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An Image Segmentation Algorithm for Gradient Target Based on Mean-Shift and Dictionary Learning

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***Abstract*—**In electromagnetic imaging, because of the diffraction limited system, the pixel values could change slowly near the edge of the image targets and they also change with the location in the same target. Using traditional digital image segmentation methods to segment electromagnetic gradient images could result in lots of errors because of this change in pixel values. To address this issue, this paper proposes a novel image segmentation and extraction algorithm based on Mean-Shift and dictionary learning. Firstly, the preliminary segmentation results from adaptive bandwidth Mean-Shift algorithm are expanded, merged and extracted. Then the overlap rate of the extracted image block is detected before determining a segmentation region with a single complete target. Last, the gradient edge of the extracted targets is recovered and reconstructed by using a dictionary-learning algorithm, while the final segmentation results are obtained which are very close to the gradient target in the original image. Both the experimental results and the simulated results show that the segmentation results are very accurate. The Dice coefficients are improved by 70% to 80% compared with the Mean-Shift only method.

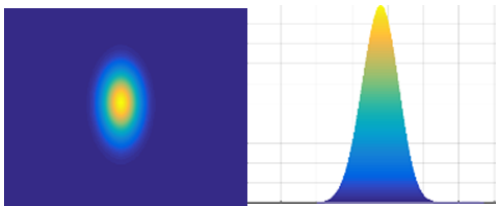
***Keywords*—**Gradient image, segmentation and extract, mean-shift algorithm, dictionary learning.

I. Introduction

IMAGE recognition and extraction is important in analyzing electromagnetic images, targets can be processed and analyzed separately after extraction. Some digital image segmentation and extraction methods that are commonly used include edge-based segmentation method [1], threshold-based segmentation method [2], [3] and region-based segmentation method [4]. However, different from common digital images, an electromagnetic image (as shown in Fig. 1) is fuzzier with its boundary pixels changing slowly due to the effect of diffraction limited and test system condition. It is difficult to determine the location of the boundary accurately by using the edge-based segmentation method. In addition, the system function of diffraction limited system is similar to the *sinc* function. The pixel value could vary a lot with extremum in the target region, while the threshold of threshold-based segmentation method is uncertain; therefore, the region-based segmentation method is used more frequently in electromagnetic images. In this method, the image is divided into different regions according to the similarity criterion, among which Mean-shift algorithm is used in reducing the error caused by change of pixel values in the blur boundary and region [5].

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(a) (b)

Fig. 1 (a). Single target of electromagnetic image; (b). The pixel value change of the target

Selecting the appropriate initial seed, setting reasonable average and drifting size judgment criteria are key to Mean-shift algorithm. However, it is difficult to determine the initial value, the mean-value threshold and the drift distance threshold for electromagnetic images because the target regions could vary significantly in size and shape. To address this issue and improve the stability of algorithm, image merging and expansion methods are combined, *i.e.,* target regions with similar pixel mean are merged and selected after applying the mean-shift algorithm. Meanwhile, the gradient edge of the targets segmented need to be kept and blur targets need to be completed through the function of imaging system, in order to preserve the information in the whole image. The complete targets lay a foundation for the analysis and reconstruction of the electromagnetic image and other image processing.

To solve the above problems, this paper proposes an algorithm based on mean-shift and dictionary-learning. By combining the image merging and selection with Mean-shift algorithm, a preliminary segmentation and extraction of image targets are obtained. Then the gradient edge of the target region is rebuilt to get the complete and precise segmentation and extraction result. [6]

II. Theory

Mean-shift is an iterative algorithm for kernel density estimation without parameters. It uses kernel to cluster samples in feature space. For n samples $\{ x^i , i=1,2,\ldots,n\}$ in L dimensional feature space, the probability density function of x is estimated by a kernel function k, i.e.,

$$\hat{p}_k(x) = \frac{c_k}{nh^L} \sum_{i-1}^{n} k(\| \frac{x - x_i}{h} \|^2) \quad (1)$$

