A Geometrical Feature Based Sensor Fusion Model of GPR and IR for Detection and Classification of Anti-Personnel Mines

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Abstract

The Ground penetrating radar (GPR) and Infrared (IR) imaging have become two established sensors for detecting buried anti-personnel mines (APM) which contain no or a little metal. The paper introduces the GPR and IR techniques briefly and compares the two sensors with respect to their strengths and weaknesses for target detection and emphasizes the necessity of fusion to harness the advantages of each of the methods. We propose a geometrical feature based sensor fusion framework, combining GPR and IR, as an effective technique for detection and classification of APM, which will reduce the false alarm rate significantly. We consider the basic geometrical shape descriptor features of an object and construct a feature vector for each of the objects. These feature vectors are used to train a Probabilistic Neural Network (PNN) for the classification of APMs. The method gives almost perfect detection accuracy.

1. Introduction

Landmines are causing enormous problems to both human and environment (for example, they endanger life and make the land uninhabitable) in a large number of areas throughout the world. Based on the estimation of International Red Cross, there are about ten billion mines buried in eighty countries [1]. Detecting and classifying minimum-metal/non-metal mines buried in soil offers considerable challenges. The most significant tools used to-date for mine detection, are GPR and IR imaging.

Mainly there are two types of mines, anti-tank mines (ATM) and anti-personnel mines (APM). ATM is usually large in size and contains metal, so conventional metal detectors can detect it. APM on the other hand is smaller in size (60-120mm in diameter and 40-70mm in thickness) (Figure 1) and is mostly made of plastic. The dielectric properties of plastic being similar to soil makes the reflected signal from the mine weak and may well be masked by its background. For this reason alone, it becomes more difficult to detect APM.

Most mine detection techniques, based on sensor data and image, consist of signal processing, image processing and decision processes. In this paper, we shall discuss briefly the GPR and IR techniques and their use in APM detection. We provide a comparison between the two techniques and show that one technique can complement of the other thus justifying their fusion. The proposed GPR and IR geometrical feature level fusion is expected to provide better detection and classification of APM, and reduce false alarm rate.

In recent studies [2-5], single/hybrid sensors have achieved significant improvement on APM detection. However, there are limitations on soil conditions, ground penetration depth, false alarm rate, classification and orientation of the mine. Classification and orientation of the buried mine is very important for safe and efficient demining. To determine correct classification and orientation we require better imaging technique based on GPR and IR sensors.

Figure 1. Typical Anti-personnel mines PMN (left) and VS-50 (right).

For optimum performance, an understanding of the limitations of the sensors induced by the environment like soil type, soil structure, humidity, temperature and vegetation is necessary. We discuss particular situations where the two techniques can be most useful.
and emphasize that no single sensor has the potential to increase mine detection and classification probability and decrease the false alarm rate for all types of mines. Here, we propose a multi-sensor fusion system framework to combine both GPR and IR techniques. We extract the geometric features from GPR and IR data (image) and construct a feature vector from these features for each APM. We use PNN to classify the feature vectors. This proposed fusion system is likely to decrease the mine detection time while maintaining high probability of mine detection and classification.

2. Ground Penetrating Radar Techniques

GPR consists of an active sensor, which emits electromagnetic (EM) waves through a wideband antenna (Transmitter) and collects signals reflected from its surroundings. The data is generally acquired with a handheld or vehicle mounted GPR scanner by moving it along a line in sequence over the area where a mine may be buried. GPR data can be represented in three different forms, A-scan, B-scan, and C-scan. The collected signal is presented in the form of a group of signal strength versus time delay. A-scanned signal is a 1D signal. B-scan signal is obtained as the horizontal collection from the ensemble of A-scans. C-scan signal (3D) is obtained from the ensemble of B-scans, measured by repeated line scans along the plane.

2.1. Pre-processing

The acquired data usually has some clutter or noise due to vegetation (e.g. grass, bushes) and the local variations in the material in the ground. It is necessary to remove the clutter to enhance the quality of the data. Based on the present techniques the pre-processing can be done in two ways: i) signal processing of the GPR raw data (A scan) and/or ii) constructing an image using the GPR raw data and then enhancing this image.

