Two Dimensional Template Matching Method for Buried Object Discrimination in GPR Data

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ABSTRACT

In this study discrimination of two different metallic object classes were studied, utilizing Ground Penetrating Radar (GPR). Feature sets of both classes have almost the same information for both Metal Detector (MD) and GPR data. There were no evident features those are easily discriminate classes. Background removal has been applied to original B–Scan data and then a normalization process was performed. Image thresholding was applied to segment B-Scan GPR images. So, main hyperbolic shape of buried object reflection was extracted and then a morphological process was performed optionally. Templates of each class representatives have been obtained and they were searched whether they match with true class or not. Two data sets were examined experimentally. Actually they were obtained in different time and burial for the same objects. Considerably high discrimination performance was obtained which was not possible by using individual Metal Detector data.

Keywords: GPR, template matching, discrimination.

1. INTRODUCTION

Underground object detection is an important topic; scientific disciplines have been investigating different sides of this area. The requirement may be detection of ancient remainders, pipes, cables or landmines. Quite a few sensors may be used for this purpose, such as Metal Detector (MD), Magnetometers, Cable Detectors (CD), Infrared Sensor (IR), Non-Linear Junction Detector (NLJD), Acoustic Sensor (AS), Ground Penetrating Radar (GPR), Vapor Sensors (VS), etc.[1] There are number of methods in the detection of buried objects, depends on the application. Some of them are given in [2],[3]. Moreover, identification of buried object is needed, in most cases. If discriminative features can be obtained, classification process would be easier.

In general case, when the numbers of sensors are increased, it is expected to obtain better detection and identification performance. But there should be a compromise between number of sensors and performance.

In most cases Metal Detector (MD) and GPR (Ground Penetrating Radar) sensors can be used for underground inspection applications. There are some studies to classify buried metallic objects utilizing their metal density profiles. [4]. Metal density profile may give discriminative features for most metallic objects [4]. But in some situations it is not easy to classify them from metal density profiles, unfortunately. For this case GPR sensor data comes into value.

2. THE PROPOSED METHOD

In this study 2-D template matching method is proposed to discriminate buried objects, utilizing GPR images those have approximately the same metal density profiles. A problematic set of GPR images and MD channels are given Fig. 1 for two different object classes. These objects have approximately the same metallic density profiles [4]. In addition to this, sensitive metal density channel gives more or less the same information which shows saturation profile of metallic object [4]. Sizes are almost equivalent, but in the point of thread, they are different. Both members of classes nearly have rectangular prism shape. This problematic case can only be solved by using GPR sensor data. In the scope of this motivation, the following method is proposed to overcome this situation. Steps of the proposed method are given in Fig. 2.
\( a_i(z) \) : One dimensional A-Scan signal obtained in position \( x_i \).

\( B(x,z) \) : Two dimensional B-Scan image obtained through a scanning path.

\( N \) : Number of A-Scan signal in B-Scan image.

\( L \) : Length of A-Scan signal.

Depth variable \( z \) contains the equivalent information in time with a difference of scaling factor, is proportional with propagation velocity of the electromagnetic wave.

\[ a_i(z) : \text{One dimensional A-Scan signal obtained in position } x_i \]

\[ B(x,z) : \text{Two dimensional B-Scan image obtained through a scanning path} \]

\[ N : \text{Number of A-Scan signal in B-Scan image} \]

\[ L : \text{Length of A-Scan signal} \]

Fig. 1. GPR images, metal density and sensitive metal density channels of class-1 and class-2 buried objects.
There is another point that signature of buried object may change depends on the scanning direction. Due to this reason, it is needed to collect the data at least 4 different directions depicted in Fig. 3. In reality, these are not completely enough, but it can be accepted roughly.

### 2.1 Background subtraction

If it is guaranteed that the starting location does not contain any target signature, a pre-defined number of A-scan signal is averaged and the difference calculation is performed to reveal target signature along the path given in the following equation [5]. This background subtraction method is especially convenient for robotic scanning.
Fig. 3. Scanning directions

\[ a_{BG}(z) = \frac{1}{P} \sum_{i=1}^{i=P} a_i(z) \]  

(1)

\[ B_{BR}(x_i, z) = B(x_i, z) - a_{BG}(z), \quad \forall \quad 0 < i < N \]  

(2)

where \( P \) represents the number of A-scan signals obtained from initial clear region, \( a_{BG} \) and \( B_{BR} \) represents background signal estimate and background removed B-scan image, respectively.