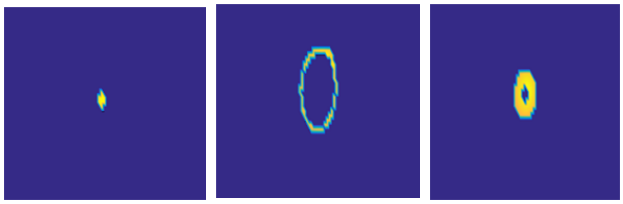
where h is the size of cluster window (cluster bandwidth). Define the translation vector as:

$$m_{h,G}(x)=\frac{\sum_{i=1}^{n} x_i g(\| \frac{x-x_i}{h} \|^2)}{\sum_{i=1}^{n} g(\| \frac{x-x_i}{h} \|^2)}-x \quad (2)$$

where, $g(x)=-k'(x)$, $k(x)$ is the contour function of the kernel function, h is the segmentation bandwidth set by the algorithm. An image can be expressed as a P dimensional vector on a two-dimensional grid on which every point represents a pixel. So for the gray image, the spatial information and grayscale information make up a three-dimension vector $x=(x^s+x^r)$, where, x^s is the coordinate and x^r is the grayscale feature. Usually, the gauss function is chosen as the kernel function, then

$$g(\| x \|^2)=\exp\left(-\frac{\| x^s \|^2}{2\sigma_s^2}\right)\exp\left(-\frac{\| x^r \|^2}{2\sigma_r^2}\right) \quad (3)$$

Set $h_s=2\sigma_s^2$ and $h_r=2\sigma_r^2$, where h_s is the spatial information bandwidth and h_r is the grayscale information bandwidth [7]-[9].



(a) (b) (c)

Fig. 2 Error segmentation by Mean-Shift algorithm ((a), (b), (c) are three target images respectively)

In the iterative of Mean-shift algorithm, the bandwidth h decides the distance and pixel value gradient among the segmentation area, *i.e.*, decides the speed and quality of the image segmentation. Due to the great difference of the target area of the electromagnetic image and the obvious change of pixel value, h of different images is determined by calculating the image roughness as well as the average of pixel value. The roughness works as the spatial information bandwidth h_s, while the average of pixel value works as the grayscale information bandwidth h_r. However, for wide-band, diffraction limited imaging system, the roughness and targets size of the different areas in one image varies a lot. In the same time, the edge gradients of the image are small and the edge fuzzy is worse as the image is polluted by noise. The segmentation areas remain errors with being irregular in shape after Mean-shift iterative. The gradient-slow-changing edge will be truncated and the same target may be erroneously segmented, as shown in Fig. 2. The changing gradient of the target makes the algorithm divide the edges into other regions. Therefore, the image segmented and extracted is adjusted by subsequent image merging and expansion, and the error is compensated. The main segmentation errors are as follows:

A. Incomplete Segmentation Area

Using image roughness as the segmentation bandwidth of Mean-shift algorithm takes more consideration into the small targets, while the large targets beyond the bandwidth will be truncated. To avoid incomplete area, expand the segmentation region to a regular rectangle before the target area is extracted, in order to retain and recover the blurred edges of the targets.

B. Extracted Region Overlap

The extracted segmentation images after expansion appear overlapping because they are not mutually exclusive. Contrast the ratio of overlap of extracted images, if two blocks overlap rate reaches 50%, the two images are determined to be the same target area and are merged.

After image adjustment, the segmented and extracted images contain the main information of single targets, while the gradient edge of the targets is still partially missing. Therefore, the algorithm further uses image reconstruction based on dictionary-learning to process and compensates the edge, so that the segmentation image can be restored better and the integrity of the image is preserved.

The image reconstruction based on dictionary-learning is mainly dependent on the sparsity of the complete gradient image. For the image with complete edge, the pixel matrix is a sparse matrix. The small image blocks segmented, the matrix sparsity is more obvious. Divide the whole electromagnetic image into several small blocks and form a dictionary. The original non-sparse images with incomplete edges can be reconstructed as the closest complete edges by using dictionary-learning method. But as the exact whole-edge image cannot be obtained, a sparse image dictionary needs to be trained by iterative ways firstly.

To build the dictionary, K image blocks sized $\sqrt{n}\times\sqrt{n}$ are randomly extracted in the whole image, and the pixel values of these blocks are arranged as a column vector x_i, respectively. Arrange these vectors as matrix D according to the extraction order. D is a dictionary sized $n*K$ $(K>n)$. Supposed D is already known, then every complete-edge image block x can be represented as:

$$\hat{\alpha}=\arg\min_{\alpha} \| \alpha \|_0, D\alpha \approx x \quad (4)$$

The real image blocks y_i is an incomplete image block with noise, which cannot be represent by the sparse dictionary. Therefore, use maximum likelihood method to solve (4):

$$\hat{\alpha}=\arg\min_{\alpha} \| \alpha \|_0, \| D\alpha - y \|_2^2 \le T \quad (5)$$

while the reconstruction image is received by $\hat{x}=D\hat{\alpha}$.

