Automatic Feature Recognition for GPR Image Processing

Yi-an Cui, Lu Wang, Jian-ping Xiao

Abstract—This paper presents an automatic feature recognition method based on center-surround difference detecting and fuzzy logic that can be applied in ground-penetrating radar (GPR) image processing. Adopted center-surround difference method, the salient local image regions are extracted from the GPR images as features of detected objects. And fuzzy logic strategy is used to match the detected features and features in template database. This way, the problem of objects detecting, which is the key problem in GPR image processing, can be converted into two steps, feature extracting and matching. The contributions of these skills make the system have the ability to deal with changes in scale, antenna and noises. The results of experiments also prove that the system has higher ratio of features sensing in using GPR to image the subsurface structures.

Keywords—feature recognition, GPR image, matching strategy, salient image

I. INTRODUCTION

GROUND-penetrating radar(GPR) is a geophysical method that uses radar pulses to image the subsurface. This non-destructive method uses electromagnetic radiation in the microwave band (UHF/VHF frequencies) of the radio spectrum, and detects the reflected signals from subsurface structures. GPR can be used in a variety of media, including rock, soil, ice, fresh water, pavements and structures. It can detect objects, changes in material, and voids and cracks. [1]

Currently most recognition methods of GPR images are based on artificial visual approach. As the detection of larger areas, it will be an annoying work and inefficient. Meanwhile, the recognition results are very dependent on experience and skills of concerned people. [2] Therefore, a stable and reliable features recognition method for GPR images is very necessary. Currently proposed feature region extraction methods for GPR images includes time-frequency analyzing and neural network methods mainly. Time-frequency analyzing method extracts echo area with similar frequency characteristics, and makes it a feature region by using of short-time Fourier transform or wavelet transform of the GPR data. But for low SNR(Signal Noise Ratio) region, the result is always not satisfactory. And the algorithm requires a longer computation time. Artificial

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neural network, although it can be more accurately assort feature region, but it needs a mass of known data to do their training. And its computing speed is also not well suited for on-site detection.

So, for the reason of faster speed, template matching method was proposed. As a digital image processing method, template matching method uses the template images to match the GPR images [3], then find the feature region. The calculation speed is very fast. Similarly, the paper presents a new automatic features recognition system, that is reliable and effective while it is used in GPR image processing.
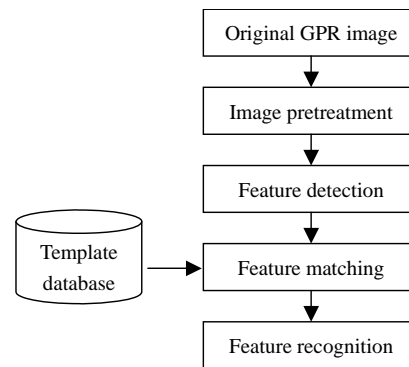

Fig. 1 Flow of automatic feature recognition

In this system, there are two key steps to realize automatic features recognition. First, we detect features from GPR image by detecting salient local image regions. We improve the invariance by extracting salient local image regions as feature to replace the whole image to deal with large changes of GPR images. And the number of interest points is reduced effectively, which makes the processing easier. Then, the second step is features matching by comparing the detecting feature and template feature. Fuzzy recognition strategy is designed to recognize the features, which can strengthen the contribution of individual feature for GPR image recognition. The flow chart of the system is showed by figure 1.

II. FEATURE DETECTION

Researches on biological vision system indicate that organism (like drosophila) often pays attention to certain special regions in the scene for their behavioral relevance or local image cues while observing surroundings [4]. These

regions can be taken as feature marks to effectively represent and distinguish different environments. Inspired by those, we use center-surround difference method to detect salient regions in multi-scale GPR image spaces. The opponencies of color and texture are computed to create the saliency region.

Input is provided in the form of static color GPR image named as G0. Multi-scale image spaces G1-G4 (1:1 to 1:64) are created by Eq.1 and 2.

$$G_{n0} = w*G_{n-1} \qquad (1)$$

$$G_n = Subsampled \ G_{n0} \ \ n \in [1,4] \qquad (2)$$

Here, w is a Gaussion low-pass filter, and "*" denotes convolution operation. Let Centers are $\{G1, G2\}$ and Surroundings are $\{G3, G4\}$, the definition of opponency among scales is the feature difference between Centers and Surroundings denoted by "Θ", which means that the Surroundings are interpolated and then subtract the Centers pixel by pixel.

