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RPPR Final Report
as of 06-Apr-2023

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Final Report for Period Beginning 01-Sep-2014 and Ending 31-Dec-2021

Title: Target Detection, Clutter Discrimination, and Heterogeneous Fusion for Multi-Sensor Handheld Subsurface Object Detector

Begin Performance Period: 01-Sep-2014

End Performance Period: 31-Dec-2021

Report Term: 0-Other

Submitted By: Dominic Ho

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Distribution Statement: 1-Approved for public release; distribution is unlimited.

STEM Degrees: 5

STEM Participants: 5

Major Goals: The major goals are:

- develop algorithms for handheld unit of landmine detection by the ground penetrating radar,
- develop algorithms for handheld unit of landmine detection by the metal detector,
- develop fusion algorithms for metal detector and ground penetrating radar, to improve landmine detection performance for handheld unit,
- improve algorithms for vehicle mounted landmine detection by the ground penetrating radar,
- develop and investigate algorithms for tracking a moving target from infrared or color images.

Accomplishments: We have successfully developed the algorithms and evaluated them from the field data. We have transferred the technologies to the Army in terms of codes, reports, and presentations.

Training Opportunities: We have trained a number of graduate students related to engineering practices, analysis skills and research techniques.

Results Dissemination: We have transferred the technologies to the Army in terms of codes, reports, and presentations. We also disseminate the outcomes of this research project to the public by conference presentations and paper publications.

Honors and Awards: Nothing to Report

Protocol Activity Status:

Technology Transfer: We have transferred the technologies developed to the Army in terms of processing codes, reports and presentations.

PARTICIPANTS:

Participant Type: PD/PI

Participant: Dominic Ho

Person Months Worked: 1.00

Funding Support:

Project Contribution:

National Academy Member: N

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Participant Type: Co-Investigator

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Person Months Worked: 1.00

Funding Support:

Project Contribution:

National Academy Member: N

Participant Type: Graduate Student (research assistant)

Participant: Brendan Alvey

Person Months Worked: 12.00

Funding Support:

Project Contribution:

National Academy Member: N

Participant Type: Graduate Student (research assistant)

Participant: Matt Cook

Person Months Worked: 12.00

Funding Support:

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Participant Type: Graduate Student (research assistant)

Participant: Daniel Nabelek

Person Months Worked: 12.00

Funding Support:

Project Contribution:

National Academy Member: N

Participant Type: Graduate Student (research assistant)

Participant: Pooparat Plodpradista

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Funding Support:

Project Contribution:

National Academy Member: N

Participant Type: Graduate Student (research assistant)

Participant: Sam Harris

Person Months Worked: 12.00

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Volume: 57 **Issue:** 9 **First Page #:** 6929
Date Submitted: 6/27/21 12:00AM **Date Published:** 5/2/19 5:00AM
Publication Location: United States
Article Title: A Large-Scale Multi-Institutional Evaluation of Advanced Discrimination Algorithms for Buried Threat Detection in Ground Penetrating Radar
Authors: Jordan M. Malof, Daniël Reichman, Andrew Karem, Hichem Frigui, K. C. Ho, Joseph N. Wilson, Wen-Hsiao
Keywords: ground penetrating radar, landmine detection, buried threat detection
Abstract: In this paper we consider the development of algorithms for the automatic detection of buried threats using ground penetrating radar (GPR) measurements. GPR is one of the most studied and successful modalities for automatic buried threat detection (BTD), and a large variety of BTD algorithms have been proposed for it. Despite this, large-scale comparisons of GPR-based BTD algorithms are rare in the literature. In this work we report the results of a multi-institutional effort to develop advanced buried threat detection algorithms for a real-world GPR BTD system. The effort involved five institutions with substantial experience with the development of GPR-based BTD algorithms. In this paper we report the technical details of the advanced algorithms submitted by each institution, representing their latest technical advances, and many state-of-the-art GPR-based BTD algorithms. We also report the results of evaluating the algorithms from each institution on the large experimental dataset.
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Date Received: 14-Jul-2016 **Conference Date:** 20-Apr-2015 **Date Published:**
Conference Location: Baltimore
Paper Title: Anomaly Detection of Subsurface Objects Using Handheld Ground-Penetrating Radar
Authors: K.C. Ho, Samuel Harris, Alina Zare, Matthew Cook
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Date Received: 14-Jul-2016 **Conference Date:** 20-Apr-2015 **Date Published:**
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Paper Title: Multiple instance dictionary learning for subsurface object detection using handheld EMI
Authors: Alina Zare, Matthew Cook, Brendan Alvey, Dominic K. C. Ho
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Date Received: 04-Oct-2018 **Conference Date:** 18-Apr-2016 **Date Published:** 15-Jul-2016
Conference Location: Baltimore
Paper Title: Adaptive coherence estimator (ACE) for explosive hazard detection using wideband electromagnetic induction (WEMI)
Authors: Brendan Alvey, Alina Zare, Matthew Cook, Dominic K. C. Ho
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Conference Location: Baltimore
Paper Title: Buried object detection using handheld WEMI with task-driven extended functions of multiple instances
Authors: Matthew Cook, Alina Zare, Dominic K. C. Ho
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Paper Title: On the Use of Log-Gabor Features for Subsurface Object Detection using Ground Penetrating Radar
Authors: Samuel Harris, K.C. Ho, Alina Zare
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Conference Location: Anaheim, CA
Paper Title: LBP Features for Hand-Held Ground Penetrating Radar
Authors: Samuel Harris, Brendan Alvey, Dominic Ho, Alina Zare
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Conference Location: Anaheim, CA
Paper Title: Fourier features for explosive hazard detection using a wideband electromagnetic induction sensor
Authors: Brendan Alvey, Alina Zare, Dominic Ho
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Conference Location: Orlando, FL
Paper Title: Sample spacing variations on the feature performance for subsurface object detection using handheld ground penetrating radar
Authors: Brendan Alvey, Dominic K. C. Ho, Alina Zare
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Date Received: 04-Oct-2018 Conference Date: 15-Apr-2018 Date Published: 31-Aug-2018
Conference Location: Orlando, FL
Paper Title: Analyzing three dimensional radar voxel data using the discrete Fourier transform for SAEH detection
Authors: Pooparat Plodpradista, James M. Keller, Dominic K. C. Ho, Mihail Popescu, Andrew R. Buck
Acknowledged Federal Support: **Y**

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Conference Location: Baltimore
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Authors: Dominic K. C. Ho, Pooparat Plodpradista
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Paper Title: Doing More With Less: Similarity Neural Nets and Metrics for Small Class Imbalanced Data Sets
Authors: Charlie Veal, Jeffrey Schulz, Andrew Buck, Derek Anderson, James Keller, Mihail Popescu, Grant Scott
Acknowledged Federal Support: **Y**

