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基于稀疏重构的光学传感器扩展目标量测划分

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摘 要:提出一种稀疏重构框架下利用幅度实现扩展目标量测划分的方法.利用衍射受限光学系统特性对像平面进行网格采样,建立稀疏重构模型及"超完备字典".通过重构挖掘像元幅度值中的有效信息并基于成像机理对重构出的非目标量测进行抑制处理,利用重构出的亚像元级目标位置、幅度信息实现目标量测的划分.仿真结果表明:信噪比为 6 dB 时,本文算法比传统方法在实现对所有扩展目标量测的正确划分上提前 30s,对目标探测信息能充分利用,在量测划分准确性上比依靠距离划分的传统方法有较大提高,尤其在低信噪比条件下较传统方法量测划分的准确性提升明显.

关键词:天基监视;光学传感器;空间近邻目标;扩展目标;量测划分;稀疏重构
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Partition Algorithm for Extended Targets in Optical Sensor Using Sparse Reconstruction

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Abstract: A partition algorithm method with sparse reconstruction was proposed to partition measurements making full use of the information of the extended targets. The grid sampling of the image plane was carried out by using diffraction limited optical system's features, a sparse reconstruction model was set up with a "super complete dictionary". Effective information in the amplitude of every pixel was extracted by sparse reconstruction, non-target measurement was eliminated by physical features. Partitioning measurements was realized by using the reconstructed sub-pixel-level target location and amplitude information. Simulation results indicate that the proposed method correctly partitions all the targets as separate measurements about 30s earlier than traditional distance-based partitioning method when signal noise ratio is 6 dB. Due to the full and effective use of target information, the proposed method outperforms the traditional distance-based partitioning methods in terms of the partitioning results' accuracy, especially in the cases of poor signal noise ratio.

Key words: Space based surveillance; Optical sensor; Closely spaced objects; Extended target; Partitioning; Sparse reconstruction
OCIS Codes: 120.0120; 280.4788; 100.4993

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0 Introduction

With the rapid development of optical sensors, the targets on sensors' focal plane became more detailed. Many targets tracked by optical sensors can be treated as extended targets[1-3]. Refs. [4-6] emphasized the importance of measurements partition in the extended targets tracking filter. And there were many methods to partition measurements for optical sensor's images, traditional methods usually partitioned measurements according to their distances between each other. And Ref. [7] summarized the advantages and disadvantages of existing partitioning methods. Traditional methods usually relied on the distances among the measurements' clustering centers and the performance depended on the distance threshold which was difficult to be determined. So Ref. [7] proposed a method using H-K clustering with k-means to partition the initial clusters into sub-clusters, that are final measurements' partitioning results. The advantage of method in Ref. [7] is making use of the amplitude information (as well as position information), but it did not use the amplitude information sufficiently especially the sub-pixel amplitude information.

In fact, a lot of previous works proposed methods to make use of sub-pixel amplitude information. Ref. [8] introduced Markov random field to describe the relationship between optical dim targets and background, the method used the amplitude information hidden in target's shape. Ref. [9] proposed a method named reversible jump markov chain Monte-Carlo method to extract the sub-pixel information. Ref. [10] used particle swarm optimization to make full use of the amplitude information in IR image data. As an important part of extended target tracking filter, measurements partitioning required not only the accuracy of partitioning but also timesaving. Ref. [11] compared the efficiency of exsiting methods and proposed a sparse reconstruction method to super-resolute the targets in an IR image data.

This paper proposed a high efficiency measurements partitioning method under the framework of sparse reconstruction. The space-based optical sensor was modeled first. Then primary optical parameters were listed, based on these, target's features on the focal plane were analyzed. Image on focal plane could be sampled by small grids to describe in more defail the targets. Based on the model and the sparsity of the targets information in the optical images, sparse reconstrcution was introduced in this paper to extract the sub-pixel information and two kinds of non-target measurements are analyzed, the method for eliminating these non-target measurements is also presented. Then the measurements partitioning is realized by H-K clustering in grid sampling domain because it is more detailed than the image data. In order to verify the effectiveness of the algorithm, a simulation experiment is designed. Simulation results indicate that proposed method partitions measurements more precisely than traditional partitioning methods.