Typical background removed class-1 and class-2 images are depicted in the following Fig. 4 and Fig. 5.

Fig. 4. Typical background removed class-1 GPR images in different scanning directions and data set
2.2 Normalization

GPR signal has a wide range of [-32767… +32767]. After the background subtraction, it is needed to normalize $B_{BR}$ image to [0…255], because most of the gray scale images can be represented by 255 quantization level and image segmentation can be performed easily.

2.3 Binarization

Image segmentation has a wide area and there are different methods dedicated to specific applications. The simplest way of image segmentation is thresholding. A survey study can be found in [6]. The best thresholding method must be determined according to the application requirements. In our application, segmentation of bright region is important. A typical GPR image histogram is given in Fig. 6. It is shown that it is not easy to find bright regions by peak and valley detection process.

![Fig. 6. A sample image histogram of background removed B-Scan GPR image](image)

In this stage different thresholding methods have been tested given in [6]. It is found that Minimum Error Thresholding method of Kittler an Illingworth [7] is convenient for this purpose. The method defines segmented region according to image histogram statistics and cumulative probability distribution of image intensity. The optimum value of this thresholding method is given in (3)
In this equation: $TV_{opt}$ is the optimum threshold value, $P(T)$ is the cumulative probability distribution of image histogram, $\sigma_0(T)$ and $\sigma_1(T)$ are the background and foreground standard deviations separated by threshold value $T$.

Typical binarized Class-1 and Class-2 images are given in Fig. 7 and Fig. 8 for different scanning directions respectively.

Fig. 7. Typical binarized images of class-1 GPR images in different scanning directions and data set

Fig. 8. Typical binarized images of class-2 GPR images in different scanning directions and data set
2.4 Morphological process

There are two options in this stage. In the first one, morphological process can be applied to binarized images and templates, then template matching is performed. Skeletonization [8] can be used to obtain characteristic patterns of the images as 1 pixel thick. But we obtained that skeletonization decreases the discriminative properties of the images. The second option is to apply template matching directly to binarized images.

2.5 Template Matching

Calculation of the correlation between two signals is a standard approach for feature detection. The use of cross correlation for template matching is motivated by the squared Euclidian distance measure which is given in (4)

\[
d^2_{x,z}(x,z) = \sum_{u,v} [B(u,v) - S(u - x,v - z)]^2
\]  

(4)

In order to obtain a normalized cross correlation function, the equation given in (5) can be calculated which gives maximum value of 1 in best matching situation of sub-image and template. In spite of this process has a high computational complexity, it may be performed in a fast way explained in [9].

\[
y(x,z) = \frac{\sum_{u,v} [B(u,v) - \bar{B}_{u,v}] (S(u - x,v - z) - \bar{S})}{\left[\sum_{u,v} [B(u,v) - \bar{B}_{u,v}] \right]^2 \left[\sum_{u,v} [S(u - x,v - z) - \bar{S}]^2 \right]^{1/2}}
\]  

(5)

\[
S : \text{Two dimensional template image}
\]

\[
K : \text{Number of rows in } S
\]

\[
M : \text{Number of columns in } S
\]

\[
\bar{S} : \text{Mean value of template image}
\]

\[
\bar{B}_{u,v} : \text{Mean value of sub image in search region}
\]

\[
u, v : \text{Spatial scanning variables of search region}
\]

\[
x, z : \text{Spatial variables}
\]

Typical bulk and skeleton templates are given for different scanning directions in Fig. 7. for two object classes.

<table>
<thead>
<tr>
<th>Direction-3</th>
<th>Direction-9</th>
<th>Direction-6</th>
<th>Direction-12</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Bulk Templates</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Class-1 Object, templates</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Class-2 Object templates</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Skeleton Templates</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Class-1 Object, templates</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Class-2 Object templates</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Fig. 9. Typical bulk and skeleton templates of class objects in different directions
2.6 Decision

In the last step it is needed to define the class of buried object. For this purpose the class/subclass is selected as best matched one which has maximum value in $\gamma$.

3. RESULTS

In this chapter experimental results are given over two data sets. Each data set has been collected in different dates. Soil type is sand and scanning velocity is 20 cm/sn. $P=10$ was used in background subtraction. Buried metallic objects has prism like shapes which are approximately 12x20x5 cm and 12x20x3 cm sizes. Sample template matching results are given in Table 1. and Table 2. In these tables underline letters represents the ideal results and bold letters represents the maximum value of the template matching process. In a few case the highest matching were obtained in different direction data of buried object, but they were accepted as true classification.