Publication Type: Conference Paper or Presentation **Publication Status:** 1-Published
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Conference Location: virtual
Paper Title: Improving explosive hazard detection with simulated and augmented data for an unmanned aerial system
Authors: B. Alvey, D. T. Anderson, J. M. Keller, A. Buck, G. Scott, D. K. C. Ho, C. Yang, and B. Libbey
Acknowledged Federal Support: **Y**

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Date Received: 28-Jun-2021 Conference Date: 03-Apr-2021 Date Published: 01-Jun-2021
Conference Location: virtual
Paper Title: Wire detection by GPR using the Hough transform
Authors: J. Moeller, B. Young, D. K. C. Ho, and D. T. Anderson
Acknowledged Federal Support: **Y**

Partners

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RPPR Final Report
as of 06-Apr-2023

I certify that the information in the report is complete and accurate:

Signature: Dominic Ho

Signature Date: 4/5/23 7:57PM

Final Report

Target Detection, Clutter Discrimination, and Heterogeneous Fusion for Multi-Sensor Handheld Subsurface Object Detector

W911NF1410584 / 66398-CS

Dominic Ho

Electrical Engineering and Computer Science Department

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SUMMARY

During the grant period, we have developed the following machine learning techniques and algorithms for subsurface explosive object detection using the forward looking and ground penetrating radar (GPR):

- MH Prescreening Algorithm
- Local Binary Pattern Feature
- FOMIACE Technique
- Log-Gabor Time-Frequency Processing

In the extended period, using the IR camera data, we have developed and investigated

- Target Tracking by Random Finite Set Statistics

They have been transferred to the US Government and the Government contractors. Most of the developed techniques have been implemented and being used in the actual systems in operation for helping soldiers and civilians.

The research and development outcomes approved for public release by the government have resulted in several publications that have been published and disseminated. We summarize the techniques, the major results and conclusions below.

I. MH Prescreener

We have developed an anomaly detection algorithm for subsurface object detection for the handheld GPR. The algorithm is based on the Mahalanobis distance measure with adaptive update of the background statistics. It processes the data sequentially for each data sample in a causal manner to generate detection confidences. The algorithm is applied to process the data from two different radars, an impulse and a step-frequency, for performance evaluation.

Background

The goal of subsurface object detection is to create systems that are capable of safely locating and accurately identifying different types of buried targets. Such detectors typically utilize one or more physical sensors in order to attain a digital representation of an underground area. This data is then analyzed by several algorithms in order to determine if a landmine or other type of explosive is present.

Electromagnetic induction sensors, commonly referred to as metal detectors, have long been used for subsurface object detection. However, these sensors are only effective at locating objects with high metal content and many modern explosives contain little or no metal. It has been shown that ground penetrating radar (GPR) can be used to identify these targets.

Two popular platforms for GPR in subsurface object detection are vehicle mounted and hand-held. The vehicle mounted platform focuses on the detection of anti-tank targets and performs the detection in a relatively fast pace by driving down a road. The hand-held system, on the other hand, requires an operator to sweep the detector back and forth over the ground while moving forward and the detection is a relatively slow pace. The main advantage of the hand-held system is that it can operate in different terrain.

There are a number of popular hand-held detection systems, including the AN/PSS-14¹⁻² and the Mine Hound³. The former uses a step-frequency GPR whilst the latter a pulse GPR. In addition to GPR, both contain the EMI sensor as well to improve the detection for anti-personnel targets.

Due to the improvement of technology, better hand-held GPRs may be available to improve the hand-held detector performance. In this paper, we shall revisit the signal processing algorithm and propose an anomaly detector that can act as a prescreener to identify alarm locations that potentially contain targets, so that more sophisticated algorithms can be applied there to ascertain if targets are present.

MH Prescreener

The MH prescreening algorithm has three components: ground alignment, background removal and test statistic generation.

A. Ground Alignment

Due to the roughness of the ground and the mechanical vibration of the robot arm caused by movement, the ground level shown in the acquired data is drifted up and down. The first step in the processing is to align the data from one sample to the next so that the ground level at each sample appears at the same depth bin. Each sample refers to a vector that consists of 256 points.

Ground alignment uses cross-correlation to determine the translation between the current and the reference sample. The reference sample is obtained by the average of the first few samples. The ground of the reference sample is placed such that its minimum value appears at depth bin 25. Each data sample is correlated with the reference to determine the relative shift so that it aligns with the reference. Figure I-1 shows an example of the data before and after the alignment. It clearly illustrates the effectiveness of the alignment method.

B. Background Removal

The background consists of the self-signature of the radar and the radar return from bare soil. The background can be very strong such that it can dominate the radar return. This can occur even when a target appears whose response is super-imposed in the overall return. The background is non-stationary and varies dynamically. We model the background response in the current sample by a weighted sum of the past few samples,

$$\mathbf{b}(j) = \sum_{l=P}^{P+L-1} a_l(j) \mathbf{x}(j-l)$$

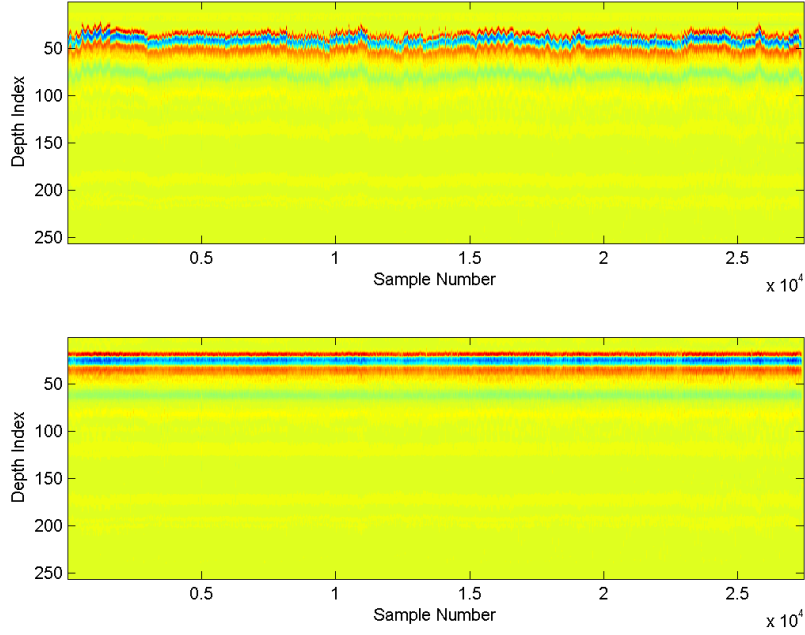


Figure I-1. Data before (top) and after (bottom) ground alignment

where $\mathbf{b}(j)$ is a column vector that represents the background estimate at sample j , P is the number of guard samples, L is the number of samples used to estimate the background, $a_l(j)$ is the weighting coefficient and $\mathbf{x}(j)$ is the j -th sample of the data. The subscript c that indicates the channel is dropped for notation simplicity. In the current processing, we set P to five and L to unity.