To compute the desired color opponencies, it is necessary to convert the RGB space into RGBY space for emphasizing the opponencies of red/green and blue/yellow [5]. The space is calculated by

$$R=r-(g+b)/2 \quad G=g-(r+b)/2$$
$$B=b-(r+g)/2 \quad Y=(r+g)/2-|r-g|/2-b.$$

So, the color opponencies are computed by

$$RG(c,s)=|(R(c)-G(c)) \Theta (G(s)-R(s))|$$
$$BY(c,s)=|(B(c)-Y(c)) \ \Theta \ (Y(s)-B(s))|.$$

Here, $c \in$ Centers, $s \in$ Surroundings. $RG(c,s)$ denotes the opponency between red and green; $BY(c,s)$ denotes the opponency between blue and yellow.

To compute the texture opponencies, Gabor filter is selected because of its ability of acquiring local optimum either in the time domain or in the frequency domain. Researches on human psychophysics and vision physiology show that it resembles human attention mechanism [6].

Gabor filter is defined by $h(x,y)=g(x,y)e^{2 \pi j(ux+vy)}$. Because Gabor filter is polar symmetric in the frequency domain, the orientation $0-\pi$ can cover the whole frequency domain. Generally only 4 orientations 0°, 45°, 90°, 135° are considered.

The texture of 4 orientations are computed by

$$T_\theta(x,y)=| G_n (x,y)*h_\theta(x,y)|.$$

Now we can compute the texture opponencies by

$$T(c,s,\theta)=| T_{c\theta}(x,y) \ \Theta \ T_{s\theta}(x,y) |.$$

Here, $c \in Centers$, $s \in Surrounds$, $\theta \in \{ 0°, 45°, 90°, 135°\}$.

Then all opponencies are combined according to Eq.3, 4, 5 to create the saliency map S. The definition of normalizing operator $N(\ )$ can be found in Ref.[5].

$$\overline{C} = \overset{2}{\underset{c=1}{\oplus}} \overset{4}{\underset{s=3}{\oplus}} [N(\ RG \ (c,s)) \ + \ N(\ BY \ (c,s))] \qquad (3)$$

$$\overline{T} = \sum_{\theta \in \{0°,45°,90°,135° \}} N \ (\overset{2}{\underset{c=1}{\oplus}} \overset{4}{\underset{s=3}{\oplus}} T(c,s,\theta)) \qquad (4)$$

$$S = w_1\overline{C} + w_2\overline{T} \qquad (5)$$

Here w_1 and w_2 are weights that denote the significance of color and texture. We also design an algorithm using LMS to learn w_1 and w_2 offline. Figure 2(b) shows the saliency obtained feature regions where the position with difference has more salience.
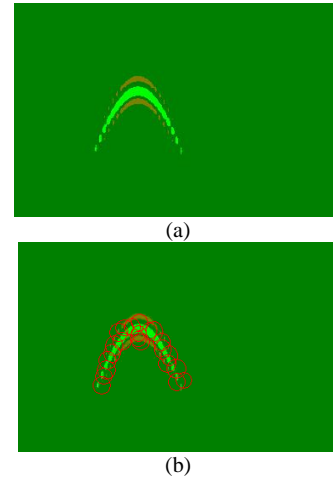

(a)

(b)

Fig. 2. Saliency detection on a real GPR images
(a: original image, b: obtained feature regions)

Follow-up, sub-image centered at the salient position in S is taken as the feature region. The size of the feature region can be decided adaptively according to the changes of gradient orientation [7] of the GPR image.
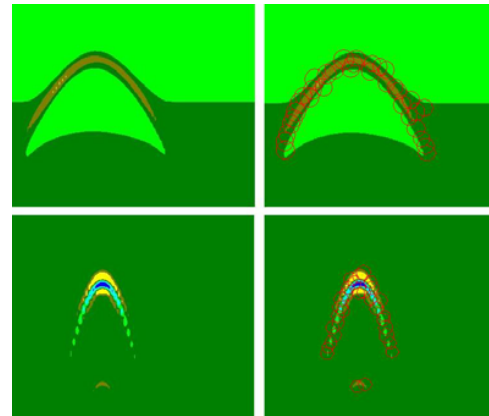

Fig. 3. Experiment on antenna changes

Radar survey requires that feature regions should be detected stably when interference change to some extent. To validate the repeatability on feature detection of our approach, we have

done some experiments on the cases of scale, antenna and noises changes etc. Figure 3 shows that the pipeline object region is detected for its saliency when antenna changes. More detailed analysis and results about scale and rotation can be found in our previous works [8].