2.2. Image Processing and Target Detection

Gray-scale morphology has been used for gradient extraction, contrast enhancement and region segmentation (watershed algorithm) as well as noise removal and smoothing which are typical applications of binary morphology [6]. The Semi-automatic segmentation (cue-based analysis) is another option for mine detection where the user defines the image information (cues) and a software system interprets these cues; such as distance, vector, entropy, intensity and global image parameters [7].

3. Infrared Imaging Techniques

The use of thermal IR technique is based on the thermal radiation contrast of objects, with respect to their backgrounds. For landmine detection, landmines are thought of as a thermal barrier in the natural flow of the heat inside the soil, which produces a perturbation of the expected thermal pattern on the surface. The detection of these perturbations (anomalies) provides evidence of presence of potential landmine targets [8].

3.1. Pre-processing

To the captured IR data we need to apply the image enhancement techniques in order to enhance the low contrast. Some of the common image enhancement techniques include the application of Karhunen-Loeve transformation, the Kittler-Young transformation [9], and the Gaussian filtering [10], etc.

3.2. IR Image Processing and Target Detection

One of the popular methods for mine detection is the Tophat filtering [12] to detect local maxima in an image within the region of a structuring element. Detection performance can be improved by using more relevant information in the detection process. One way to include this information is by means of features (size, shape and intensity) of regions of interest (ROI) [11]. The feature combination methods based on the Mahalanobis distance and the Fisher mapping have also been used [12] for object classification.

4. Comparison of GPR and IR Techniques

It is clear from the above sections that collecting data and creating image from the data requires more effort in employing GPR than IR. GPR data needs serious pre-processing at signal processing level to create an image. While IR data does not require such pre-processing, rather image enhancement is necessary, which is also required by GPR for better performance.

Since it is usually easier to interpret visual images than data, IR technique can be appealing [6]. On the other hand, GPR data can be controlled by an operator both during collection and processing. GPR seems to possess extra attraction for APM detection.

In GPR the mine size has effect on image; therefore calibration of wavelength proportional to mine size is necessary. This is also true for polarization. Experiments have shown that circular mine image taken with linear polarization distorts the shape of the circular mine [13]. Where as in IR, only the mine size
affects the thermal image, the larger the mine size the clearer the thermal signatures.

The placement height of GPR antenna above the surface also has influence on the GPR image. As the height increases the spatial resolution decreases [14]. This ultimately causes a blurred image and increases the detection complexity. There is no such predicament in case of IR imaging.

GPR data capturing however is more complicated. Usually an operator performs scanning by a hand held system. Both measuring conditions and operator skills pose weaknesses for the GPR scanning method [15]. In contrast, IR imaging is highly dependent on surrounding environment conditions. Operator’s body temperature, motion and vibration of the camera can even bias it.

Air-soil interface also has a significant effect on both GPR and IR data capturing. In GPR scanning, it introduces the air-soil interface clutter [16] and in IR imaging it causes clutter due to the uneven sunlight absorption of the surface [17]. Rough surfaces lead to distortion in signals on GPR sensing because of the irregular surface reflection. Since IR image is based only on the temperature measurement, soil surface irregularity is not a strong barrier for IR imaging.

Soil moisture has strong effect on GPR signals. It is known that a slight increase in water content in soil around non-metallic landmines improves detection in sand but not in clay [18]. On the other hand, soil moisture has significant positive effect on thermal signature [19].

GPR can provide 3D structure of the buried mine including depth information, while thermal IR gives only the shape features. The additional feature for the IR imaging is that it estimates texture of background clutter and objects [20]. Migration algorithms (both in time and frequency domain) are used in GPR mine detection to give an idea of the exact physical position (depth information) and shape of the reflectors in the subsurface [21]. However, such a technique is not feasible in IR imaging.