The background-removed sample is obtained by

$$\mathbf{y}(j) = \mathbf{x}(j) - \mathbf{b}(j) .$$

To take into account the dynamic variation of the background, the weighting coefficient $a_l(j)$ is estimated by minimizing the L_2 norm of $\mathbf{y}(j)$:

$$a_P(j) = \frac{\mathbf{x}^T(j) \mathbf{x}(j-P)}{\mathbf{x}^T(j-P) \mathbf{x}(j-P)} .$$

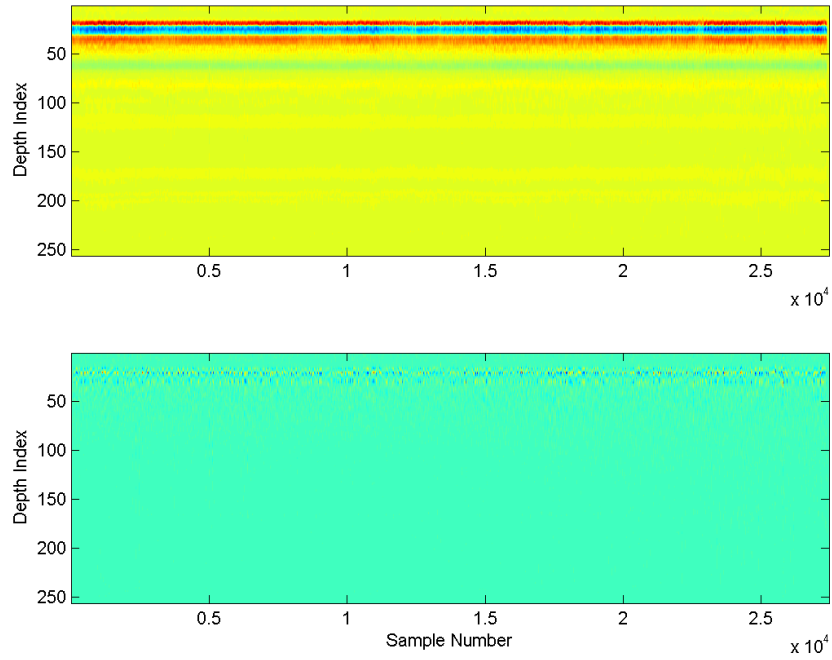


Figure I-2. Data before (top) and after (bottom) background removal

Figure I-2 depicts the data before and after background removal. The data is much cleaner after removing the background.

C. Test Statistic

The detection statistic is generated using the Mahalanobis distance. Assuming $\mathbf{y}(j-1)$ is a background sample, the running mean and the running covariance matrix for the current sample $\mathbf{y}(j)$ are obtained by

$$\mathbf{m}(j) = \lambda \mathbf{m}(j-1) + (1-\lambda) \mathbf{y}(j-1)$$

$$\mathbf{C}(j) = \lambda \mathbf{C}(j-1) + (1-\lambda) (\mathbf{y}(j-1) - \mathbf{m}(j-1))^T (\mathbf{y}(j-1) - \mathbf{m}(j-1)) .$$

The smoothing constant λ is set to 0.999.

The detection statistic is

$$f(j) = (\mathbf{y}(j) - \mathbf{m}(j))^T \mathbf{W}(j) (\mathbf{y}(j) - \mathbf{m}(j)).$$

The matrix $\mathbf{W}(j)$ is the inverse of the running covariance of $\mathbf{C}(j)$. To reduce computation, we apply the Woodbury matrix identity⁹ to update $\mathbf{W}(j)$ directly,

$$\mathbf{W}(j) = \frac{1}{1-\lambda} \left(\mathbf{W}(j-1) - \frac{\mathbf{W}(j-1)(\mathbf{y}(j-1) - \mathbf{m}(j-1)) (\mathbf{y}(j-1) - \mathbf{m}(j-1))^T \mathbf{W}(j-1)}{(1-\lambda)/\lambda + (\mathbf{y}(j-1) - \mathbf{m}(j-1))^T \mathbf{W}(j-1) (\mathbf{y}(j-1) - \mathbf{m}(j-1))} \right).$$

For the next sample, we update the running mean $\mathbf{m}(j+1)$ and covariance inverse $\mathbf{W}(j+1)$ is updated if the detection statistic $f(j)$ is less than a certain threshold, which indicates $\mathbf{y}(j)$ is considered as a background sample. Otherwise, we simply set $\mathbf{m}(j+1)$ to $\mathbf{m}(j)$ and $\mathbf{W}(j+1)$ to $\mathbf{W}(j)$, without updating the background statistics.

To improve performance, we apply range gating to process the data below the ground bounce only. Furthermore, we separate the data into two depth regions evenly, shallow and deep, with slight overlap. The detection statistics are generated separately for the two depth segments. The final detection statistic is the maximum of the two.

Experimental Results

The data for performance evaluation were collected in March of 2014, using the robot mounted hand-held GPR system. The dataset contains twelve lanes with one run in each. Each lane contains a variety of targets, including anti-personnel (AP), anti-tank (AT) and wire, with high, low and no metal content. We shall illustrate the performance in terms of the Receiver Operating Characteristic (ROC) curves.

The data have three channels and the developed algorithm was applied to each channel separately. The detection values of the three channels were merged together into a single surface map for scoring. The ground truth locations with 0.25 m halo size are overlaid in a surface map to generate the correct detections and false alarms. Figure I-3 shows the surface detection map of one lane. The targets are buried in the middle of the lane at regular spacing.

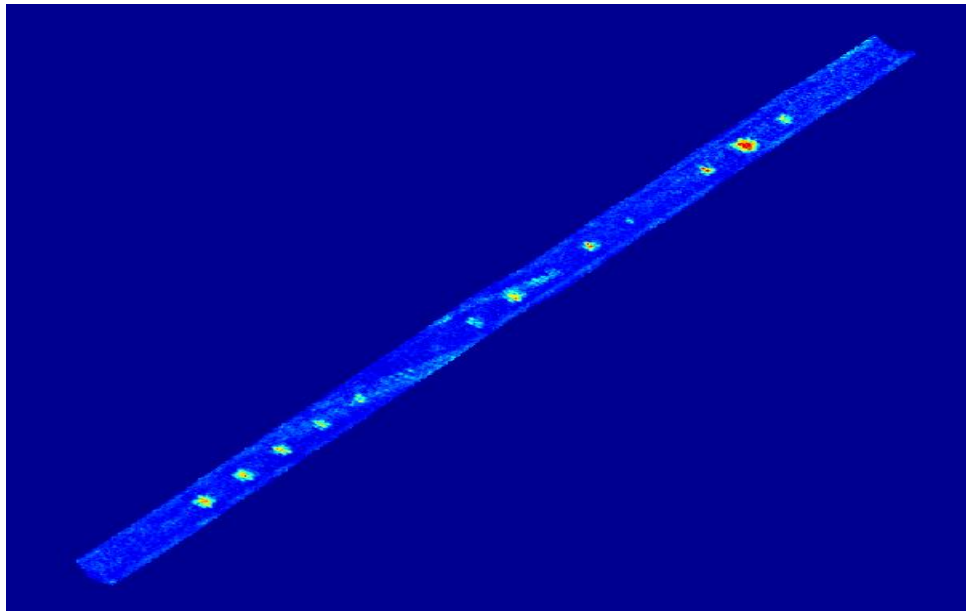


Figure I-3. The surface detection map produced by the proposed algorithm at a certain lane.

