Sensor-Fused Detection of Explosive Hazards

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ABSTRACT

Forward-looking ground-penetrating radar (FLGPR) has received a significant amount of attention for use in explosive hazards detection. A drawback to FLGPR is that it is sensitive to not only explosive hazards but also to benign objects, which results in an excessive number of false detections. This paper presents our analysis of the explosive hazards detection system developed by Planning Systems Inc (PSI). The PSI system combines FLGPR with an infrared (IR) camera. We present an FLGPR target detection algorithm that leverages the multiple observations aspect of FLGPR. The FLGPR target detections are then projected into the IR imagery. A Mahalanobis-metric classifier is then used to reduce the number of false detections. We show that our proposed FLGPR target detection algorithm, coupled with our IR-based false alarm reduction method, is effective at detecting explosive hazards while reducing the number of false alarms.

Keywords: forward-looking explosive hazards detection, sensor fusion, ground-penetrating radar, infrared, false alarm reduction

1. INTRODUCTION

Remediation of the threat of explosive hazards is an extremely important goal, as these hazards are responsible for uncountable deaths and injuries to both civilians and soldiers throughout the world. Systems that detect explosive hazards have included ground-penetrating-radar (GPR), infrared (IR) cameras, and acoustic technologies. Both handheld and vehicle-mounted GPR-based systems have been examined in recent research and much progress has been made in increasing detection capabilities. Forward-looking synthetic aperture GPR (FLGPR) is an especially attractive technology because of its ability to detect hazards before they are encountered; standoff distance can range from a few to tens of meters. FLGPR has been applied to the detection of side-attack mines and mines in general. A drawback to these systems is that FLGPR is not only sensitive to objects of interest, but also to other objects, both above and below the ground. This results in an excessive number of false detections.

The Planning Systems Incorporated (PSI) forward-looking explosive-hazard detection system is equipped with two sensors: an FLGPR and an IR camera. FLGPR is able to detect surface-laid, sub-surface and road-side targets. FLGPR alarm locations can be transformed into IR image space, allowing the surrounding areas to be examined in the IR imagery. The IR imagery can provide valuable information for determining whether a location contains an explosive hazard or is, most likely, a false alarm.

This paper presents a sensor-fusion algorithm that detects explosive hazards in FLGPR scans and uses associated IR imagery to reduce the number of false alarms. Section 1 briefly describes the evolutionary strategy by which we co-register the FLGPR and IR imagery. Section 2 describes our proposed FLGPR-based target detection algorithm. Another advantage of FLGPR is that each object is present in multiple radar scans. Our algorithm leverages these multiple observations to improve the receiver-operating characteristics (ROC) of the system. Section 2 also describes a method to link target-detections, which results in fewer overall detections without reducing probability of detection (Pd). This section also examines the ROC of different center frequencies and bandwidths used for the synthetic aperture beamforming. Section 3 describes the method by which we combine the FLGPR data with the IR imagery in order to further reduce the number of false detections. Finally, Sec. 4 presents test results and Sec. 5 concludes this paper.
2. INFRARED CAMERA REGISTRATION

To effectively use the IR imagery for screening FLGPR alarm locations, an accurate transformation between two-dimensional world coordinates, as reported by the FLGPR, and IR image coordinates is needed. No information about the IR camera, specifically the internal camera parameters, or the camera’s pose or location on the vehicle is assumed. The only information available is ground truth locations of several targets that are visible in the IR images, and the heading and location of the vehicle when each IR image was taken. This was the situation for the original data used in development and testing of the techniques in this paper. However, for the data used in the experiments whose results are described here, the camera location and pose on the vehicle are recorded. But as shown in [11], the technique described here is superior to a direct solution based on ray-tracing. Below is a brief description of the IR camera registration method; reference [11] has a more detailed description of this method.

A generalized perspective projection model, based on an ideal pinhole camera, is used to represent the transformation from camera reference frame coordinates \((X_c, Y_c, Z_c)\) to two-dimensional image coordinates \((X_i, Y_i)\). In this model, each point in the image corresponds to the intersection of a line with the image plane, running from a point in the camera reference frame through the center of projection.