Equation (5) is a NP-hard problem and its solution is to use Augmented Lagrangian Method. Construct a Lagrange multiplier and change the limitation into a penalty items in (6):

$$\hat{\alpha}=\arg\min_{\alpha} \| D\alpha - y \|_2^2 + \mu \| \alpha \|_0 \quad (6)$$

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The dictionary is unknown in the algorithm in this paper, so training of D is needed by iterative method. Equation (6) turns into:

$$\{\hat{D},\hat{\alpha}_{ij},\hat{X}\}=\arg\min_{\hat{D},\alpha_{i,j},X}\lambda\|X-Y\|_2^2+\sum_{ij}\mu_{ij}\|\alpha_{ij}\|_0+\sum_{ij}\|D\alpha_{ij}-R_{ij}X\|_2^2 \quad (7)$$

While solving the equation above, firstly initial X=Y, dictionary D is comprised of the extracted image blocks from Y, image to be reconstructed, i.e.,

$$\hat{\alpha}_{ij}=\arg\min_{\alpha}\mu_{ij}\|\alpha\|_0+\|D\alpha-x_{ij}\|_2^2 \quad (8)$$

Using OMP to calculate the optimum coefficient matrix $\hat{\alpha}$ and update the dictionary next by singular value decomposition based on $\hat{\alpha}$ and the image matrix X. In order to increase the upload speed and the accuracy of the dictionary, upload the atoms used in the dictionary representation each time. Then fix the dictionary D uploaded and the representation coefficient matrix $\hat{\alpha}$.

$$\hat{X}=\arg\min_{X}\lambda\|X-Y\|_2^2+\sum_{ij}\|D\hat{\alpha}_{ij}-R_{ij}X\|_2^2 \quad (9)$$

Set $X_{i+1}=\hat{X}$, that is image X is uploaded and the iteration process is repeated until the error of (6) is less than the threshold set. [10], [11]

The image matrix is sparse after reconstructed by dictionary-learning. The edge of target segmented basically restores the gradient edge of image. The segmented image is more similar to the original undivided image, and can better reflect the actual situation of each target.

III. Simulation

In this paper, the segmentation algorithm is validated by simulation of several multi-targets electromagnetic images.

Firstly, the algorithm is validated by images of roughly the same size. In the simulation, three electromagnetic interference sources of the same frequency are set up. The three radiation targets of the sources through diffraction limited electromagnetic imaging system are generally the same, and the electromagnetic radiation distribution image is obtained as shown in Fig. 3. It can be seen in the figure that there are three targets, while their edge pixels change slowly. And the power value of one of the three targets is smaller, closer to the background. For the multiplicative noise caused by the interference in the image, homomorphic filtering is used to filter out the noise. Then use the algorithm proposed by the paper to segment and extract the targets from the whole image, forming single target images. (Fig. 4).

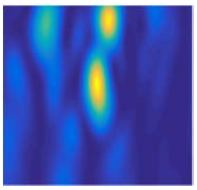
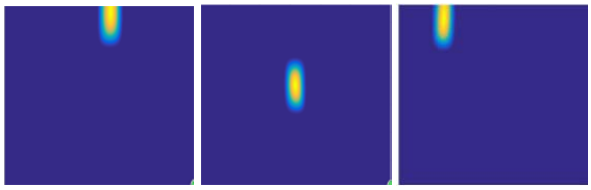
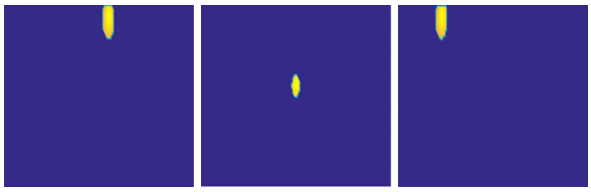


Fig. 3 Simulation image of three sources of same frequency



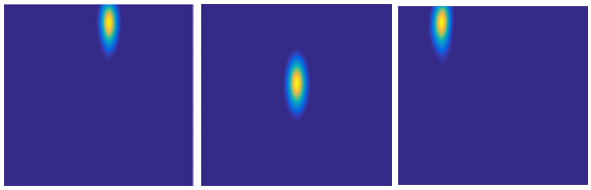
(a) (b) (c)