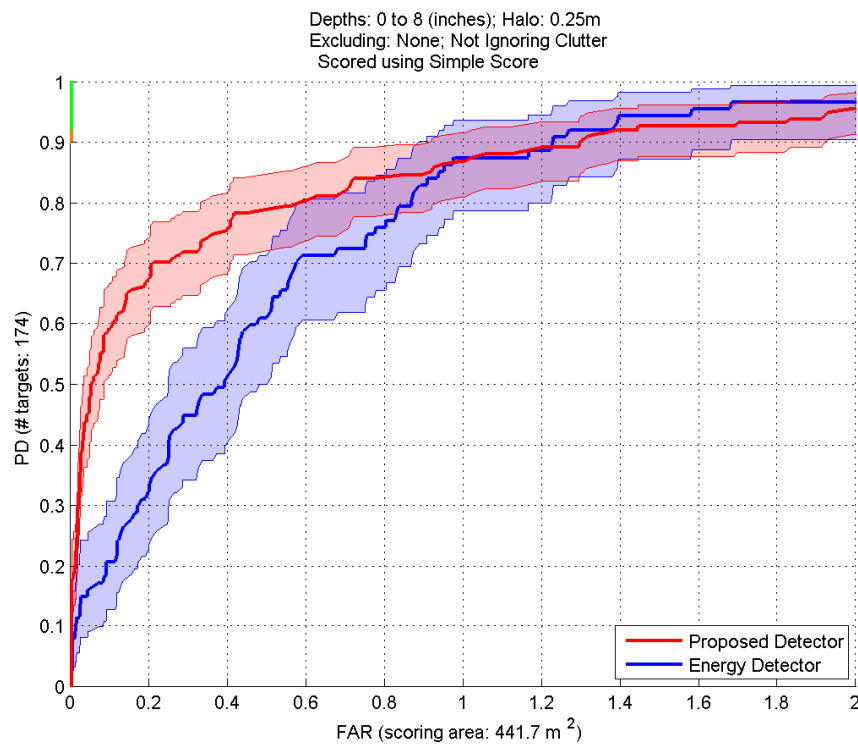


Figure I-4. Detection performance of all targets including AP, AT and wires of various metal content

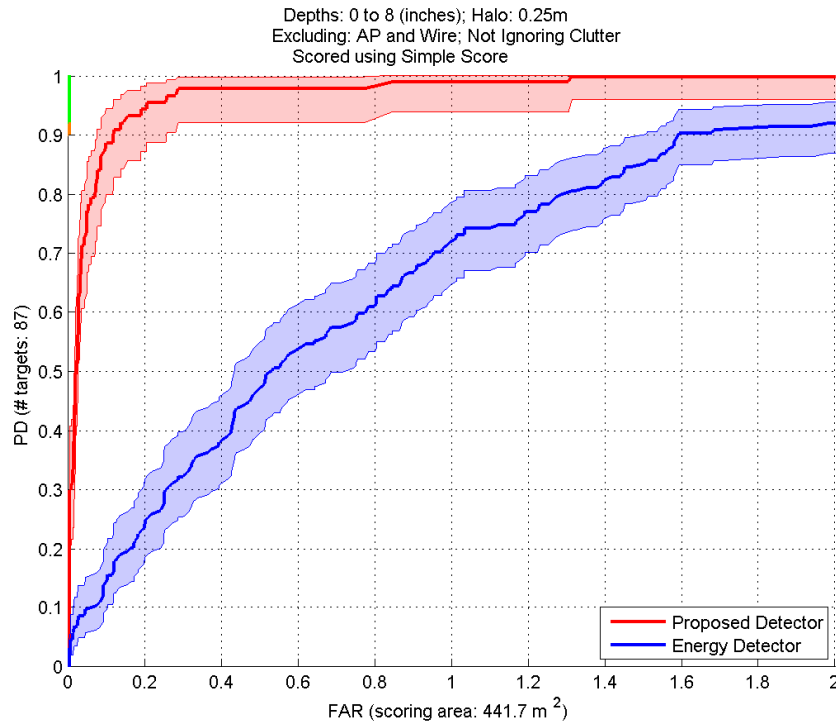


Figure I-5. Detection performance without counting AP and wires.

Figure I-4 gives the ROC curve for all targets, where the shaded area denotes the 90% confidence interval of detection at a given false alarm rate. Also shown is the performance of the energy detector after range gating to remove the ground bounce. The proposed algorithm works much better than the energy detector. There are a number of anti-personnel targets that are very difficult to detect by the GPR.

Figure I-5 shows the performance when we do not count the anti-personnel targets and wires. The results are much better compared to Figure I-4, and we are able to reach 90% detection at a false alarm rate of 0.15/m².

Conclusions

We have developed an anomaly detector for the hand-held GPR system. It can act as a pre-screener to identify alarm locations that potentially contain a target, where more sophisticated algorithms can be applied to improve the detection performance. The

proposed detector consists of ground alignment, background removal, depth segmentation and Mahalanobis distance computation. The performance of the proposed detector outperforms the energy detector significantly.

II. Local Binary Patterns (LBP)

GPR has the ability to detect buried targets with little or no metal content. Achieving superior detection performance with a hand-held GPR can be very challenging due to the quality of the data, inconsistency of target signatures, variety of target types, and effects of a human operator. In this paper, we investigate the use of a LBP feature vector for target versus non-target discrimination from hand-held GPR data. First, a prescreener algorithm is applied to the GPR data. Then, a GPR B-scan is gathered at each prescreener alarm location and separated into several spatial and depth regions. LBP processing is applied to each spatial and depth cell individually and the LBP features from each cell are group together to form a feature vector. The resulting LBP features are invariant to amplitude scaling and represent the texture in the data. Using this feature vector, a classifier is trained to perform target versus non-target discrimination at each prescreener declaration. Experimental results illustrate the ability of the LBP features to improve detection of buried targets, especially low-metal and non-metal anti-tank (AT) and anti-personnel (AP) targets.

Background

Subsurface object detection systems can be implemented on a variety of platforms, such as vehicle mounted and hand-held systems. Vehicle mounted systems can scan large plots of land relatively quickly and typically focus on AT targets. However, since the sensors are attached to a rolling vehicle, these systems can only be used on terrain that can be traversed by the vehicle. Hand-held systems are more easily used on land that is difficult to access or traverse. However, hand-held systems require a human operator to sweep the detector back and forth over the ground, resulting in very slow rate of advance. Furthermore, it is often not possible for human operators to sweep the detector with a high level of precision. Even small variations in the speed or height of a sweep can significantly impact the quality of the data being collected, which can make it more difficult to achieve a high detection rate.