In homogeneous coordinates, the projection onto the image plane can be represented as the following matrix equation, where \(P\) is the 4x4 projection matrix.

\[
\begin{bmatrix}
X_i \\
Y_i \\
1
\end{bmatrix}
= P
\begin{bmatrix}
X_c \\
Y_c \\
Z_c \\
1
\end{bmatrix}
\]

Knowing the projection matrix \(P\) allows transformation from camera reference frame coordinates to a pixel position in the image plane. The full projective model cannot be used in our particular case because the \(Z\)-coordinate of the calibration objects is unknown. Hence, we assume a flat earth, where \(Z_c = 0\). This assumption reduces the projection model to

\[
\begin{bmatrix}
X_i \\
Y_i \\
1
\end{bmatrix}
= P
\begin{bmatrix}
X_c \\
Y_c \\
1
\end{bmatrix},
\]

where \(P\) is now a 3x3 matrix. Additionally, we can project pixel coordinates in the image plane to the camera reference plane with the inverse transformation
This model assumes that the two-dimensional coordinates \((X_c, Y_c)\) are in the camera reference frame, i.e. situated relative to the position and heading of the camera. However, the FLGPR alarm locations are reported as two-dimensional world coordinates. These world coordinates must first be transformed into the camera reference frame before projection into the image plane can occur. This transformation is possible since the heading and location of the vehicle when each image was taken is known. The matrix equation

\[
\begin{bmatrix}
    X_c \\
    Y_c \\
    1
\end{bmatrix} = P^{-1} \begin{bmatrix}
    X_f \\
    Y_f \\
    1
\end{bmatrix},
\]

can be used to transform two-dimensional world coordinates \((X_w, Y_w)\) into camera reference frame coordinates. The point \((X_c, Y_c)\) is the location of the vehicle, and \(\theta\) is the vehicle heading.

Although the camera is located on the vehicle, the reported heading and location of the vehicle is not the exact heading and location of the camera itself; the camera is pointed towards the side of the road. However, the camera is fixed on the vehicle; hence, the transformation between the vehicle heading and location and the camera heading and location is static. This transformation can be modeled by a static 3x3 transformation matrix \(R\). The final transformation model is

\[
\begin{bmatrix}
    X_f \\
    Y_f \\
    1
\end{bmatrix} = PR \begin{bmatrix}
    X_c \\
    Y_c \\
    1
\end{bmatrix}.
\]

The parameters of both \(P\) and \(R\) are unknown and can simply be combined into a single 3x3 matrix. We refer to this projection matrix, aptly, as \(PR\).

Fig. 2. Example of FLGPR and IR co-registration. Left image is an FLGPR scan with target ground-truth locations shown by crosshair. Right image shows FLGPR scan projected into the camera reference frame. Green lines show FLGPR-IR correspondence.
The parameters $PR$ are approximated by using an evolutionary optimization algorithm called CMA-ES. The training data are composed of images of several targets whose ground-truth locations, as well as the vehicle headings and locations, are known. The CMA-ES algorithm chooses candidate projection matrices and then computes error by computing the difference between the projected ground-truth coordinates and the pixel coordinates of the training targets. The candidate partitions are then evolved by the CMA-ES algorithm at each iteration until an acceptable solution is found. Figure 2 illustrates the results of approximating $PR$ by showing the correspondence between the FLGPR image and the IR image for several targets. In the absence of ground-truth information for the target locations, this method could also be used to approximate $PR$ by gleaning the target locations directly from the FLGPR.

3. FORWARD LOOKING GROUND PENETRATING RADAR

The PSI FLGPR generates scan images as the vehicle travels down the lane. The images are created for the area -2m to 5m in the cross range direction, where negative numbers indicate to the left of the vehicle, and from 10m to 18m in the downrange direction, in front of the vehicle. The resolution of each scan is 0.1m, resulting in a 80x70 pixel scan image. Scan images are computed at intervals of about 1.0m of vehicle travel (in the downrange direction). The nominal center frequency is 1300MHz and the nominal bandwidth is 1000MHz. Figure 3 shows five consecutive scan images. An explosive hazard is indicated by the white box in the image. We denote the $s$th scan images as $G_s(u,v)$, where $u$ is the pixel-coordinate in the horizontal direction and $v$ is the pixel coordinate in the downrange direction. The origin is placed at the downrange-crossrange coordinate of (10,-2): the lower-left corner of the scans.

Reference [15] describes our previous efforts detecting land mines in FLGPR data. The algorithm we present in this paper is an adaptation of the algorithm described in [15].