Fig. 4 Segmented target images by algorithm proposed ((a), (b), (c) are three target images respectively)



(a) (b) (c)

Fig. 5 Segmented target images by Mean-Shift only ((a), (b), (c) are three target images respectively)



(a) (b) (c)

Fig. 6 Gold standard image for segmentation ((a), (b), (c) are three target images respectively)

To evaluate the algorithm segmentation effect, images of separate different targets in the corresponding position are gained from simulation of the same imaging system respectively, as shown in Fig. 6. The three images in Fig. 6 correspond to three dividing targets in Fig. 4. Take the three images in Fig. 6, as the gold standard image (GT), and calculate the Dice coefficients of the segmented image relative to the gold standard image to evaluate the segmentation effect of the algorithm. The Dice coefficient calculates the coincidence ratio between the segmented image SEG and the golden standard image GT. The concrete formula is as follows [12]-[14]:

$$Dice_Ratio=2\times\frac{sum(SEG(:)\bigcap GT(:))}{sum(SEG(:)\bigcup GT(:))} \quad (10)$$

After calculation, compare the Dice coefficients using Mean-Shift algorithm only [15] (Fig. 5) and using the algorithm in this paper to quantify the image segmentation results. (Table I)

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TABLE I
DICE COEFFICIENT OF SEGMENTED IMAGE AND GOLD STANDARD IMAGE OF SAME FREQUENCY

	Target region 1	Target region 2	Target region 3
Mean-Shift only	0.2770	0.2960	0.1049
Algorithm proposed	0.8317	0.8881	0.9011

It can be seen in Table I that using Mean-Shift algorithm only to extract the targets region cannot meet the requirements and it will result in loss mass information of the image targets. However, after segmented by the algorithm in this paper, the Dice coefficients of the single target images are about 80% to 90%, which shows that the coincidence ratio between the extracted target image and the gold standard image is relatively high. It implies that the segmentation effect of the algorithm is better, without mass information lost, nor extra information increase. Furthermore, the algorithm is validated by images of targets with large difference in size. Three electromagnetic sources of different frequency are set up. The three radiation targets of the sources through diffraction limited electromagnetic imaging system are widely different in size and the electromagnetic radiation distribution image is obtained, as shown in Fig. 7. The image requires high adaptability of the segmentation algorithm. The size of the targets and the radiation intensity is quite different, while the biggest target is the least intensive one. Homomorphic filtering is also used to filter out the noise. Then using the algorithm proposed by the paper to segment and extract the targets from the whole image, forming single target images (Fig. 8).

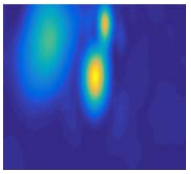
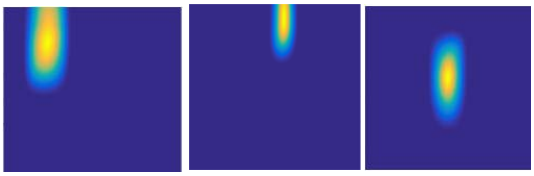
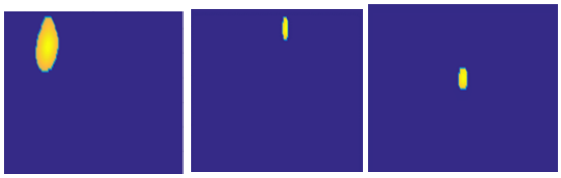


Fig. 7 Simulation image of three sources of different frequency



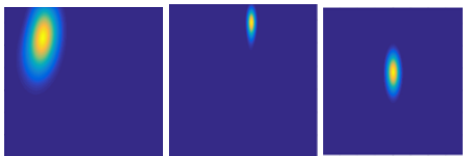
(a) (b) (c)

Fig. 8 Segmented target images by algorithm proposed ((a), (b), (c) are three target images respectively)



(a) (b) (c)

Fig. 9 Segmented target images by Mean-Shift only ((a), (b), (c) are three target images respectively)



(a) (b) (c)

Fig. 10 Gold standard image for segmentation ((a), (b), (c) are three target images respectively)