1 Space-based optical sensor

1.1 Sensor's optical model

As we know, space-based optical sensor's optical sub-system could be treated as a diffraction-limited system with a point spread function which is not Delta function. The instantaneous field of vision θ_{IFOV} and the pixel's length L_{d} affect a lot on the focal plane's intensity distribution

$$I(\theta)=I_0\left[\frac{2\mathrm{J}_1(\pi D\sin(\theta)/\lambda)}{\pi D\sin(\theta)/\lambda}\right]^2 \tag{1}$$

where, J_1 stands for the Bessel function of first kind, I_0 represents the original intensity reaching the focus plane, θ represents the off-axis angle:

$$\theta(x,y)=\arcsin\left[\frac{\sqrt{x^2+y^2}}{f_{\mathrm{optical}}}\right]^2 \tag{2}$$

The first ring contains 84% of the total energy is so-called airy pattern, Airy pattern's diameter d_{Airy} is the limiting resolution

$$d_{\mathrm{Airy}}=\frac{2.44\lambda_i}{D\cdot\theta_{\mathrm{IFOV}}} \tag{3}$$

The main parameters for the sensors discussed in this paper were analyzed in Ref. [7] and listed in Table 1.

Table 1 Space-based optical sensor's main parameters

Parameters	Focal length f_{optical}	Pixel length d_{pixel}	θ_{IFOV}	Aperture D
Value	134 cm	60 μm	100 μrad	0.5 m

With the primary optical parameters, we can get the energy distribution for optical sub-system just shown in Fig. 1, and we can come to the conclusion that d_{Airy} is about 0.9588 pixels on the focal plane.

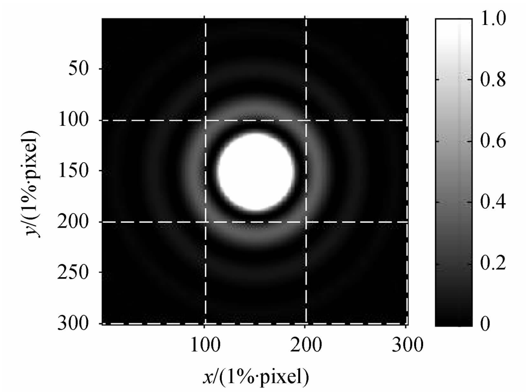

Fig. 1 Energy distribution for Airy pattern

1.2 Sampling image by grids

According to Eqs. (1) and (2), $I(\theta)$ can be written as $p(x, y)$, we can get one pixel's amplitude through the integration in specific domain.

$$g(x_c, y_c)=\int_{x_c-d_{\text{pixel}}/2}^{x_c+d_{\text{pixel}}/2}\int_{y_c-d_{\text{pixel}}/2}^{y_c+d_{\text{pixel}}/2} p(x, y)\,\mathrm{d}x\mathrm{d}y \tag{4}$$

For a single target which could be treated as point source because it's usually very far away from the space-based optical sensor, once its project position on focal plane is fixed, we can use a matrix to describe its energy distribution, we can call the matrix guide matrix. Suppose there are n targets altogether and $u_{\max}\times v_{\max}$ pixels for imaging. So amplitude $\boldsymbol{z}$ could be calculated by:

$$\boldsymbol{z}=\boldsymbol{g}\boldsymbol{s}+\boldsymbol{n} \tag{5}$$

where $\boldsymbol{z}$ is $u_{\max}v_{\max}\times 1$ vector, $\boldsymbol{g}$ is $u_{\max}v_{\max}\times n$ guide matrix

$$\boldsymbol{g}=[g(u,v,x_1,y_1)\cdots g(u,v,x_n,y_n)]_{v=1,\cdots,v_{\max}}^{u=1,\cdots,u_{\max}}$$

Eq. (5) was made up of a series of Eqs like

$$z_j=\sum_{i=1}^{N_T} A_{r,i} g_j(x_{r,i}, y_{r,i})+\varepsilon_j \quad j=1,\cdots,u_{\max}v_{\max}.$$