One common strategy is to first apply a prescreener algorithm to the hand-held GPR data. The goal of this algorithm is to detect potential anomalies in the incoming data and report any alarm locations that might contain a target. The reported alarm locations can then be analyzed by subsequent algorithms to lower the false alarm rate (FAR). If there is enough data available to train a classifier, reducing the FAR can be approached as a supervised learning task. Once a feature set is computed and a classifier is trained, new GPR data can be fed into the classifier to obtain a target or non-target prediction. The generalizability of such a model is usually gauged by testing its performance on data that was not used during training.

We use the LBP feature set along with support vector machine (SVM) to improve the performance of an existing anomaly detection algorithm. Hand-held GPR B-scans are first split into several spatial and depth regions and LBP features are computed within each of the resulting cells. The feature set is reduced and used to train a linear kernel SVM to perform target versus non-target classification. Probability estimates are obtained from the model and fused with the prescreener confidence values to achieve a lower FAR. The proposed algorithm is evaluated using two hand-held GPR datasets.

LBP Feature

Although the two are not identical, GPR B-scans are similar to traditional image data in many ways. Thus, classifying GPR B-scans into target and non-target classes can be approached as an image classification problem. In image processing tasks, it is often helpful to extract features which capture local texture information about an image. One such feature extraction method is called the local binary patterns⁶. LBP first performs a nonlinear transformation on an image, or any similar 2-dimensional data sample, as follows. First, a 3x3 neighborhood of pixels is extracted from the data. Then, each of the 8 pixels located on the perimeter of the 3x3 neighborhood are individually compared to the pixel in the center of the neighborhood. Each perimeter pixel containing a value greater than or equal to that of the center pixel is assigned a binary value of 1. The perimeter pixels that contain a value less than that of the center pixel are assigned a

binary value of 0. Each of the 8 perimeter pixels is numbered from 1 to 8. Then, each perimeter pixel is assigned a weight of $2^{(i-1)}$, where i is the pixel number. The binary values that were assigned to the perimeter pixels are then multiplied by the corresponding weights. Finally, the weighted values are summed to obtain a single, unsigned integer. This process is illustrated in Figure II-1. The final integer value uniquely describes the local texture of the 3x3 neighborhood.

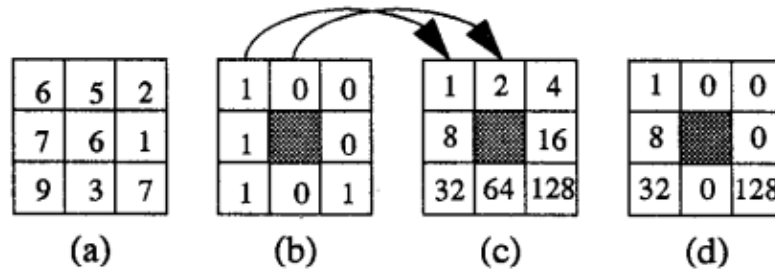


Figure II-1. LBP example (from T. Ojala, *et al.*, 1994). This figure illustrates how to perform LBP on a single, 3x3 neighborhood. (a) Original 3x3 neighborhood that has been extracted from some 2-dimensional data sample. (b) Binary values that are assigned to each perimeter pixel. (c) Weights of the perimeter pixels. (d) Result of applying the weights to the binary values. In this example, the perimeter pixels in (d) would be summed to obtain a final LBP value of 169 for this center pixel.

This process is then repeated for each 3x3 neighborhood in the image, resulting in a new LBP matrix of unsigned integer values. Each element of this matrix represents the local texture observed within the corresponding neighborhood in the original image. Since the pixels on the edges of the original data matrix cannot be center pixels of any 3x3 neighborhood, the LBP matrix is of size $(r-2) \times (c-2)$, where r and c are the number of rows and columns in the original data matrix, respectively. Once the LBP matrix has been computed, features are extracted by summing the number of occurrences of each integer in the LBP matrix. Since there are 8 perimeter pixels in each neighborhood, there are 256 possible LBP patterns. Thus, the resulting feature vector consists of 256 features.

Uniform Patterns

Although 256 different LBP values are possible, some patterns are more intuitively meaningful than others. For example, the patterns shown in Figure 2 all correspond to typical edge behaviors, such as horizontal walls, vertical walls, or diagonal edges. However, the patterns shown in Figure 3 do not clearly correspond to any intuitively meaningful structures. A distinction is drawn between these two pattern types, known as uniform and non-uniform patterns.

The distinction between uniform and non-uniform patterns is drawn more rigorously by observing the number of 0 to 1 and 1 to 0 transitions encountered while circularly traversing the 8 perimeter pixels in the local neighborhood. Uniform patterns have two or fewer transitions, while non-uniform patterns have 3 or more transitions. With a 3x3 neighborhood, there are only 58 possible uniform patterns. These uniform patterns often represent the majority of the meaningful texture information in an image, while the remaining non-uniform patterns frequently represent noise in the data.

0	0	0
0		0
1	1	1

0	0	1
0		1
0	0	1

1	1	0
1		0
0	0	0

Figure II-2. Uniform pattern examples. When circularly traversed, each of these patterns has only two 0 to 1 or 1 to 0 transitions. Thus, each of these patterns is uniform. Notice that each pattern can be intuitively understood as a horizontal, vertical, or diagonal edge texture within the data sample.

1	1	0
0		0
1	0	1

0	1	0
1		0
0	0	1

1	0	1
0		0
1	0	1

Figure II-3. Non-uniform pattern examples. When circularly traversed, each of these patterns has greater than two 0 to 1 or 1 to 0 transitions. Thus, each of these patterns is non-uniform.

Feature Extraction and Classification

A. Feature Extraction

At each prescreener alarm location, a GPR B-scan consisting of 60 successive A-scans was split into 3 overlapping spatial regions and 4 non-overlapping depth regions. The leftmost spatial region consisted of A-scans 1 through 30, the center spatial region consisted of A-scans 16 through 45, and the rightmost spatial region consisted of A-scans 31 through 60. The intention of these spatial regions was to capture the rising edge patterns of each target pattern in the leftmost spatial region and the falling edge patterns in the rightmost spatial region. The center region was included to capture the horizontal textures for wide target patterns and to potentially capture the entire pattern for smaller targets. The 4 depth regions were defined in order to limit the effect of background noise at one depth on the features computed at a different depth.

Due to the oscillation behavior of the signal received by the GPR, the GPR data incrementally shifts between positive and negative values as the depth increases. In order to reduce the effect of this oscillating between positive and negative on the LBP features, the absolute value was taken at each element in the GPR B-scan. Using the absolute value of each element, the LBP matrix for each of the 12 cells was then computed. Features were extracted by counting the number of occurrences of each uniform pattern in each cell, resulting in 58 features per cell. The feature vectors for each of the 12 cells were concatenated, resulting in a vector of 696 LBP features.

