewritten as:

$$\underset{x}{\operatorname{argmin}} ||\tilde{\boldsymbol{D}} x - \tilde{y}||_2^2 + \mu ||x||_1 \tag{4}$$

where $\tilde{\boldsymbol{D}} = \begin{bmatrix} F\boldsymbol{D}_l \\ \beta G\boldsymbol{D}_h \end{bmatrix}$, $\tilde{y} = \begin{bmatrix} Fl \\ \beta w \end{bmatrix}$. And parameter β dominates the balances of matching weight between the input feature of low resolution image and adjacent high resolution image patches. Solving the formula (4) by using BP algorithm, the optimal sparse representation x^* of low resolution image l is obtained, and the high resolution patch can be reconstructed by $h = \boldsymbol{D}_h x^*$. Considering l is not exactly equal to $\boldsymbol{D}_l x$ and affected by image background noise at the same time, the super resolution reconstruction image H_0 obtained from above method does not exactly satisfy the global reconstruction constraint [13], either.

$$BS\boldsymbol{H} = \boldsymbol{L} \tag{5}$$

where B represents blurring filter and S is the down sampling operator, $\boldsymbol{H}$ and $\boldsymbol{L}$ represent high and low resolution image respectively. Using the formula from literature [13], the final super resolution image is obtained:

$$\boldsymbol{H}^* = \underset{\boldsymbol{H}}{\operatorname{argmin}} ||BS\boldsymbol{H} - \boldsymbol{L}||_2^2 + c||\boldsymbol{H} - \boldsymbol{H}_0||_2^2 \tag{6}$$

3. Star image centroid subdivision and calibration of star sensor

The major component of star map preprocessing includes denoising, star extraction and centroid location. In order to reduce the redundant matching of star identification, improve the accuracy of recognition, it is necessary to locate the star centroid more precisely, which means the precision of star centroid breakthrough CCD detector pixel scale, and achieve subpixel locating [14]. In this paper, square weighted centroid method in subpixel locating method based on grey level is put to use, and the principle is complained as follows: it is assumed that there are n pixel points in a connected domain, the coordinate and grey of each pixel point are $(u_i,v_i)(i = 1, 2, \ldots, n)$ and $g(u_i,v_i)$, respectively. Then the subpixel centroid is:

$$u = \frac{\sum_{i=1}^{n} g^2(u_i, v_i) u_i}{\sum_{i=1}^{n} g^2(u_i, v_i)}, \; v = \frac{\sum_{i=1}^{n} g^2(u_i, v_i) v_i}{\sum_{i=1}^{n} g^2(u_i, v_i)} \tag{7}$$

Therefore the centroid coordinates of star in CCD sensor can be achieved according to formula (7). And then consult the literature [15], cubic polynomial surface fitting:

$$\begin{aligned}
x_s &= k_1(u-k_{21})^3 + k_2(u-k_{21})^2(v-k_{22}) + k_3(u-k_{21})(v-k_{22})^2 + k_4(v-k_{22})^3 + k_5(u-k_{21})^2 + k_6(u-k_{21})(v-k_{22}) + k_7(v-k_{22})^2 + k_8(u-k_{21}) + k_9(v-k_{22}) + k_{10} \\
y_s &= k_{11}(u-k_{21})^3 + k_{12}(u-k_{21})^2(v-k_{22}) + k_{13}(u-k_{21})(v-k_{22})^2 + k_{14}(v-k_{22})^3 + k_{15}(u-k_{21})^2 + k_{16}(u-k_{21})(v-k_{22}) + k_{17}(v-k_{22})^2 + k_{18}(u-k_{21}) + k_{19}(v-k_{22}) + k_{20} \\
z_s &= \sqrt{1 - x_s^2 - y_s^2}
\end{aligned} \tag{8}$$

can be used to convert the star centroid coordinates to vectors $\vec{S}_s$ that stars with respect to CCD sensor. It's assumed that right ascension and declination of nautical star are (α, δ), and the vectors of nautical star in inertial system is

$$\vec{S}_i = [x_i, y_i, z_i]^T = [\cos\delta_i \cos\alpha_i, \cos\delta_i \sin\alpha_i, \sin\delta_i]^T \tag{9}$$

This paper aims to study whether the precision of subdivided locating is improved after the super resolution reconstruction of star map. Therefore platform misalignment small angles ϕ_x and ϕ_y in the horizontal direction and drift angle ϕ_z measured by magnetometer are negligible, and then with the longitude and latitude (λ, L) in observation location, the vernal equinox Greenwich hour angle GHA at observation time, we can finally obtain the star vectors in CCD sensor coordinate system [17] $\vec{S}_s$:

$$\vec{S}_s = \begin{bmatrix} -\sin\lambda & \cos\lambda & 0 \\ -\sin L \cos\lambda & -\sin L \sin\lambda & \cos L \\ \cos L \cos\lambda & \cos L \sin\lambda & \sin L \end{bmatrix} \begin{bmatrix} \cos(GHA) & -\sin(GHA) & 0 \\ \sin(GHA) & \cos(GHA) & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \cos\delta\cos\alpha \\ \cos\delta\sin\alpha \\ \sin\delta \end{bmatrix} \tag{10}$$

Then the parameters $k_i(i = 1, \ldots, 22)$ in formula (8) can be obtained by fitting $\vec{S}_s$ with least squares, and star vectors $\vec{S}_s$ that real star related to CCD sensor is finally obtained by the polynomial fitting.