Optik 126 (2015) 1133–1137

Contents lists available at ScienceDirect

Optik

journal homepage: www.elsevier.de/ijleo

Denoising star map data via sparse representation and dictionary learning

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ARTICLE INFO

Article history:
Received 16 February 2014
Accepted 27 February 2015

Keywords:
Sparse representation
Redundant dictionary
Star pattern recognition
Noise suppression

ABSTRACT

As the highest precision devices of celestial navigation system [1], star sensors have been getting more and more attention in recent years. In which the star image positioning and recognition is the key technology of CNS, while the extraction of stars from star maps is the first step. By the background noise, there are some error extractions when traditional methods are used, which can even lead to the failure of star map matching. To solve this problem, a denoising method based on overcomplete sparse representation is presented in this paper. This method uses the adaptive sparse decomposition of star map in the redundant dictionary to process the threshold, as a result, the reliability of star extraction is improved. The experimental results show that the correct rate of this method that extracting star after reducing background noise of star map is close to 100%.

1. Introduction

For star pattern recognition and attitude determination using star sensor is the method of celestial navigation with the highest precision. Celestial navigation with star sensor is the most precise navigation system. Star sensors use cameras' detect unit shooting the star directly at a certain moment, and process the obtained star map by centroid extraction, star pattern recognition and attitude solution. And the instantaneous pointing information of star sensor is achieved. After the corresponding coordinate transformation according to the installation position of the star sensor in the aircraft, the attitude information of aircraft is ultimately obtained. The correct rate of star pattern recognition is affected by the accuracy and reliability of star image preprocessing directly, so the star image preprocessing is one of the key technologies of the star pattern recognition.

The traditional methods used in star image preprocessing include method of gray weighed, centroid method with threshold, curved surface approximation and star extraction of centroid compensation, etc. [2,3]. Considering the influence of background noise, improved methods such as wavelet image denoising [4,5] and partial differential equation model for optics image denoising [6] are proposed by some scholars. By choosing an appropriate wavelet transform filter, the correlation between different characteristics extracted from the image can be greatly reduced, so it can express the one-dimensional signal with singular point perfectly. However, one-dimensional singular feature such as edge and texture included in two-dimensional image signal is not presented as well as the former circumstances. The mount of coefficient is no doubt getting larger with the scale increasing, when presenting the image with wavelet by the linear singularity that approximated by point singularity, the ability of wavelet sparse representation decreased rapidly. Hence, a method for depressing noise of star map based on sparse representation [7] is put forward in this paper, so that the correct rate of star extraction is improved.

Sparse representation has been widely researched in recent years, and the problems solved by which is to search for the most concise representation of a signal in terms of linear combination of atoms in an over-complete dictionary. Sparse representation tends to offer better effect in image denoising, therefore it is an extremely powerful tool for engineering [8,9]. But account for the scale of redundant dictionaries which consists of kinds of cascaded basic functions [10] is large, hindering the application in engineering practice. An image denoising method based on KSVD over-complete dictionaries learning is proposed in literature [11,12], and obtained very good results.

All of the previous searches of sparse representation algorithm on restraining noise are simulated and analyzed based on adding Gauss white noise artificially, and we can generate a picture with noise in the same way by matlab shown in Fig. 1. However, there

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http://dx.doi.org/10.1016/j.ijleo.2015.02.091
0030-4026/

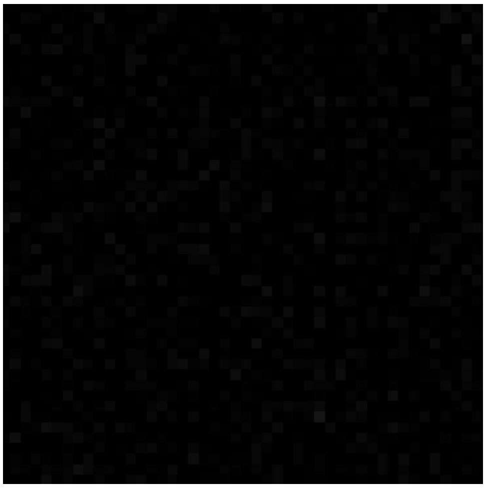

Fig. 1. The black background added the Gauss white noise with variance of 0.0005 simulated by matlab.