Fig. 3. Five sequential FLGPR scans – target location indicated by white box.

Fig. 4. Maximum order-filtered images of FLGPR scan images shown in Fig. 3 – target location indicated by white box.
3.1 Alarm Identification

As Fig. 3 shows, the explosive hazard appears in the FLGPR scan as a red “hot spot”. Our detection method first computes a maximum order-filtered image with a $3\text{m} \times 1.5\text{m}$ kernel. We denote this order-filtered image as $O_{s}(u,v)$. In essence, each pixel in the scan image is replaced by the maximum pixel value within a $3\text{m}$ crossrange by $1.5\text{m}$ downrange rectangle. Figure 4 shows the associate order-filtered images for the scans shown in Fig. 3. As this figure shows, the order-filter reduces the noise-induced artifacts in the image and shows the local maxima as large squares in the image. Alarms are identified by the operation

$$A_{s} = \arg\{G_{s}(u,v) \geq \min\{O_{s}(u,v),2\}\},$$

where $A_{s}$ is the set of scan-image local-maxima locations. The minimum operator prescreens alarm locations that have a very low FLGPR return. We choose a value of 2 for this threshold as this only eliminates alarms with the lowest of confidence. We use this prescreening threshold merely to minimize the computational cost of the algorithm, not to reduce the number of false alarms (Sec. 3 further discusses a thresholding method to reduce the number of false alarms). We also augment each alarm location $(u,v)$ in $A_{s}$ with the value of the scan image pixel at that location, which we denote as $G_{s}(A_{s})$. This pixel value is, in effect, the confidence of the alarm – the higher the pixel value (FLGPR return), the higher the confidence.

Fig. 5. Alarm locations and confidence values for FLGPR scan images shown in Fig. 3. – target location indicated by white box, alarm locations indicated by white circles. First number next to alarm indicates confidence value post multiple-observation-persistence check, second number indicates FLGPR return value, and ‘SL’ indicates sidelobe.
3.2 Sidelobe Identification

Sidelobes are a known artifact of FLGPR. Assume that a target is an ideal point-reflector; the return image of this target will include not only a hot spot at the target location but also a collection of sidelobes, or additional hot spots, in the surrounding area of the target. Sidelobes can, therefore, appear as local maxima in the FLGPR scan image, causing false detections. We identify sidelobes by first computing the absolute distance between each scan image pixel and the vehicle location. Denote this distance by $D_{SL}(u,v)$. Figure 6 illustrates $D_{SL}(u,v)$ for the geometry of the scan images presented in this paper.

Sidelobes are identified by examining the FLGPR return of alarms that lie on the same distance radius from the vehicle. Assume that we wish to identify the sidelobes of an alarm in scan image $s$ with the coordinates $(u_1,v_1)$. First, we locate all other alarms in scan image $s$ that satisfy

$$\{(u,v) \in A_s : |D_{SL}(u,v) - D_{SL}(u_1,v_1)| < 0.5, G(u,v) < G(u_1,v_1)/2\},$$

where $\{(u_{SL},v_{SL})\}$ are the set of alarm locations that are approximately within the same radius of the alarm $(u_1,v_1)$ and, additionally, have less than half the FLGPR return. Figure 5 illustrates sidelobe detection by denoting a sidelobe with the letters ‘SL’.

3.3 Multiple Observation Persistency

The alarm locations shown in Fig. 5 illustrate that alarms corresponding to an explosive hazard have high relative confidence values and are, additionally, spatially persistent in the scan images. In contrast, clutter or noise-induced alarms have low relative confidences and are not persistent. We use these spatial persistence characteristics of the alarms to reduce the confidence of alarms that are not persistent between scans. First, we choose the parameter $m$, which is the number of scans that the multiple observation persistency (MOP) algorithm will use to determine the persistency of each alarm. In this paper, we use $m = 2$ scans. Second, we choose a neighborhood radius – this radius determines the size of the neighborhood in which persistency is considered. We use a radius value of $\sigma = 1$ meter. In essence, alarms that persist between scans within a 1m radius will be considered “good” alarms.