$g_j(x_{r,i}, y_{r,i})$ represents energy contributed by the target projected on $(x_{r,i}, y_{r,i})$ for z_j. If we define $\boldsymbol{\theta}_{r,i}=(x_{r,i}, y_{r,i})$, then z_j can be expressed by linear combination of $\boldsymbol{s}_r=[A_{r,1}, A_{r,2},\cdots,A_{r,N_T}]^{\mathrm{T}}$ and $g_j(\theta_{r,i})$ with additive noise. We can use $\{(\hat{\boldsymbol{\theta}}_k, \hat{A}_k)\}_{k=1}^{N_T}$ as the optimization of all the partitioned measurements for the focal plane response caused by all the targets. $(x_{r,i}, y_{r,i})$ could be any real number pairs other than integers.

In fact, we can get the optical energy amplitude for any position on the focal plane through Eqs. (1), (2), (5), not limited to where the pixel located at. Ref. [7,9-11] indicated that the image(or the pixels on focal) can be sampled by grids to get detailed information. For example, we can sample a single pixel with $N_g\times N_g$ grids and define

$$\boldsymbol{\Theta}\triangleq\{\boldsymbol{\theta}_{g,l}\}_{l=1}^{L}=\{(x_{g,l}, y_{g,l})\}_{l=1}^{L} \tag{6}$$

where, $L=u_{\max}v_{\max}\cdot N_g^2$. Based on this, we can get a new huge guide matrix

$$\boldsymbol{G}(\boldsymbol{\Theta})=[g(\theta_{g,1}),\cdots,g(\theta_{g,L})] \tag{7}$$

2 Partition via sparse reconstruction

2.1 Sparse Reconstruction (SR)

By sampling the pixel with $N_g\times N_g$ grids, we get a new guide matrix $\boldsymbol{G}(\boldsymbol{\Theta})$. While s_r and $\theta_{r,i}$ always came in pairs, we have to extend s_r because $\theta_{r,i}$ are extended by grid sampling, we can use a single method as follows

$$A_{g,l}=\begin{cases}A_{r,i} & \text{when}\quad \theta_{r,i}=\theta_{g,l}\\ 0 & \text{otherwise}\end{cases} \tag{8}$$

So Eq. (5) can be rewritten as

$$z=\sum_{l=1}^{L} A_{g,l} f(\theta_{g,l})+\varepsilon=\boldsymbol{G}(\boldsymbol{\Theta})s_g+\varepsilon \tag{9}$$

The problems of optimizing $\{(\hat{\theta}_k, \hat{A}_k)\}_{k=1}^{N_T}$ are translated into finding K basis in $\boldsymbol{G}(\boldsymbol{\Theta})$ to make the $\boldsymbol{G}(\boldsymbol{\Theta})s_g$ and $\boldsymbol{z}$ be the most approximate. Because the N_g we use is usually larger than 1, so the problem was a typical sparse reconstruction problem. Refs. [7],[11] summarized some mathematical forms for the sparse reconstruction problem we faced, and it was recommended that we should use

$$\min\|\boldsymbol{z}-\boldsymbol{G}(\boldsymbol{\Theta})s_g\|_2^2+\lambda\|s_g\|_1 \tag{10}$$

The optimization sparse reconstruction results can be marked as $\hat{\boldsymbol{s}}_g$, in this paper we used the tool kits "l1_ls"[12] provided by Stanford University to solve the problem described in Eq. (10).

$\hat{\boldsymbol{s}}_g$ satisfied only $\hat{N}_T\approx\|\hat{\boldsymbol{s}}_g\|_0$. In $\hat{\boldsymbol{s}}_g$, there exist some non-target measurements because of the sensor's noise and the mathematical model bias. These non-target measurements brought higher amount of calculation and estimation error. So we'd better eliminate these measurements before we go through next processing. Non-target measurements were caused by either "over sparse estimation" or "isolated sensor's noise".

