Multi-Classifier Buried Mine Detection Using MWIR Images
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ABSTRACT
The fundamental challenges of buried mine detection arise from the fact that the mean spectral signatures of disturbed soil areas that indicate mine presence are nearly always very similar to the signatures of mixed background pixels that naturally occur in heterogeneous scenes composed of various types of soil and vegetation. In our previous work, we demonstrated that MWIR images can be used to effectively detect the buried mines. In this work, we further improve our existing method by fusing multiple buried mine classifiers. For each target chip extracted from the MWIR image, we scan it in three directions: vertical, horizontal, and diagonal to construct three feature vectors. Since each cluster center represents all pixels in its cluster, the feature vector essentially captures the most significant thermal variations of the same target chip in three directions. In order to detect the buried mines using our variable length feature vectors, we have applied Kolmogorov-Smirnov (KS) test to discriminate buried mines from background clutters. Since we design one KS-based classifier for each directional scan, for the same target chip, there will be a total of three classifiers associated with vertical, horizontal, and diagonal scans. In our system, these three classifiers are applied to the same target chip, resulting in three independent detection results, which are further fused for the refined detection. Test results using actual MWIR images have shown that our system can effectively detect the buried mines in MWIR images with low false alarm rate.

Keywords: buried mine detection; classifier, KS test, cluster intensity variation; statistical hypothesis test

1. INTRODUCTION
The fundamental challenges of buried mine detection arise from the fact that the mean spectral signatures of disturbed soil areas that indicate mine presence are nearly always very similar to the signatures of mixed background pixels that naturally occur in heterogeneous scenes composed of various types of soil and vegetation. Behboodian (Behboodian 1999) presented a system that uses elastic surface waves and electromagnetic waves for the detection of buried landmines. It mainly uses the acoustic waves to detect the buried landmines. The depth information can be inferred from the Fourier transformed data based on the property that the penetration depth is proportional to the temporal frequency. Mine detection using infrared techniques is primarily based on exploiting temperature differences between pixels on the mines and background pixels (Bowman 1998). The use of spatial information (e.g., size, shape, and pattern) can provide additional discrimination power, particularly if the mines are resolved into multiple pixels by a high-resolution imaging sensor.

In infrared-based landmine detection applications, the thermal signature is often embedded in noise caused by fluctuations in the soil structure and the surface. To design a detector, Svensson (Svensson 2001) has modeled the characteristics of the noise. Difficulties arise when designing a detector as the infrared signatures of buried landmines vary significantly depending on external parameters such as weather, soil moisture, solar radiation, burial depth, and time of burial. In (Svensson 2002), aimed in solving these problems, both the
shape and amplitude of the mine signature are modeled as outcomes of the stochastic variables respectively with known prior distributions. Bayesian likelihood ratio test is used in the classification design. Lundberg (Lundberg 2001) proposed to model the set of possible infrared signatures as a scaling with the parameter of the convolution between the top-view shape of the buried object and a smoothing kernel depending on a smoothing parameter. The background noise is modeled by means of a quarter-plane causal AR (Auto-Regressive) process. Likelihood ratio test is used in the detection of mines.

In joint multisensor exploitation for mine detection (Beaven 2004), an abnormal detector was used to remove the background clutter. It has applied spatial cluster and size filtering to the raw filtered output to produce the object detection in both of the filtered image data sets. Joint Multisensor Exploitation is used for fusing registered multiple detector outputs, which makes the decision based on the joint distribution formed by the multiple detector outputs. An automatic detection using knowledge-based techniques is reported by Filippidis (Filippidis 1999). The fuzzy rule-based fusion is used to combine complementary information derived from sensors to produce an output image showing the likelihood of mine locations. The inputs to the fusion process are the output classification results from ART2 (Adaptive Resonance Theory 2) and the MLP together with the output of the processed IR polarization image. A GA (Generic Algorithm) tool is used to find the optimum structure and inputs of the MLP (MultiLayer Perceptron) neural networks.

In our previous work (see Ling 2006), we demonstrated that MWIR images can be used to effectively detect the buried mines. Our classifier works with the cluster thermal variations. To apply this classifier, we first cluster the target chip using our 3D ASOM (Adaptive Self-Organizing Maps) algorithm which essentially extracts the most significant pixels in terms of thermal variations. We then scan this clustered chip row-by-row (horizontal scanning) to build a cluster intensity variation profile. This profile is then statistically compared with the signature profiles in our buried mine library via Kolmogorov-Smirnov test.