Assume that we are checking for persistency of an alarm at the location $(u_1,v_1)$ in scan image $s$ with a FLGPR return $G_s(u_1,v_1)$. The MOP algorithm is shown in Algorithm 1. The MOP algorithm does not reduce the number of alarms; it reduces the confidence of the alarms that are not spatially persistent between scan images. Figure 5 shows the post-MOP confidence value as the first number beside each alarm location. Notice that persistent alarms, such as the alarm corresponding to the explosive hazard, have very little or no reduction in confidence, while the confidences of the spurious alarms are significantly reduced.
Algorithm 1. MOP Algorithm

1. FOR $n = 1$ to $m$,
2. Identify the set of alarms in scan image $s-n$ that are not sidelobes, denoted $A'_{s-n} \subseteq A_{s-n}$.
3. Calculate the set of squared distances between the alarm $(u_1, v_1)$ and alarms $A'_{s-n}$,

\[
\{d^2\} = dy^2 (u_1 - u)^2 + dx^2 (v_1 - v)^2, \text{ for } (u,v) \in A'_{s-n},
\]

where $dx$ and $dy$ are the scan image pixel spacing.
4. END FOR
5. The new confidence value for the alarm $(u_1, v_1)$ is the median of the weighted FLGPR returns $\{g\}$.

3.4 Alarm Linking

Each FLGPR alarm thus far is associated with one scan image. A location on the ground is imaged in multiple scan images, which we leveraged with our MOP algorithm. However, we can reduce the number of alarms by linking the alarms for each location into a comprehensive list of alarms. For example, the scan images in Fig. 5 show that there is an alarm in each scan image that corresponds to the explosive hazard. Although these alarms appear to move in the scan image, the actual ground location of these alarms is virtually identical. Hence, we can combine these alarms into one alarm.

First, we choose a linking radius in meters. For this paper, we use a radius of $l = 0.5$ meters. For each alarm, a check is performed to determine if that alarm is the maximum confidence alarm within the linking radius. If the check is true, the alarm is kept; if the check is false, the alarm is deleted. In essence, this linking method deletes alarms that are within $l$ meters of a higher confidence alarm; thus, redundancy is diminished without reducing the quality of the alarms in terms of ground location and confidence value.

![ROC Curves](image)

Fig. 7. ROC Curves of University of Missouri/University of South Florida (MUFL) FLGPR detection algorithm and PSI detection algorithm. (a) – Data set A, 16 total targets, (b) – Data set B, 16 total targets.
3.5 Detection Results

Figure 7 compares performance of the University of Missouri / University of South Florida (MUFL) FLGPR detection algorithm with that of the PSI detection algorithm on two sets of data, Data Set A and Data Set B. These data sets were recorded in November 2007, and each contain 16 explosive hazard targets in real-world scenarios. Each graph is a ROC curve that plots the probability of detection versus the number of false alarms. Note the difference in the horizontal (false alarms) scale in each graph. The two data sets were recorded in different conditions. The MUFL detection algorithm outperformed the PSI algorithm on both sets. Additionally, the MUFL algorithm was able to detect all the targets in Data Set B while the PSI algorithm was only able to achieve a detection probability of 83%.

In the next section, we will combine IR camera information with the MUFL detection algorithm to further reduce the number of false alarms while maintaining a 100% probability of detection.

4. FALSE ALARM REJECTION

Section 2 described our method for projecting the FLGPR detections – computed by the method in Sec. 3 – into the corresponding IR images. In essence, we are able to find the areas in the IR images that correspond to each FLGPR detection. Hence, we can use the information in the IR images to classify the types of detections from the FLGPR, assuming that the image pixels corresponding to a false detection (e.g. bushes, rocks, garbage, etc.) are different from the pixels corresponding to an explosive hazard.

The IR camera used in the PSI system is a uncooled, long-wave camera with a resolution of 640x749 pixels with a bit depth of 12 bits per pixel (bpp). Although the images were acquired using 12 bpp, or 4096 possible quantization levels, the actual bit depth of the images is between 6 and 8 bits. Hence, these images do provide a large amount of detail. Furthermore, uncooled, long-wave IR imagery is known to be especially sensitive to many environmental factors, such as time-of-day, air and ground temperature, humidity, cloud cover conditions, and the length of time that the explosive hazard has been in position. These conditions are difficult to account for because the pixel values of uncooled, long-wave IR images do not directly correspond to a specific temperature. For these reasons, we focused on developing a robust and simple method for using the IR images to classify FLGPR detections as either true or false detections. Our false alarm rejection method is closely adapted from [11] and, in this paper, we only include a brief description of the algorithm.