2.2 Eliminate non-target measurements

2.2.1 *Isolated noise elimination*

Isolated sensor's noise is caused by the optical sensor's noises especially by the pixel's electronic noise. So usually this kind of noise is isolated, no more than one pixel. But during the sparse reconstruction the tool kits "l1_ls" might assign some $(\boldsymbol{\theta}_m, A_m)$ to approach the mathematically correct solution. We can use parameters proposed in Tab. 1 to simulate a single frame of 20×20 image with noise and target and sample every single pixel by 4×4 grids. The sparse constructed results on the image was shown in Fig. 2.

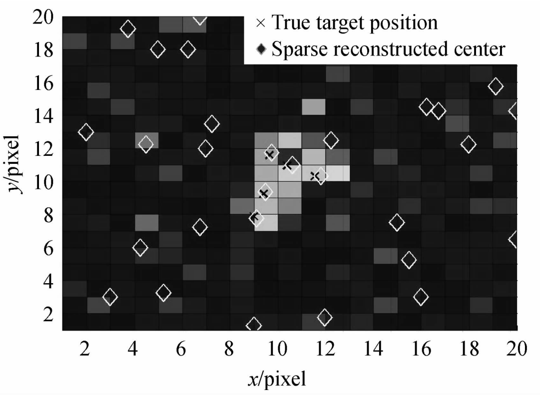

Fig. 2 Initial reconstructed results of the image

As shown in Fig. 2, the initial reconstructed results $\hat{\boldsymbol{s}}_g$ contains many items other than the true targets. From the amplitude shown in Fig. 3, the differences between targets measurements and non-targets isolated noise measurements were obvious.

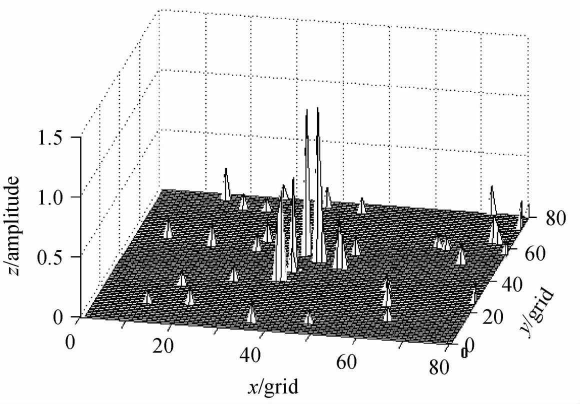

Fig. 3 Reconstructed amplitude by SR

Non-targets isolated noise measurements are usually with low amplitude and small areas. So all the $\hat{A}_{g,l}$ with an area larger than $N_g \times N_g/2$ would remain, then isolated noise elimination can be realized by following

$$\tilde{\boldsymbol{s}} = E_{\text{isolated}}(\hat{\boldsymbol{s}}_g)$$

$$\tilde{A}_l = \begin{cases} 0 & \text{if } \hat{A}_{g,l} \leqslant \mathrm{Median}(\{\hat{A}_{g,l}\}_{g=1}^{\|\hat{s}_g\|_0}) \\ \hat{A}_{g,l} & \text{otherwise} \end{cases} \tag{11}$$

2.2.2 *Over sparse items merger*

Refs. [7], [11] also referred to a kind of noise caused by over sparse, that is in the initial reconstructed results, there would be more than one measurements nearby the real targets and all the estimated measurements together approximated the final response. In fact, this kind of noise was target itself. So the method to eliminate the noise is to collect the energy together (That is items merger).

$$\tilde{\boldsymbol{s}} = E_{\text{over-sparse}}(\hat{\boldsymbol{s}}_g) =$$

$$\begin{cases} \tilde{A}_l = \mathrm{sum}(\hat{A}_{g,l}, \hat{A}_{g,k}), \text{if } \mathrm{dis}(\hat{\theta}_{g,l}, \hat{\theta}_{g,k}) < 0.5N_g \\ \tilde{\theta}_l = \{\hat{\theta}_{g,l}, \hat{\theta}_{g,k}\}, \text{ if } \mathrm{dis}(\hat{\theta}_{g,l}, \hat{\theta}_{g,k}) < 0.5N_g \\ \tilde{A}_l = \hat{A}_{g,l}, \tilde{\theta}_l = \hat{\theta}_{g,l}, \text{else} \end{cases}$$

The distance threshold was set as $0.5N_g$ (about $0.52 \cdot d_{\text{Airy}}$ in space accordingly) because Ref. [11] made lots of experiments and indicated that correct extraction ratio would be less than 50% when targets' distance is nearer than $0.6 \cdot d_{\text{Airy}}$.