III. Match strategy Based on Fuzzy logic

One of the key issues in image match problem is to choose the most effective features or descriptors to represent the original image. Due to complex survey environment, those extracted feature regions will change at pixel level. So, the descriptors or features chosen should be invariant to some extent according to the changes of scale, rotation and viewpoint etc. In this paper, we use 4 features commonly adopted in the community briefly described as followings.

GO: Gradient orientation, which has been proved that illumination and rotation changes are likely to have less influence on it [9].

ASM and ENT: Angular second moment and entropy, which are two texture descriptors.

H: Hue, which is used to describe the fundamental information of the image.
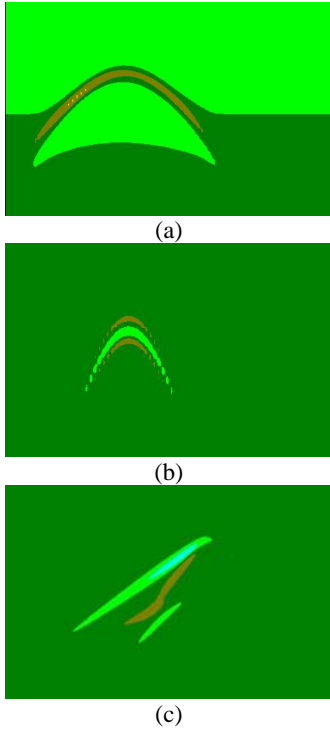

(a)

(b)

(c)

Fig. 4. Similarity computed using Jefferey divergence.
(a): the input GPR image,
(b): a template in the database whose index is 12,
(c): also a template in the database whose index is 15

Another key issue in match problem is to choose a good match strategy or algorithm. Usually nearest neighbor strategy (NN) is used to measure the similarity between two patterns. But we have found in the experiments that NN can't adequately

exhibit the individual descriptor or feature's contribution to similarity measurement. As indicated in figure 4, both image (a) and (b) come from a same subsurface. And image (c) comes from another subsurface. The Jefferey divergence of image (a) and (b) is 7.1367. But the Jefferey divergence of image (a) and (c) is only 4.6335. So the distance between (a) and (b) computed by Jefferey divergence is larger than (c). The results computed using Mahalanobis or Eucilid distance are the same as Jefferey's.

To solve the problem, we design a new match algorithm based on fuzzy logic for exhibiting the subtle changes of each features. The algorithm is described as below.

(1) First all features are fuzzyfied as below.

$$\mu_{ASM} = \sum_{k=0}^{K-1} P^2(k) < \mu_k >$$

$$\mu_{ENT} = -\sum_{k=0}^{K-1} P(k)\log[P(k)] < \mu_k >$$

where $P(k) = \dfrac{N_k}{N_{pixels}}$, $< \mu_k > = \dfrac{1}{N_k}\sum_{l=1}^{N_k}\mu_l$,

and $\mu_l = e^{-|A_{ij}-k|}$

$$GO_{ij} = \arctan(A_{ij} - A_{i+1,j}, A_{i,j+1} - A_{ij})$$

$$\mu_{GO} = \dfrac{1}{M}\sum_{k=0}^{M-1} m P_{GO}(m) < \mu_m >$$

$$H_{ij} = \arctan(\dfrac{\sqrt{3}(G_{ij} + B_{ij})}{2R_{ij} - G_{ij} - B_{ij}})$$

$$\mu_H = \dfrac{1}{M}\sum_{m=0}^{M-1} m P_H(m) < \mu_m >$$

where $P_{GO}(m) = \dfrac{N_{m\_GO}}{N_{pixels}}$, $P_H(m) = \dfrac{N_{m\_H}}{N_{pixels}}$,

$< \mu_m > = \dfrac{1}{N_m}\sum_{q=1}^{N_{m\_GO,m\_H}}\mu_q$, and $\mu_q = e^{-|GO_{ij}(H_{ij} forH)-m|}$

In these equations N_k represents the number of pixels with gray level k, N_{pixels} the total number of pixels of the image, N_{m_go} the number of pixels with angle degree m in $\{GO_{ij}\}$, N_{m_H} in $\{H_{ij}\}$. A_{ij} represents the gray value of the pixel, and $<\mu_k>$ the averaged degree attributed through the fuzzy classification to the gray level k, $<\mu_m>$ to the angular degree m. K is equal to 256 and M is equal to 360.

