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

Yanwen Li, Shuguo Xie

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 pixel boundaries 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].

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 \( \{ x^i, \ i=1,2,...,n \} \) in L dimensional feature space, the probability density function of x is estimated by a kernel function \( k \), i.e.,

\[
\hat{p}_i(x) = \frac{c_i}{nh^L} \sum_{j=1}^{n} k\left(\frac{x-x_i}{h}\right)
\]

(1)

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

\[
m_{k,G}(x) = \frac{\sum_{i=1}^{K} x_i g(||x-x_i||^2/h)}{\sum_{i=1}^{K} g(||x-x_i||^2)} - x
\]

(2)

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 \( n \times K (K > n) \). Supposed \( D \) is already known, then every complete-edge image block \( x \) can be represented as:

\[
\hat{\alpha} = \arg \min_{\alpha} ||\alpha||_0, D\alpha \approx x
\]

(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):

\[
\hat{\alpha} = \arg \min_{\alpha} ||\alpha||_0, ||D\alpha - y||_2^2 \leq T
\]

(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):

\[
\hat{\alpha} = \arg \min_{\alpha} ||D\alpha - y||_2^2 + \mu ||\alpha||_0
\]

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

$$\{\hat{D}, \hat{\alpha}, \hat{X}\} = \arg \min_{D \alpha X} \lambda \|X - Y\|^2 + \sum_y \mu_y \|\alpha_y\|_0 + \sum_j \|D\alpha_j - R_yX\|^2$$ (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.,

$$\hat{\alpha}_y = \arg \min_{\alpha} \mu_y \|\alpha\|_0 + \|D\alpha - x_y\|^2$$ (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 $\hat{\alpha}$.

$$\hat{X} = \arg \min_{\hat{X}} \lambda \|X - Y\|^2 + \sum_j \|D\hat{\alpha}_j - R_yX\|^2$$ (9)

Set $\hat{X}$, 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](image)

(a)                             (b)                                 (c)

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

(a)                               (b)                                (c)

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

(a)                             (b)                               (c)

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

(a)                               (b)                                (c)

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]:

$$\text{Dice Ratio} = 2 \times \frac{\text{sum}(\text{SEG}(\cdot) \cap \text{GT}(\cdot))}{\text{sum}(\text{SEG}(\cdot) \cup \text{GT}(\cdot))}$$ (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)
TABLE I

<table>
<thead>
<tr>
<th>Target region</th>
<th>Mean-Shift only</th>
<th>Algorithm proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.2770</td>
<td>0.8317</td>
</tr>
<tr>
<td>2</td>
<td>0.2960</td>
<td>0.8881</td>
</tr>
<tr>
<td>3</td>
<td>0.1049</td>
<td>0.9011</td>
</tr>
</tbody>
</table>

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).

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:

\[
\text{Dice coefficient} = \frac{2 \times \text{Area of SEG intersecting Area of GT} }{\text{Area of SEG} + \text{Area of GT}}
\]

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.
targets. For the image with the gradient target, the traditional
of the edge changes slowly, causing the vague edge of the
influence of the diffraction limited system. The pixel value
small edge gradient, largely changed inside pixel value targets.
segmentation effect for images which are blurred by noise with
and extract algorithm proposed in the paper has preferable
loss, distortion or extra added.
The target images are clear and complete without information
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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
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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