Images of separate different targets in the corresponding position are also gained from simulation of the same imaging system respectively, as shown in Fig. 9. The three images in Fig. 9 correspond to three dividing targets in Fig. 7. Take the three images in Fig. 9 as the gold standard image (GT), and calculate the Dice coefficients of the segmented image relative to the gold standard image to evaluate the segmentation effect of the algorithm. The Dice coefficient calculates the coincidence ratio between the segmented image SEG and the golden standard image GT. The concrete formula is as follows:

TABLE II
DICE COEFFICIENT OF SEGMENTED IMAGE AND GOLD STANDARD IMAGE OF DIFFERENT FREQUENCY

	Target region 1	Target region 2	Target region 3
Mean-Shift only	0.2532	0.1622	0.2805
Algorithm proposed	0.8439	0.8102	0.8699

Table II shows that the segmentation using only Mean-Shift algorithm is less effective, which brings mass image information lost and image distortion. However, after segmented by the algorithm proposed in the paper, the Dice coefficients of segmentation are basically 80% to 90%. The segmentation effect has been effectively improved.

IV. EXPERIMENT

Taking a complicated electromagnetic environment as an example, there are several radiation sources in the environment, and the electromagnetic imaging system is used to obtain the blurred image (Fig. 11). There is a lot of noise in the blurred image and targets of different size are randomly distributed. Use homomorphic filtering to denoise the image, as shown in Fig. 12. Then use the Mean-Shift and dictionary-learning algorithm proposed in the paper to segment and extract the single target image. The results are shown in Fig. 13. In the same way, the other experimental images are denoised, segmented and extracted, as shown in Fig. 14.

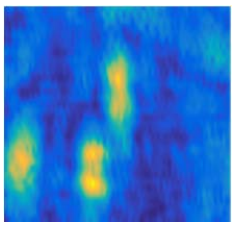


Fig. 11 Received image with noise

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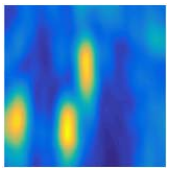
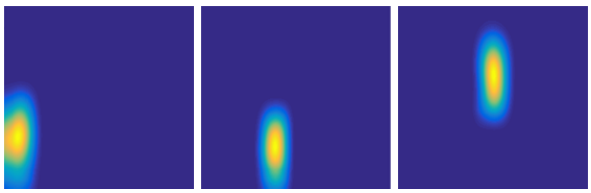


Fig. 12 Image processed by homomorphic filtering



(a) (b) (c)

Fig. 13 Segmented images by the algorithm in the paper ((a), (b), (c) are three target images respectively)

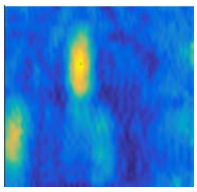


Fig. 14 Received image with noise

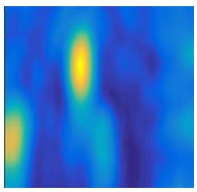
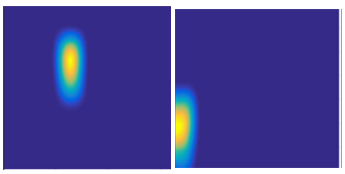


Fig. 15 Image processed by homomorphic filtering



(a) (b)

Fig. 16 Segmented images by the algorithm in the paper((a), (b), (c) are three target images respectively)

It can be seen from the above experiment, the segmentation and extract algorithm proposed in the paper has preferable segmentation effect for images which are blurred by noise with small edge gradient, largely changed inside pixel value targets. The target images are clear and complete without information loss, distortion or extra added.

V. Conclusion

In electromagnetic imaging interference detection, the pixel value in the target area of the image is gradually changed due to the influence of the diffraction limited system. The pixel value of the edge changes slowly, causing the vague edge of the targets. For the image with the gradient target, the traditional image segmentation method cannot accurately segment and extract the image. Therefore, an image segmentation and extract algorithm based on Mean-Shift and dictionary learning is proposed in this paper. The segmented image is not accurate after processing by Mean-Shift iterative, it needs to expand the image of the sub block image and detect the overlap rate, so as to obtain a more accurate block image. Then the dictionary-learning is used to reconstruct the target edges which are not very complete so that the final extract targets have gradient edges. After verification of simulations and experiments, it was shown that the image segmentation algorithm in the paper can obtain accurate target images while retaining the slow changing edge. The Dice coefficients are calculated for each simulation instance, the coincidence of the image obtained by the algorithm and the gold standard image is higher, and the segmentation effect is better.

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