In this paper, we further improve our existing method by fusing multiple buried mine classifiers. For each target chip extracted from the MWIR image, we scan it in three directions: vertical, horizontal, and diagonal to construct three feature vectors. Since each cluster center represents all pixels in its cluster, the feature vector essentially captures the most significant thermal variations of the same target chip in three directions. In order to detect the buried mines using our variable length feature vectors, we have applied Kolmogorov-Smirnov (KS) test to discriminate buried mines from background clutters. Since we design one KS-based classifier for each directional scan, for the same target chip, there will be a total of three classifiers associated with vertical, horizontal, and diagonal scans. In our system, these three classifiers are applied to the same target chip, resulting in three independent detection results, which are further fused for the refined detection. Test results using actual MWIR images have shown that our system can effectively detect the buried mines in MWIR images with low false alarm rate.

This paper is organized as follows: The wavelet-based MWIR image thresholding method is given in Section 2. Buried mine signature library development is presented in Section 3. Then in Section 4, buried mine signatures are analyzed for the false alarm elimination. Our multi-classifier based buried mine detection system is given in Section 5. And finally, the test results using MWIR images are given in Section 6.

2. WAVELET-BASED MWIR IMAGE THRESHOLDING

Suppose \( \mathbf{Y} = [Y_1, Y_2, \ldots, Y_{MN}]^T \) is a vector of pixel values of an image of size \( M \times N \). The problem of image thresholding is to find a threshold \( \lambda_{\text{image}} \) such that

\[
\hat{Y}_i = \begin{cases} 
Y_i & \text{if } Y_i \geq \lambda_{\text{image}} \\
0 & \text{if } Y_i < \lambda_{\text{image}}
\end{cases}
\] (2-1)
where $T$ is the smallest pixel value in a given image. The resulted image, $\hat{Y} = [\hat{Y}_1, \hat{Y}_2, \ldots, \hat{Y}_{MN}]^T$, is significantly compressed (i.e., most clutters are removed) if $\lambda_{image}$ is properly estimated and larger than most of clutter pixel values. The key is how to estimate this thresholding level, $\lambda_{image}$.

Let $X$ be an $M \times N$ image. Basic wavelet thresholding is performed by taking the wavelet transform of the image $X$, and then estimating the appropriate threshold based on the image content. The thresholding value in the wavelet domain can be expressed in terms of the product of $\sigma_w$ and $\lambda_w$:

$$\lambda_{wavelet} = \sigma_w \times \lambda_w$$  \hspace{1cm} (2-2)

where both $\sigma_w$ and $\lambda_w$ can be estimated based on the image content.

To estimate $\lambda_{image}$, we use the Inverse Discrete Wavelet Transform (IDWT) to map $\lambda_{wavelet}$ estimated in the wavelet domain to the image domain. A 2D discrete wavelet transform performs three decompositions along horizontal (H), vertical (V) and diagonal (Λ) directions with different threshold levels denoted as $\tau_h$, $\tau_v$, and $\tau_\Lambda$, respectively. Denote $DH_{\tau_h}$, $DV_{\tau_v}$, and $DA_{\tau_\Lambda}$ as the denoising operators at corresponding threshold levels. We have used the following inverse transform:

$$\hat{X} = W^{-1}(DH_{\tau_h}(W(X)), DV_{\tau_v}(W(X)), DA_{\tau_\Lambda}(W(X)))$$  \hspace{1cm} (2-3)

and $\hat{\lambda}_{image}$ is extracted from the resulted image.

Figure 2-1 shows an example where the original MWIR image is given in the left figure and the thresholded image is given in the right. The MWIR image contains both surface and buried mines together with fiducials (ground markers) and background clutters. It can be observed that our wavelet-based image thresholding method has successfully retained both surface and buried mines.

To locate landmines in the thresholded image, we apply our ASOM (Adaptive Self-Organizing Maps), which is essentially an unsupervised data clustering method. However, compared with other existing clustering algorithms, our method does not require any $a$ priori knowledge of the number of clusters in the data. It does the clustering by self-learning and self-teaching. Our 2D ASOM has been applied to the thresholded image to
locate potential mines. The center of each cluster indicates the location of a potential mine. Figure 2-2 shows an example of ASOM applied to the thresholded image. The clusters (small circles) and their centers have been plotted on the original MWIR image.

![Figure 2-2: Clusters obtained from the thresholded image.](image)

As we can see from Figure 2-2, the ASOM clustering method gives many possible mine locations. We window out each putative mine location based on a standard deviation of pixels around the mine location (Ling 2006).