(2) The similarity between two images is computed using individual feature, respectively. The similarity degree about the lth feature among the fuzzy set $\{\underset{\sim}{ASM}, \underset{\sim}{ENT}, \underset{\sim}{GO}, \underset{\sim}{H}\}$ is

defined as

$$r_{l\_ij} = e^{\frac{-2|\mu_{feature\_l}(i) - \mu_{feature\_l}(j)|}{\mu_{feature\_l}(i) + \mu_{feature\_l}(j)}}.$$

Then we compare the local image with every template in the database. R_{max} and r_{mean} are recorded.

(3) All similarity degrees of each feature are fused to obtain a judgement, which can be formalized as shown by Eq.7.

$$J = \bigcup_{l=1}^{4} r_{l\_ij} = \sum_{l=1}^{4} w_l r_{l\_ij} \qquad (7)$$

The weights w_l are decided according to $r_{max} - r_{mean}$ of each feature. The deviations are sorted, then w_l is assigned to be 0.4, 0.3, 0.2, 0.1, respectively according to the order.

And the template in the database whose fused similarity degree is higher than any others is taken as the best match. The match results of (b) and (c) are demonstrated by Figure 5. As indicated, this method can measure the similarity effectively between two patterns.
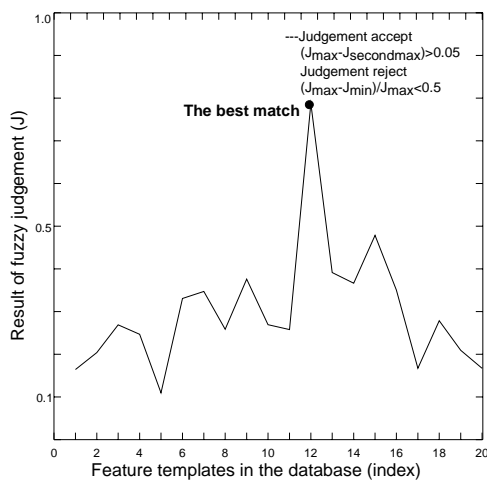

Fig. 5. Similarity computed using fuzzy strategy

IV. EXPERIMENTS AND ANALYSIS

The method has been implemented on pipeline detection, which is a survey project in an aerodrome. The used radar system is SIR 3000 with 400MHz antenna.
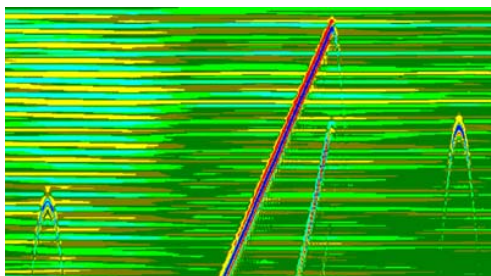

Fig. 6. Acquired GPR image

Image showed in figure 6 was obtained from the field survey. On that site, some steel tubes and other things were imbedded as civil equipments. After inputting the image into our recognition system, we get the recognition result as showed in

TABLE I
RECOGNITION RESULTS OF GPR IMAGE

Detected feature objects	Index of matching template	Recognition result	Evaluation
1	12	steel tube	ture
2	15	declining armor plate	ture
3	12	steel tube	ture

Because center-surround difference detecting and fuzzy logic are adopted to recognize the feature objects, our system has the ability to capture the discrimination about distribution of salient local image regions and distinguish similar feature effectively.

V. CONCLUSION

This paper proposes and implements a feature detecting and template matching system for GPR image recognition.

(1) Salient local image features are extracted to replace the whole image to participate in recognition, which improve the tolerance of changes in scale, 2D rotation and viewpoint of GPR image;

(2) Fuzzy logic is used to recognize the local image, and emphasize the individual feature's contribution to recognition, which improves the reliability of recognition;

(3) The results from the above experiments demonstrate that the feature recognition system has higher ratio of recognition in GPR survey.

Future work will be focused on doing more experiments to deal with the uncertainty of template selecting.

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