B. Feature Set Reduction

Once a feature vector was extracted at each alarm location, the set of alarm locations was then partitioned into 10 stratified subsets and 10-fold cross validation was carried out. At each iteration of the cross-validation process, the mean and standard deviation across each feature in the set of training targets were computed. This mean and standard deviation were used to perform z-score normalization on both the training and test set prior to training and testing. Then, a linear kernel SVM was trained on the training set and

tested on the test set. This way, a test prediction was obtained for each alarm location in the dataset. Once the cross validation was complete, the resulting SVM weight vectors were averaged and the 696 LBP features were ranked from the highest to lowest weight.

Ranking the features in this way provided insight into which features were the most useful for performing target versus non-target discrimination. With the feature ranking in place, feature selection was performed by choosing the subset of the k highest-ranked features that provided the best detection performance. A script was written to perform stratified 10-fold cross validation using every possible subset of the k highest ranked features, with k incremented from 2 up to 696. Probability estimates were derived for each prescreen alarm location. By using these probability estimates as confidence values and varying the classification threshold from 0 to 1, a receiver operator characteristic (ROC) curve was computed for each feature subset size. The feature subset that gave the largest cross-validated area under the curve (AUC) was selected. Figure II-4 illustrates the effect of this feature selection on a particular AT target in one of the datasets. Figure 5 illustrates the same feature subset on an anti-personnel (AP) target in the same dataset.

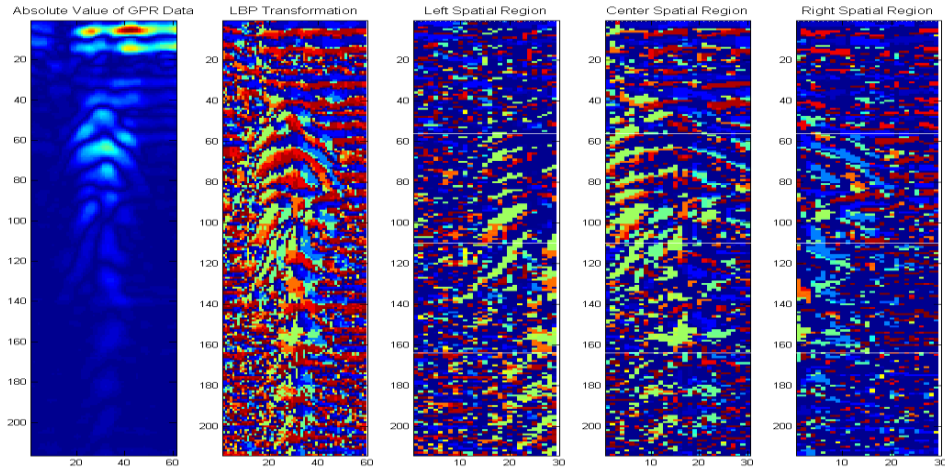


Figure II-4: Selected LBP textures (AT target example). The leftmost image shows the absolute value of the GPR B-scan at a particular alarm location. The second image from the left is the LBP matrix computed for the same alarm location, where each color represents a different local texture. The center image is the LBP matrix for the leftmost spatial region, with all eliminated textures set to 0 (dark blue). The second image to the right is the LBP matrix for the center spatial region, with all eliminated textures set to 0. The rightmost image is the LBP matrix for the rightmost spatial region, with all eliminated textures set to 0. Each feature is computed by summing the number of occurrences of a particular texture in the LBP matrix at a certain depth within a particular spatial region. The white lines in the rightmost 3 images indicate the separation among the four depth regions within each spatial region. The rising edge, middle area, and falling edge of the target pattern are clearly visible in the feature-reduced LBP transformation. This target pattern is quite large and spans across multiple depth regions. Therefore, this pattern will influence the LBP features computed across each of these depth regions. This target received a very high confidence from both the prescreener and the SVM.

C. Classification Confidence

After the optimal subset of highest-ranked features was selected, a new linear SVM was trained on this reduced feature set. Once again, stratified 10-fold cross validation was performed. Probability estimates were derived for each alarm location in each test set and these probability estimates were used as confidence values. The confidence values produced from the trained SVM were then fused with the prescreener confidence values

using the geometric mean. The result of this fusion, defined in Equation 1 below, was then used as the final confidence value for each alarm location.

$$fused_conf = prescreen_conf^{0.5} \times SVM_conf^{0.5}$$

Experimental Results

A. Pulse Radar

For the impulse radar dataset, observing the SVM weight vector allowed 334 features to be eliminated. The final 10-fold cross validation was performed using the remaining 362 features. The performance of the prescreener alone, the SVM alone, and the fusion of the two was compared by plotting the corresponding ROC curves. Figure II-5 shows these results when all targets are included in scoring. Figure II-6 illustrates the results when only AT targets are included in scoring.

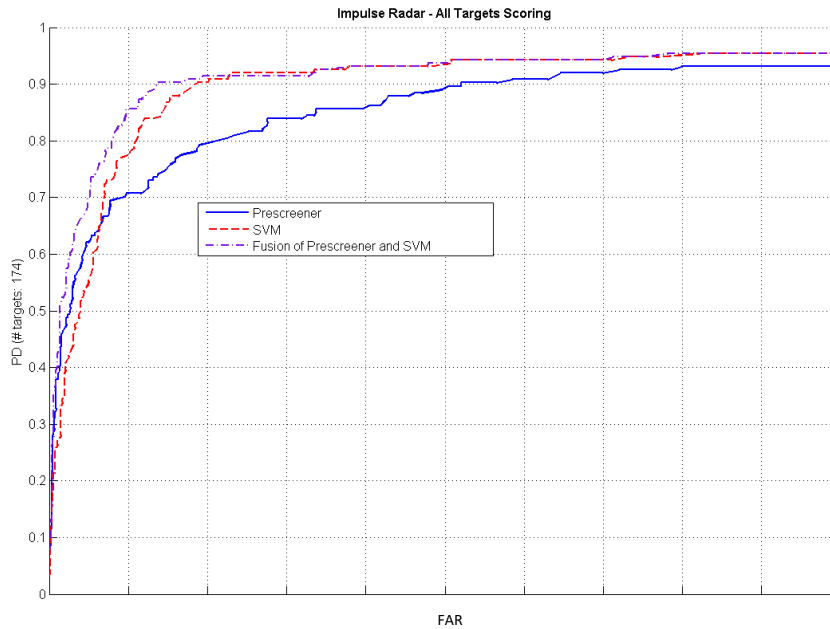


Figure II-5. Impulse radar detection results of all targets. The fusion of the prescreener confidence values and SVM probability estimates provides the best overall detection performance.