### 3. BURIED MINE SIGNATURE IN MWIR IMAGES

Our similarity-based 3D ASOM is used to find clusters in the windowed chips. For each pixel in the target chip, its location \((x, y)\) and intensity value \(z\) form a vector \((x, y, z)\) which is used for clustering. Instead of using the Euclidean distance between two vectors as a measure of dissimilarity, the Tanimoto distance is used to measure similarity between two vectors. It is defined as:

\[
S(X, Y) = \frac{X^T Y}{\|X\|^2 + \|Y\|^2 - X^T Y}
\]  

(3-1)

The clustering algorithm is similar to our ASOM clustering algorithm except that the similarity criterion given in (3-1) instead of Euclidean distance is used as the measurement. It starts with one cluster, which is the first vector. The similarity between a new vector \(X\) and existing cluster nodes \(Y_i, i = 1, 2, ..., m,\) are first calculated according to equation (3-1). If the maximum value of \(S(X, Y_i)\) is less than a predefined threshold value, which indicates the new vector is different from all the clusters, a new cluster is added. Otherwise, the winning node (the node with the largest similarity value) and its neighborhood nodes are updated.

Figure 3-1 shows an example of a 30×30 buried mine chip and its representative clusters extracted using our 3D ASOM clustering method. This chip is obtained from a MWIR image based on the groundtruth. Since the MWIR image captures the thermal variations resulted from the disturbed surface soils, the clusters represent the most significant thermal variations in this chip.

After clustering, the intensity values of the cluster centers are scanned to form a vector which is used as the buried mine signature vector. To capture the thermal variations resulted from the surface soil disturbances, we
scan the same clustered chip in three directions: horizontal, vertical and diagonal. This directional scanning schemes are illustrated in Figure 3-2.

![Figure 3-1: A buried mine chip and its clusters representing most significant thermal variations.](image)

![Figure 3-2: Three directional scanning: horizontal, vertical and diagonal.](image)

We have found that the thermal variation patterns exhibited in day time and night time are significantly different. Therefore, we have built two sets of buried mine signatures for the images in day time and night time. Since we will extract buried mine signatures through directional scanning – horizontal, vertical and diagonal, there will be total six sets of buried mine signatures shown in Figure 3-3.

![Figure 3-3: Structure of buried mine signatures extracted from MWIR images.](image)
The signature vectors can also be built through differencing method in which, for each clustered buried mine chip, the intensity values of the cluster centers are scanned into a vector \( C_i \). The \( N \)-step difference of each vector is calculated as:

\[
DC_i(k) = C_i(k+N) - C_i(k)
\]

(3-2)

The difference vector

\[
DC = [DC_1, DC_2, \ldots, DC_m]
\]

(3-3)

is used as the buried mine feature vector. Since we have three scanning directions, there will be three such difference vectors: \( DC_{\text{horizontal}} \), \( DC_{\text{vertical}} \), \( DC_{\text{diagonal}} \).

Each vector is used as a buried mine signature. In other words, we will get three signatures from each buried mine chip. Figure 3-4 shows an example of three features extracted from one buried mine chip, resulted from horizontal, vertical, and diagonal scanning.

![Figure 3-4: An example of three directional signatures associated with a target chip.](image)

It can be observed that these three signature vectors, representing the same buried mine chip, show different thermal variations. By incorporating these three different signatures into our buried mine detection system, we can reduce the false alarms and improve the system performance.

### 4. BURIED MINE SIGNATURE ANALYSIS

We have developed a software program to automatically build the buried mine signature library using MWIR images and their groundtruth. The procedure of extracting the buried mine signatures is shown in Figure 4-1. After analyzing the MWIR images, both day time and night time, we have decided to fix the buried mine chip size as: 40×40 for daytime images, 30×30 for nighttime images.

Based on the groundtruth and visual inspection (when groundtruth is missing) of MWIR images, we have chipped out all buried mine which are stored in two separate folders: Daytime Buried Mine Chips, and Nighttime Buried Mine Chips. There are total 103 daytime buried mine chips and 49 nighttime buried mine chips. Their naming convention is image_name-xxx.bmp where the image_name is the name of the image from which buried mine chips are chipped out.
In general, it is inevitable to have false alarms in any detection systems. Figure 4-2 shows an example of buried mine detection from a night time MWIR image. There are four false detections. A chip of each false detection is given together with the actual signature and its histogram. We want to understand why these four clutter chips were not rejected by our system.