Wind is another consideration that does not affect GPR data but has a significant effect on IR imaging. Increase in wind speed decreases strength of thermal signature which in turn decreases mine detection rate [22].

Studies have shown that for most soils 10cm is the maximum burial depth to detect a significant thermal signature of a mine at the surface [23]. For GPR based mine detection methods no such information is available. High frequency GPR signals can indeed provide depth information on buried mines [24].

Both GPR and IR imaging techniques have some pronounced advantages and limitations and neither of them is markedly superior to the other. We show, a fusion model combining certain features of both the GPR and IR provides enhanced performance for detection and classification of APM.

5. Fusion of GPR and IR

The choice of suitable sensor fusion level depends on the available sensor types. For GPR and IR, suitable fusion methods are at feature-level and decision level. We consider only the feature-level fusion, as it is more accurate.

The existing sensor fusion techniques [2-5, 21] suffer from large false alarm rate. None of the current techniques can efficiently classify APM or provide information about their orientation. We are proposing the geometrical feature-based fusion of GPR and IR, which may eliminate some of the identified limitations.

The overall process of the proposed technique is shown below

![Figure 2. The proposed system for the detection and classification of APM.](image)

5.1. GPR and IR Data

We use the 3D GPR data adapted from the technique developed by Milisavljevic et al. [25] for the 3D visualization (Figure 3) of mines. We simulated the IR data with the same scale as of the GPR data. Since the upper surface, edges and height are represented by different colours in the 3D visualization system, we can apply the edge detection procedure based on their grayscale value.

![Figure 3. 3D GPR image (left), its grayscale image (centre) and simulated IR image (right).](image)
5.2. Feature Extraction

Our method is based on the object edge. We applied the perceptual grouping procedure for segmenting line, circle and ellipsoidal shapes. This information is then used to determine the object shape. To achieve this, we first calculate the gradient magnitude and orientation for both GPR and IR image. Then convert these images into binary images and apply the region growing technique [26] and threshold the region with a fixed number of pixels to remove noise (Figure 4).

We search the image for a rectangular or a square shaped object that is measured from the length, width, height (in pixel length) and their corresponding angle. If no such object is identified, we carry on the operation to find circular or ellipsoidal object that is measured from radius, diameter or perimeter shape/pattern. We considered the IR image to improve upon the confidence value in shape analysis above, as shape is one of the key features in our algorithm. We also calculate the length, width (for rectangular shapes) and radius (circular or ellipsoidal shapes) for calculating the compactness of the object.

Therefore, for each APM we construct a feature vector of length eleven based on the features from GPR and IR image. The features from GPR image are shape (s), length (L) (or diameter 2r), width (W) (or radius r), height (H), ratio of L and W, and ratio of L and H. The features for the IR image are shape, compactness, length (L) and width (W) and ratio of L and W. We then input these feature vectors into a PNN for detection and classification of APM.

5.3. Probabilistic Neural Network

PNN has become an effective tool for solving many classification problems, because of its ease of training and a sound statistical foundation in Bayesian estimation theory. The architecture of a typical PNN [29] is shown in Figure 5.

The input layer unit does not perform any computation and simply distributes the input to the neurons in the pattern layer. On receiving a pattern \( x \) from the input layer, the neuron \( x_{ij} \) of the pattern layer computes its output [29]

\[
\phi_j(x) = \frac{1}{(2\pi)^{d/2} \sigma^d} \exp\left[-\frac{(x-x_j)\cdot (x-x_j)}{2\sigma^2}\right]
\]

where \( d \) denotes dimension of the pattern vector \( x \), \( \sigma \) is the smoothing parameter and \( x_j \) is the neuron vector. The summation layer neurons compute the maximum likelihood of pattern \( x \) being classified into \( C_i \) by summarizing and averaging the output of all neurons that belong to the same class

\[
p_j(x) = \frac{1}{(2\pi)^{d/2} \sigma^d} \sum_{j=1}^{N_i} \exp\left[-\frac{(x-x_j)\cdot (x-x_j)}{2\sigma^2}\right]
\]
where \( N_i \) denotes the total number of samples in class \( C_i \). If a priori probabilities for each class are the same, and the losses associated with making an incorrect decision for each class are also the same, the decision layer unit classifies the pattern \( x \) in accordance with Bayes’s decision rule based on the output of all the summation layer neurons

\[
\hat{C}(x) = \arg \max_{i=1,2,\ldots,m} p_i(x)
\]

(3)

where \( \hat{C}(x) \) denotes the estimated class of the pattern \( x \) and \( m \) is the total number of classes in the training samples.