3.1 IR Feature Extraction

Each FLGPR detection can be projected into an IR camera pixel location using the method described in Sec. 2 (assuming that the detection is within the camera field-of-view). Generally, there are multiple frames, between 5 and 20, for each FLGPR detection. The distance to the detection location differs in each frame, and, therefore, the number of pixels in the corresponding IR image differs. We are interested in examining a fixed area, in meters, around each detection location; thus, an adaptive-sized window around each detection in the IR image is selected. The projection matrix $PR$ allows us to compute the size of each image pixel, in meters, by using the inverse transformation from pixel positions to camera reference frame coordinates. Hence, it is possible to determine the appropriate window size to use for each image position, which corresponds to a chosen real world distance. We use a window size corresponding to a side length of one meter, as we discovered that this is large enough to contain all targets present in our data.

We calculate a set of features from the pixels in the windows corresponding to each FLGPR detection. First, the gradient magnitude, local standard deviation, and Laplacian images are calculated. The Laplacian is calculated using the convolution kernel

$$
\begin{bmatrix}
-1 & -1 & -1 \\
-1 & 8 & -1 \\
-1 & -1 & -1
\end{bmatrix}
$$

The gradient magnitude is calculated by first applying a Gaussian blur with a standard deviation of 1.0 to the original image. Then, partial derivatives in the horizontal and vertical directions are calculated using central differences. These
partial derivatives are squared and summed, resulting in the gradient magnitude image. The local standard deviation is calculated in a 5x5 window around each pixel.

The set of features calculated for each target detection in each of the four images (original, gradient magnitude, local standard deviation, and Laplacian) are the average, minimum, maximum, median, standard deviation, skewness, and kurtosis. In total, 28 features are calculated from the window of each frame in which an FLGPR detection is visible. Thus, each detection is represented by 5 to 20 sets of the 28 IR-based features. The median of these sets of features are calculated so that each detection is represented, finally, by 28 aggregated feature values. Additionally, we represent each detection by the magnitude of the FLGPR return: the 29th feature. We have experimented with other feature aggregation methods, including mean (both conventional and alpha-trimmed), min, and max, and discovered that median was the most effective aggregation operator for combining the features from each IR frame. In the future we hope to employ a method by which all sets of features can be used.

3.2 Mahalanobis-Metric Classifier

The 28 aggregated IR-based features and the FLGPR confidence value for each detection are used to classify the detection as either true (an explosive hazard) or false. We train a classifier by first calculating the multivariate normal distribution that best represents the feature values of the false detections for a given set of training data. Hence, the values of the false detection are assumed to be accurately represented by

$$f_X(x_1, \ldots, x_n) = \frac{1}{(2\pi)^{n/2} |\Sigma|^{1/2}} \exp\left(-0.5(x - \mu)^T \Sigma^{-1}(x - \mu)\right),$$

where $\mu$ is the mean vector and $\Sigma$ is the covariance matrix. We fit the distribution parameters to the training data using the well-known maximum-likelihood estimator. Once we have trained the classifier, we can use the Malahanobis-metric to determine how well a new feature vector $X$ fits the false detection distribution, where this distance is calculated by

$$D(X) = \sqrt{(X - \mu)^T \Sigma^{-1}(X - \mu)}.$$

If the Malahanobis-metric $D(X)$ is large-valued, this indicates that the detection does not fit the false detection distribution and is, most likely, a true detection. Hence, a threshold $T$ must be chosen such that a $D(X) > T$ indicates a true detection and a $D(X) \leq T$ indicates a false detection. The advantage of this method is that the threshold $T$ can be tuned to offer an optimal tradeoff between true and false detections, much like the gain on a radar receiver. Also, the distribution is trained on false detection data, of which there are many, rather than true detection data, of which there are few. Furthermore, the true detection features can be drastically different for different types and configurations of the explosive hazards, whereas the false detection features tend to more generalized.