**Figure 4-1:** Procedure of buried mine signature library construction.

**Figure 4-2:** An example of buried mine detection where there are four false alarms.
Figure 4-3 shows eight night time buried mine chips, their signatures and related histograms. We can observe that (1) the true signatures are relatively long (more points); (2) their histograms are peaked in the middle sections. However, the histograms in Figure 4-2 are relatively flat and signature vector lengths are short. Therefore, the signature length and flatness of signatures can be used to further eliminate false detections. The length constrain can be imposed by the ratio between the true signature and the actual signature. The flatness of signature distribution can be checked using kurtosis. Figure 4-4 illustrates this approach.

5. MULTI-CLASSIFIER BASED BURIED DETECTION

In order to perform classification, Kolmogorov-Smirnov (KS) test is used to compare each windowed image chip and each of the reference vectors. The null hypothesis is that they have the same distribution. The test result for each target chip is 0, which means the hypothesis can be accepted. The test result for the
background is 1, that is, the hypothesis must be rejected. Since we design one KS-based classifier for each directional scan, for the same target chip, there will be a total of three classifiers associated with vertical, horizontal, and diagonal scans. In our system, these three classifiers are applied to the same target chip, resulting in three independent detection results, which are further fused for the refined detection.

For an image, we perform the following procedures:

**Thresholding:** In this procedure, the original image is thresholded based on our wavelet thresholding algorithms. This is also the first step towards the successful image segmentation, a extremely difficult problem.

**Clustering:** The thresholded image is processed by our ASOM, an unsupervised clustering algorithm. The center of each cluster represents one potential buried mine.

**Windowing:** A small window is formed around the center of each cluster. This windowed area is treated as a target chip.

**Detection Based on KS Test:** In this procedure, the windowed target chip is processed for signature extraction in all three scanning directions. They are statistically compared with KS test.

**False Alarm Mitigation:** The detected mines are further processed to check if they pass the ratio and kurtosis tests.

These five procedures and three classifiers are illustrated in Figure 5-1. In our system, we are able to perform image segmentation using wavelet-based image thresholding and unsupervised clustering methods. Each windowed target chip is processed against all buried mine signatures, either day time or night time, from our buried mine signature library. False alarms can be eliminated based on signature analysis and multi-classifier fusion.

![Figure 5-1: Components in our buried mine detection system.](image-url)
As we continue to further test and improve our system with additional data, new methods for false alarm mitigation and fusion methods will be developed and new results will be reported in the future.

6. SYSTEM TESTING RESULTS

In order to demonstrate the buried mine detection process and verify the detection algorithms, we tested both day time and night time images taken from MWIR data collected as part of Lightweight Airborne Multispectral Minefield Detection (LAMD) program.

Figure 6-1 shows one MWIR night time image where there are total seven buried mines. The clusters in the right figure indicate the potential buried mines. Around each cluster center, a window is generated and the target chip is subsequently chipped out.

Three signature vectors are extracted from each target chip and they are processed by three classifiers capable of discriminating buried mines through three directional signatures – horizontal, vertical and diagonal. Therefore, for one MWIR image, we will have three detection results. Figure 6-2 shows these three detection results for the image given in Figure 6-1.

![Figure 6-1: A night time MWIR image and clusters.](image1)

![Figure 6-2: Three classification results from the image in Figure 6-1.](image2)
In Figure 6-2, there are three false detections from the horizontal classifier, three false detections from the vertical classifier, and four false detections from the diagonal classifier. The detection results from these three classifiers can be fused to achieve a refined detection. Here we use a simple fusion scheme: a buried mine is declared only if it is detected by all three classifiers. One advantage of this type of fusion is the low false alarm rate since three classifiers may not report the same false detection in the same image. Figure 6-3 shows the fused detection based on three detections shown in Figure 6-2.

![Fused detection from three classifiers shown in Figure 6-2.](image)

Since not all false alarms are detected by all classifiers, there are only two false alarms in the final fused detection while six true detections are preserved. This example shows that three classifiers designed to process three directional signatures can effectively reduce the false alarms.

7. CONCLUSION

We have developed a buried mine detection system using multiple buried mine classifiers. For each target chip extracted from the MWIR image, we scan it in three directions: vertical, horizontal, and diagonal to construct three feature vectors. Since each cluster center represents all pixels in its cluster, the feature vector essentially captures the significant thermal variations of the same target chip in three directions. In order to detect the buried mines using our variable length feature vectors, we have applied Kolmogorov-Smirnov (KS) test to discriminate buried mines from background clutters. Since we built one KS-based classifier for each directional scan, for the same target chip, there will be a total of three classifiers associated with vertical, horizontal, and diagonal scans. In our system, these three classifiers are applied to the same target chip, resulting in three independent detection results, which are further fused for refined detection. Test results using actual MWIR images have shown that our system can effectively detect the buried mines in MWIR images with low false alarm rate.

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