6. Experimental Results

In our experiment, we considered two types of APM: PMN and VS-50. We construct a total of thirteen vectors of length eleven (six features for GPR image and five features for IR image) for each of the mine types. Since the available data is clutter free, for our simulation we construct seven noise/clutter vectors by randomly choosing three features from GPR and two from IR image. The two class-type of APM and the generated class noise/clutter are coded into three classes. In all, we used a total of thirty-three feature vectors for our model to train and test the Probabilistic Neural Network.

In the Tables 1 and 2 below we compare performance of the proposed sensor fusion model with individual GPR and IR feature vectors. The system is implemented using MATLAB and the cross-validation procedure is considered as our data size unfortunately is very small. The results show an average accuracy of 78.8% for GPR and 75.7% for IR, while the fused GPR and IR feature vectors achieve an accuracy of 96.9%. Clearly the results demonstrate that our technique provides better accuracy in detection and classification of APM.

### Table 1: Confusion Matrix

<table>
<thead>
<tr>
<th>Feature vector</th>
<th>Number of APM/Noise</th>
<th>Classified as</th>
<th>VS-50</th>
<th>PMN</th>
<th>Noise</th>
</tr>
</thead>
<tbody>
<tr>
<td>GPR</td>
<td>13 (VS-50)</td>
<td></td>
<td>11</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>13 (PMN)</td>
<td></td>
<td>0</td>
<td>12</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>7 (Noise)</td>
<td></td>
<td>1</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>IR</td>
<td>13 (VS-50)</td>
<td></td>
<td>10</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>13 (PMN)</td>
<td></td>
<td>0</td>
<td>12</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>7 (Noise)</td>
<td></td>
<td>2</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Fusion of GPR &amp; IR</td>
<td>13 (VS-50)</td>
<td></td>
<td>13</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>13 (PMN)</td>
<td></td>
<td>0</td>
<td>13</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>7 (Noise)</td>
<td></td>
<td>0</td>
<td>1</td>
<td>6</td>
</tr>
</tbody>
</table>

### Table 2: APM Detection Accuracy

<table>
<thead>
<tr>
<th>Feature-vectors</th>
<th>No of Features</th>
<th>No. of class</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GPR</td>
<td>26</td>
<td>7</td>
<td>3</td>
</tr>
<tr>
<td>IR</td>
<td>26</td>
<td>7</td>
<td>3</td>
</tr>
<tr>
<td>Fusion of GPR &amp; IR</td>
<td>26</td>
<td>7</td>
<td>3</td>
</tr>
</tbody>
</table>

7. Conclusion

We note that both GPR and IR have some limitations under certain conditions of environment and mine type. It is unlikely that any single technique will provide a breakthrough necessary to substantially improve mine detection effort and time. To achieve substantial decreases in mine detection time while maintaining high probability of detection and classification as well as a low false alarm rate, an efficient approach is a necessity. Rather than focusing on individual sensor operating in isolation, we have demonstrated that a design of an integrated, multi-sensor system can overcome the limitations of any single-sensor technology. A multi-sensor fusion system that combines geometrical features of GPR and IR is proposed and is shown to be significantly better in the detection and classification of APM.

8. References


[28] J. M. Geusebroek, A. R. Hanson, and E. M. Riseman, "Interpretation Sciences, 1999 (last accessed on 19/Jan/06).


[37] J. M. Geusebroek, A. R. Hanson, and E. M. Riseman, "Interpretation Sciences, 1999 (last accessed on 19/Jan/06).