<table>
<thead>
<tr>
<th>Object</th>
<th>Threshold</th>
<th>Direction</th>
<th>Template matching results of B-scan image and class-1 templates</th>
<th>Template matching results of B-scan image and class-2 templates</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>3  6  9  12</td>
<td>3  6  9  12</td>
</tr>
<tr>
<td>Class-1</td>
<td>165</td>
<td>3</td>
<td><strong>0.9332</strong> 0.7424 0.7644 0.8087</td>
<td>0.8113 0.6876 0.7332 0.8118</td>
</tr>
<tr>
<td>Class-1</td>
<td>154</td>
<td>6</td>
<td>0.7617 <strong>0.9743</strong> 0.7985 0.9069</td>
<td>0.6483 0.8321 0.6598 0.7580</td>
</tr>
<tr>
<td>Class-1</td>
<td>162</td>
<td>9</td>
<td>0.7892 0.8013 <strong>0.9705</strong> 0.8038</td>
<td>0.7479 0.8337 0.8125 0.6795</td>
</tr>
<tr>
<td>Class-1</td>
<td>157</td>
<td>12</td>
<td>0.8285 0.8989 0.7867 <strong>0.9346</strong></td>
<td>0.6838 0.7840 0.6707 0.8012</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Object</th>
<th>Threshold</th>
<th>Direction</th>
<th>Template matching results of B-scan image and class-1 templates</th>
<th>Template matching results of B-scan image and class-2 templates</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>3  6  9  12</td>
<td>3  6  9  12</td>
</tr>
<tr>
<td>Class-2</td>
<td>160</td>
<td>3</td>
<td>0.8479 0.6618 0.7514 0.7378</td>
<td><strong>0.9642</strong> 0.6805 0.8054 0.7619</td>
</tr>
<tr>
<td>Class-2</td>
<td>157</td>
<td>6</td>
<td>0.6435 0.7720 0.7952 0.7503</td>
<td>0.6060 <strong>0.9648</strong> 0.7265 0.5641</td>
</tr>
<tr>
<td>Class-2</td>
<td>156</td>
<td>9</td>
<td>0.7606 0.6834 0.8266 0.7161</td>
<td>0.8105 0.7838 <strong>0.9580</strong> 0.6599</td>
</tr>
<tr>
<td>Class-2</td>
<td>156</td>
<td>12</td>
<td>0.8082 0.7248 0.6516 0.8013</td>
<td>0.7538 0.6286 0.6293 <strong>0.9363</strong></td>
</tr>
</tbody>
</table>

Performance results are listed in Table 3, Table 4. and Table 5. for two data set and overall data.

<table>
<thead>
<tr>
<th>Number of B scan image</th>
<th>Number of true matching</th>
<th>Number of false matching</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>40</td>
<td>40</td>
<td>0</td>
<td>100</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Number of B scan image</th>
<th>Number of true matching</th>
<th>Number of false matching</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>40</td>
<td>35</td>
<td>5</td>
<td>87.5</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Number of B scan image</th>
<th>Number of true matching</th>
<th>Number of false matching</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>80</td>
<td>75</td>
<td>5</td>
<td>93.75</td>
</tr>
</tbody>
</table>

It is obtained that the automatically calculated threshold value fairly affects the template matching results. Thresholding method of Kittler calculates threshold value between 143 and 167 for two data sets, generally. However, in five cases of
data set-2 it calculates threshold value between 78 and 80, for these cases buried object patterns is almost disappeared and matching results goes down. If the handicap of thresholding method doesn’t care, the overall result is obtained as %100. When skeletonization process was applied to both binarized images and their templates, it is obtained that the overall matching performance decreased to % 85 percent for all data set. This situation was based on that skeletons of image and templates have less information then the originals.

4. CONCLUSIONS

In this study template matching approach was applied to buried object discrimination process. For this purpose two data set were used those have approximately the same metallic and physical properties. First data set was the one that we obtained templates. The second one is another data set obtained for the same objects but in different dates with new burials. It is observed that the threshold value obtained from automatic thresholding method has a big importance. The proposed method can be applied to search activity by a robotic scanning system. Otherwise undesired movement of sensor may affect the results negatively.

5. REFERENCES