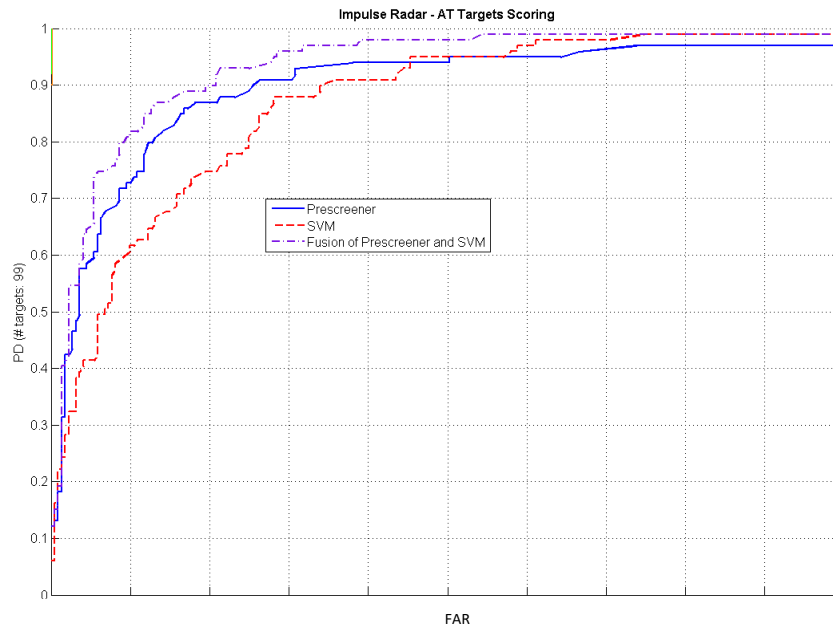


Figure II-6. Impulse radar detection performance of AT targets. The SVM alone provides poorer AT target detection than the prescreener. However, the fusion of the SVM probability estimates with the prescreener confidence values provides the best AT target detection.

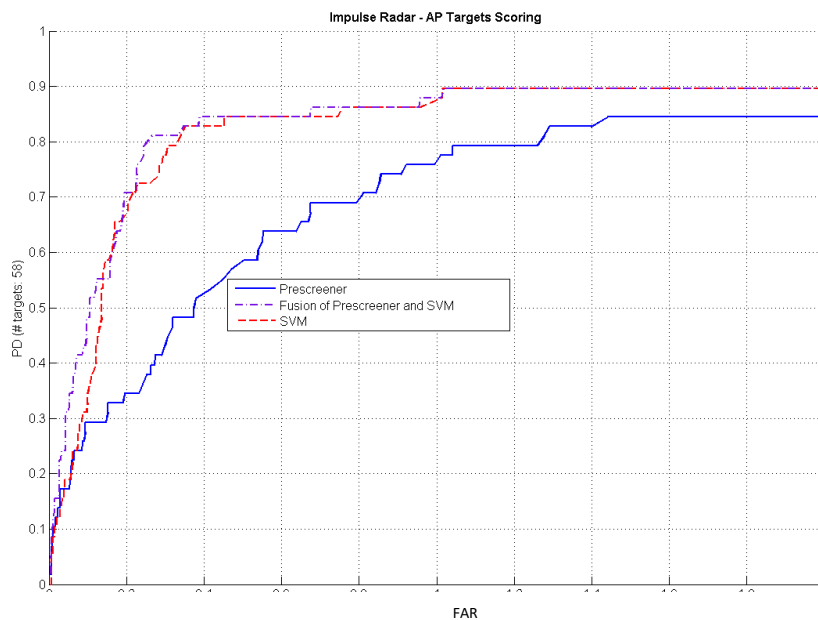


Figure II-7. Impulse radar detection performance of AP targets. The SVM alone provides very good AP target detection. The fusion of the prescreener confidence values and SVM probability estimates yields slightly better detection than the SVM alone.

Figure II-7 gives the results when scoring only AP targets. The SVM alone provided very good AP target detection. In all cases, the fused confidence values provided better detection performance than either the prescreener or SVM alone.

B. Step-Frequency Radar

For the step-frequency radar dataset, observing the SVM weight vector allowed 472 features to be removed. The final 10-fold cross validation was performed using the remaining 224 features. The performance of the prescreener alone, the SVM alone, and the fusion of the two by Equation 1 was compared by plotting the corresponding ROC curves. Figure II-8 shows the results when all targets are included in scoring. Figure II-9 are the results when only AT targets are included in scoring. Figure II-10 gives the results when only AP targets are scored. As was observed in the impulse radar dataset, the SVM provided very good AP target detection

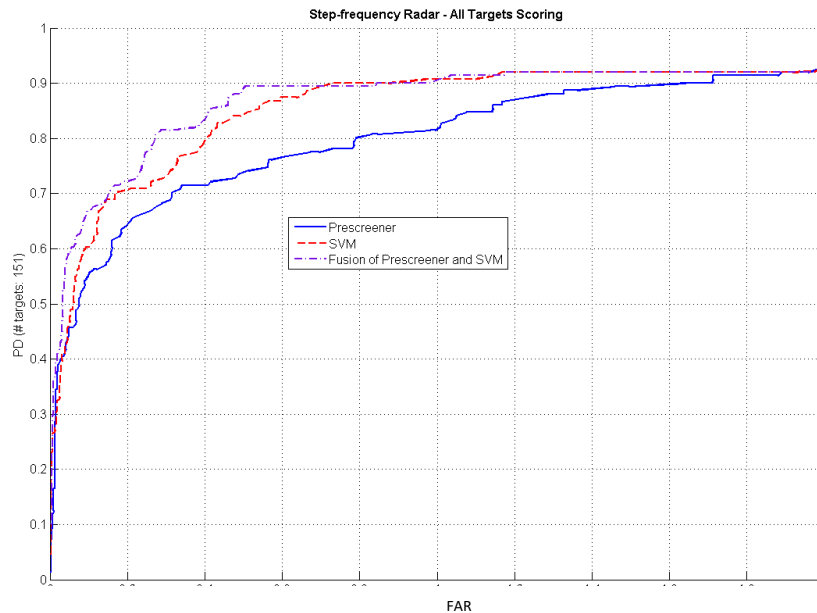


Figure II-8. Step-frequency radar detection results of all targets. The fusion of the prescreener confidence values and SVM probability estimates provides the best overall detection performance.