3.3 Feature and Threshold Selection

There are a total of 29 features for each FLGPR detection. It is unlikely that all of these features are necessary or effective for training an optimal classifier. Additionally, given a set of features we must choose the threshold $T$ which determines whether an input feature vector is classified as a true or false detection. We use a forward sequential search (FSS) to find the $N$ best features. Essentially, FSS determines exhaustively the best feature, then using this best feature, determines the best combination of two features, and so on (it is popularly known as a greedy search). At each step of the FSS, the threshold $T$ is set such that each target in the training data has at least one associated detection. Note that a target can have more than one associated detection; however, the FSS may choose a $T$ that eliminates one or more of those detections, leaving at least one detection. In this manner, the optimal $T$ eliminates the most false detections while maintaining a $P_D = 100\%$. Thus, the FSS determines the $N$ best features and associated classifier parameters, $\mu$, $\Sigma$, and $T$. For some comprehensive results on this classification scheme, please refer to [11].
5. RESULTS

Figure 8 shows the combined results of our FLGPR detection algorithm and IR-based false alarm rejection. Figures 8(a,b) show the results if we choose the optimum set of IR features to perform the false alarm rejection. The optimum number of features for Data Set A was 14, while the optimum number of features for Data Set B was 3. Figures 8(c,d) show the ROC curves for a false alarm classifier based on the four best IR features.

As Fig. 8 shows, the MUFL FLGPR detection algorithm coupled with the MUFL IR-based false alarm rejection is the best performing system. In all cases, the MUFL FLGPR / IR system has the best performance. Figures 8(a,c) show that the MUFL FLGPR / IR system reduces false alarms by about 95% compared to the PSI FLGPR system. Figures 8(b,c) show that the PSI FLGPR system is unable to detect all the targets, achieving a $P_D = 88\%$, while the MU FLGPR system achieves a $P_D = 100\%$ (at about the same false alarm rate). However, Figs. 8(b,d) show that the IR false alarm rejection method performs better on the PSI FLGPR detections. We believe that this is because the PSI algorithm did not obtain a $P_D = 100\%$; hence, the Mahalanobis-metric could be set at a higher threshold, resulting in a higher reduction in false alarms.
The results in Fig. 8 are resubstitution results – the IR classifier was trained on the same data set from which the ROC curve was computed. Figure 9 shows test results, where the IR classifier is trained on the other data set, i.e. the classifier is trained on Data Set A and the ROC curve is computed for Data Set B, and vice versa. The results shown in Fig. 9 properly show the overall efficacy of our IR false alarm rejection. Additionally, the results are more indicative of the real-world performance of this system.

The ROC curves in Fig. 9(a) show that training the IR classifier on Data Set B and then using this classifier on Data Set A only resulted in a negligible reduction in false alarms. In contrast to Fig. 9(a), the ROC curves in Fig. 9(b) show that training the IR classifier on Data Set A and using this classifier on Data Set B resulted in a moderate reduction in false alarms. The difference in the test results illustrates the importance of good training data. We believe that Data Set A is the better training set because:

1) The ability of the FLGPR to pinpoint the targets in Data Set A was better. This leads us to conjecture that the FLGPR false detections in Data Set A were more “target-like”. Hence, training the IR classifier on these “target-like” detections allowed the classifier to separate the true target detections from the “target-like” detections; thus, reducing the false alarms for both the easy false detections (those that are not target-like) and the difficult “target-like” detections.
2) There were a large number of false detections in Data Set B. Hence, the IR classifier was trained on a large variety of detections. This variety causes the Gaussian model for the false detections to be relatively broad, which reduces the separability of the true detections from the false detections. In essence, the feature values of the true targets and feature values of the false detections are more mixed.

6. CONCLUSION

The MUFL FLGPR detection algorithm coupled with the IR-based false alarm rejection method is superior in performance to the existing PSI FLGPR-based algorithms. Section 5 showed that our algorithms reduced the number of false detections by up to 95%. Additionally, our FLGPR detection method detected all the targets in the test data, while the PSI system was unable to detect all the targets. The test results in Fig. 9 show that our system is somewhat generalizable, if the IR classifier is properly trained. As with all classifiers, the training data must be representative of the real-world data.

In the future we will examine ways in which our algorithm can be tuned to different types of explosive hazards. For example, different center frequencies and bandwidths may be optimal for different types of targets. We are also experimenting with different IR-based features, such as more complex texture-based measures and Zernike moments.
Finally, the methods described in this paper used the FLGPR to detect the targets and the IR to reduce the false alarms. We believe that the IR could be used in tandem with the FLGPR to detect targets, and we have already begun work in this realm. Overall, the FLGPR/IR explosive hazards detection approach shows promise for significantly contributing to the remediation of the explosive hazards threat.

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REFERENCES