2.3 Partition by H-K clustering

After eliminating the non-target measurements, there were only a measurement in the results $\tilde{s}$. Suppose that there were N_c positionsand amplitude marked as $\{(\tilde{\theta}_k, \tilde{A}_k)\}_{k=1}^{N_c}$. Ref. [7] introduced Bayesian information criteria to determine which of the N_c couples would be the best combination as follows

$$\hat{N}_T = \arg\min_{k,\text{comb}}\{-2\ln p(\boldsymbol{z}|\{(\hat{\theta}_{\text{comb},k}, \hat{A}_{\text{comb},k})\}) + 0.5kd\ln(V)\}$$

Where, $V = u_{\max} v_{\max}$, and other arguments can be set according to Ref. [7].

Hoshen-Kopelman (HK) clustering method is generally accepted as an excellent clustering method. Because the precision of $\{(\tilde{\theta}_k, \tilde{A}_k)\}_{k=1}^{N_c}$ in grid sampling domain was good enough. This paper applies HK method directly to $\{(\tilde{\theta}_k, \tilde{A}_k)\}_{k=1}^{N_c}$. Then divided by N_g, positions can be easily translated into image's row and column. It was obvious that using HK in image domain we can not partition one pixel into two different measurements but we can do that by apply HK in sampled domain.

3 Simulation and analysis

In order to verify the effectiveness of the proposed algorithm in engineering application, an simulation experiment was designed.

3.1 Simulation design

Ref. [13] provided a framework for simulating space-based optical sensor's images. This paper would apply this framework, but point spread function designed by Eqs. (1), (2), (4) is applied to replace Gauss PSF in references.

Main parameters of the simulation scenario is shown in Table 2, and all the five targets were designed to be located in the center of sensor's view. So the 20×20 pixels' data in the center of every image frame are research objects. And every pixel is sampled by 4×4 grids. The signal noise ratio for 5 targets are set as random between 4~8, there would be some poor SNR targets. At the beginning of the simulation scenario, the 5 targets begin to diffuse from the same initial position at random speed.

Table 2 Main parameters of Simulation Scene

Parameters	Orbital height/km	Distance/km	Target numbers	Frequency
Value	1600	6000	5	10 Hz

Three frames of different moments(10 s, 30 s and 50 s) are chosen to be processed both by HK partitioning method with *k*-mean and partitioning method proposed by this paper. The results by HK partitioning method with *k*-mean in Ref. [7] are marked with "HK", the results by proposed method are marked with "SR".

3.2 Simulation results and analysis

3.2.1 *Case of Targets not resolved*

All the 5 targets are not resolved 10s after the scene began. The measurements partitioning results by two method are shown in Fig. 4. In Fig. 4, partitioning results by spare reconstruction method are numbered in smaller italics; partitioning results by H-K with *k*-means are numbered in bigger bold.

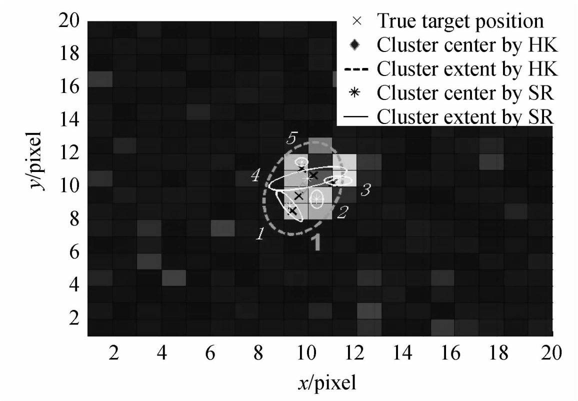

Fig. 4 Partitioning results at 10s

In Fig. 4, it is obvious that HK method partitions all the 5 targets in the image as one measurement. SR method partitions the 5 targets as 5 different measurements. Although measurement No. 2 by SR is in fact a false measurement, the rest partitioned results are basically right with certain position error and amplitude error.