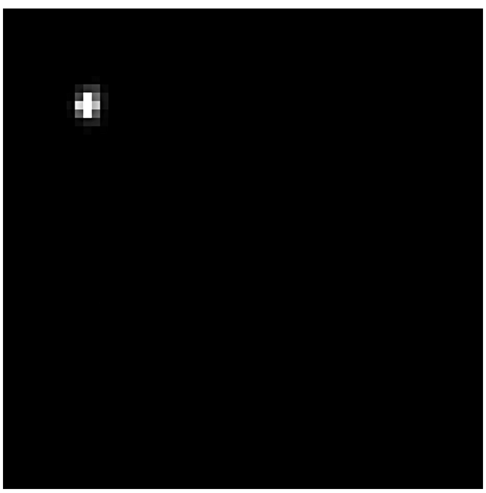

Fig. 2. Mixed noise of real star map (amplified).

are various of irregular noises in original star map such as the noise from CCD image sensor, electronic circuit [13], background light, A/D conversion, atmospheric disturbance and from other unpredictable factor shot by star sensor in practical engineering, which is shown in Fig. 2. Although it is difficult to distinguish by the naked eye, simulated noise is not as persuasive as the noise shot in real star map. Therefore, it aims to explore how well it works of sparse representation algorithm in real image denoising and improve the method of overcomplete dictionaries construction.

2. Method of sparse representation of signal

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 overcomplete 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,

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

And it can be expressed as:

$$y = Dx + b = \sum_{i=1}^{L} d_i x_i + b \tag{2}$$

where the matrix $\boldsymbol{D}$ is the overcomplete dictionary, and d_i is one of the atoms of the $\boldsymbol{D}$. $x = [x_0, x_1, \ldots, x_L]^T$ is the coefficient matrix, and b is the residual component. The problem of sparse representation is to find an $L \times 1$ coefficient vector x, such that $y = \boldsymbol{D}x + b$ and $\|x\|_0$ is minimized, i.e.,

$$x = \min \|x\|_0 \quad s.t. \quad \left\| y - \sum_{i \in D_{n\times m}} d_i x_i \right\|_2 \le \varepsilon \tag{3}$$

where $\|x\|_0$ is the ℓ_0 norm and is equivalent to the number of nonzero components in the vector x. However, rarely vector is with the most coefficients equal to zero strictly in the actual signal representation, so it is not effective enough to measure the sparseness by l_0 norm. This is more so especially when there is noise in signal. Hence it turns to be an NP problem how to get the optimal solution. An approximate solution is put forward by replacing the ℓ_0 norm in formula (3) with the ℓ_1 norm, as follows:

$$x = \min \|x\|_1 \quad s.t. \quad \left\| y - \sum_{i \in D_{n\times m}} d_i x_i \right\|_2 \le \varepsilon \tag{4}$$

In fact, this way to solve the NP problem is convex relaxation method and greedy tracking method, all of these algorithms and the improvements such as MP [14], OMP [15] and BP [16] solve the NP problem availably.

3. Algorithm of noise depression in image based on learning

It is assumed that D is the dictionary and adaptive updates are performed by using K-SVD method in this paper in order to depress noise in image effectively with the lossless image as possible at the same time. So a thought is put forward based on the former researchers [17] that dividing the image into blocks and suppressing noise by iterative residuals.

KSVD is another method of atomic base training which was put forward by Aharon et al. [12]. The main contribution lies in the update of atomic base, and it is not necessary to inverse matrix, but process the atoms in base one by one. Meanwhile, the atom base of KSVD and the corresponding representation coefficient are updated at the same time, which save the training time. KSVD method names from the core step used singular value decomposition, and repeats K times to finish.

SVD is defined as follows: it is assumed $\boldsymbol{A}$ is real matrix with the size $m \times n$, and $rank(\boldsymbol{A}) = r$, then there must exist m order orthogonal matrix U and n order matrix V subject to,

$$A = U \Lambda V^T = U \begin{bmatrix} \Sigma & 0 \\ 0 & 0 \end{bmatrix} V^T, \quad UU^T = I, \quad VV^T = I \tag{5}$$

In which $\Sigma = diag(\lambda_1, \lambda_2, \cdots, \lambda_r)$, $\lambda_1 \ge \lambda_2 \ge \cdots \ge \lambda_r > 0$ are all nonzero singular values of $\boldsymbol{A}$ with the amount of r, and columns of U and V are respectively as the feature vector $\boldsymbol{A}\boldsymbol{A}^T$.

According to formula (4), when meeting the sense of minimum mean square error, we can update the dictionary by using the method of atomic update one by one by iteration. Dictionary learning can be integrated into the Bayesian maximum a posteriori estimation (MAP) [18], in other words, if dictionary D is unknown as well, for a given image, the atom $\hat{d}_{ij}$ of sparse representation can be achieved by solving NP problem [19], then using the K-SVD