3.2.2 *Case of Targets partly resolved*

Some of the 5 targets can be resolved 30s after the scene began. The measurements partitioning results by two method are shown in Fig. 5. From Fig. 5, HK method partitions all the 5 targets in the image as two measurements, especially there is one false measurement by HK method which was numbered 1, that because the SNR for the scene is relatively low.

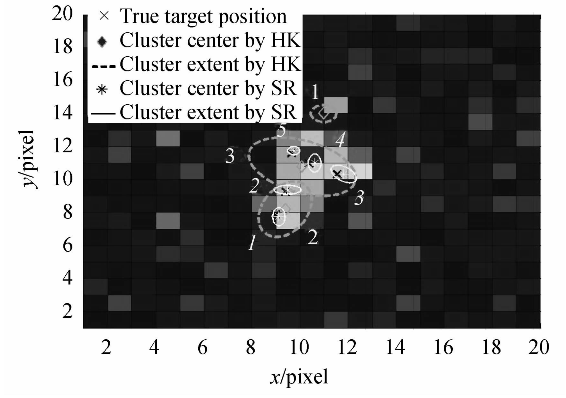

Fig. 5 Partitioning results at 30s

SR method partitioned the 5 targets as 5 separate measurements, the cluster centers almost coincide with the true targets' projection separately, only the one numbered 1 deviates the corresponding target's projection because of its poor SNR. As for the shape of partitioned measurements, because the distance between arbitratry two targets at this moment is not far, the partitioned measurements doesn't cover its corresponding area.

3.2.3 *Case of Targets basically resolved*

All the 5 targets are basically resolved 50s after the scene begins. The measurements partitioning results by two method are as shown in Fig. 6.

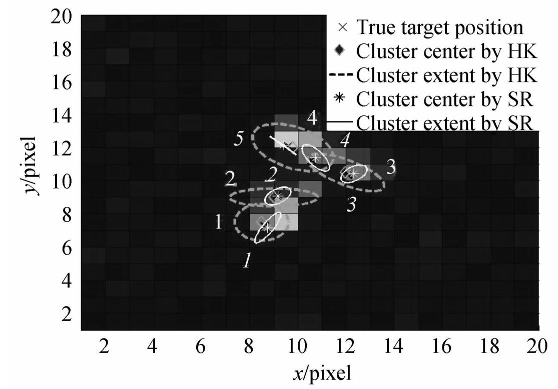

Fig. 6 Partitioning results at 50s

From Fig. 6, HK method partitioned all the 5 targets in the image as 4 separate measurements. Because the distance between each pair of targets is far enough, so the measurements' partitioning results of HK method is basically right, only the target numbered 4 by SR method can't be correctly partitioned as a separate measurement due to poor signal noise ratio.

SR method partitions the 5 targets as 5 separate measurements, the cluster centers and shape both coincided with the true corresponding targets very well. Even for the poor SNR target numbered 4, SR method partitions it as a separate measurement with the right shape. Although some targets' projection are connected domains, proposed SR method applies HK method in sampling grids where sub-pixel information can be made full use of.

4 Conclusion

To deal with measurements partitioning problem in optical extended target tracking, a partitioning method with sparse reconstruction is proposed. Sparse reconstruction is applied to extract sub-pixel information based on grid sampled images, the methods for eliminating two kinds of non-target measurements are introduced, then H-K clustering is appled on grid sampled images to partition the reconstructed results as precise measurements.

To verify the proposed method, a simulation scenario is designed. Simulation result indicates the proposed SR method is effective and has better performance than traditional methods, especially for the poor signal noise ratio targets. In the simulation, the proposed SR method correctly partitions all the targets as separate measurements about 30s earlier than traditional method, that is important for an extended targets tracking filter.

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