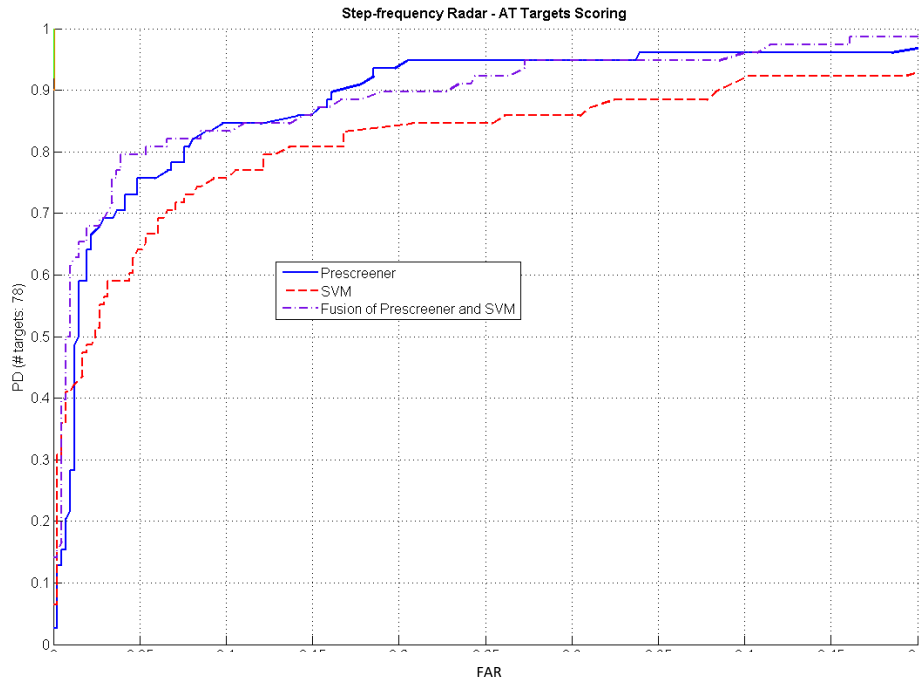


Figure II-9. Step-frequency radar detection performance of AT targets. The SVM alone provides significantly poorer AT target detection than the prescreener. However, the fused confidence values perform comparably to the prescreener on AT targets.

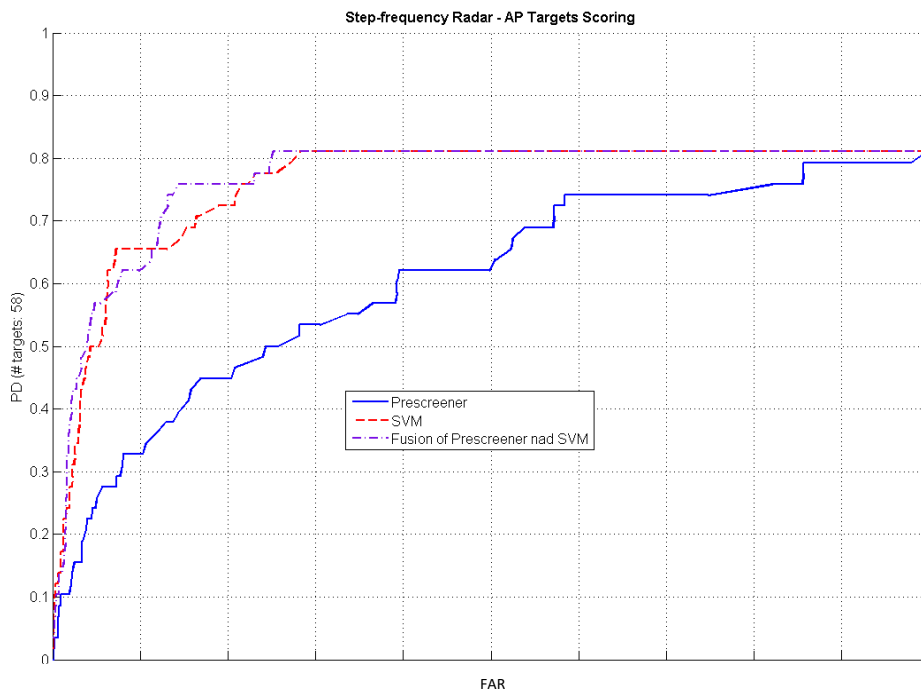


Figure II-10. Step-frequency radar detection performance of AP targets. The SVM provides very good AP target detection. The fusion of the prescreener confidence values and SVM probability estimates performs comparably to the SVM alone.

Conclusions

We have developed the LBP features to improve the detection performance of a hand-held GPR system. GPR B-scans were extracted from prescreener alarm locations. Each B-scan was split into 3 spatial regions and 4 depth regions, and LBP features were computed within each of the resulting 12 cells. The feature set was reduced using a linear-kernel SVM, and another SVM was trained to perform target versus non-target classification with the reduced feature set. Using 10-fold cross validation, probability estimates were derived for each alarm location. These values were then coupled with the prescreener confidence values to increase the detection performance. The proposed features were tested on two datasets collected from two different GPRs. For both datasets, the use of LBP features yielded improved performance over the prescreener alone. Although the composite result improved in both cases, the most drastic improvement in detection performance was observed among the AP targets.

III. FOMIACE

The hand-held system often has the EMI sensor. Sensor which uses EMI to excite a response in conducting bodies has been investigated for the purpose of detecting buried explosives. In particular, wide band EMI sensors which use a relatively low number of operating frequencies have been used to discriminate between types of objects, and to detect objects with very low metal content.¹ In this paper, Fourier features are extracted using the 2D Fourier transform from the complex data; both spatially, and across operating frequencies. Then, the Multiple Instance Adaptive Coherence Estimator (MI-ACE) is used to learn cross-validated target signatures from these features. These signatures, as well as learned background, statistics are used with ACE to generate confidence maps, which are clustered into alarms. Alarms are scored against a ground truth and compared to other detection algorithms

Background

EMI sensors typically emit electromagnetic radiation via a transmit coil. This radiation causes metallic elements below the sensor to generate their own induced electromagnetic fields. The electromagnetic response is then picked up by one or more receive coils on the sensor. The specific EMI sensor we considered in the study here is Wideband and operates over twenty-one, logarithmically-spaced frequencies from 330Hz to 90.03KHz. Each sample collected by this sensor is stored as a twenty-one dimensional complex vector which represents the phasor difference between the emitted and the received signals at each of the operating frequencies. The WEMI sensor is attached to a cart, which also has GPS sensors attached to it, to record the UTM spatial coordinates corresponding to each sample.

The data measured by the sensor is filtered in time and space by convolving it with a zero-mean sine filter. This filtering has at least four benefits. First, the ground response is attenuated by differencing nearby sections of ground. For similar reasons, the drift in the

system is also mostly removed by this filtering. In addition, the filter has the effect of averaging nearby points which increases the signal to noise ratio. Lastly, the filtered data has a maximum response directly over targets, rather than a minimum due to the geometry and positioning of the coils in this particular sensor. In addition, after sine filtering, the data is uniformly down-sampled in time and space so that each sample is about 1cm from the previous sample.

FOMIACE

FOMIACE stands for Fourier Multiple Instance ACE. This algorithm applies to the 2D FFT of the EMI data. The Fourier transform is, perhaps, one of the most powerful tools in signal processing. An interpretation of the transform is to look at it as a change of basis from impulses in time, to sinusoidal waves of various frequencies. An advantage of applying the transform is that some functions can be more compactly represented and more easily understood after the change of basis. In a simple case, a perfect sinusoid can be represented by just a frequency and amplitude, instead of with an infinite amount of samples in the time domain. Samples are collected in time from the EMI sensor. Feature vectors are extracted by simply applying the 2D Fourier transform to the filtered data, with the operating frequency and space as the two dimensions.

Over ground with no targets or clutter there is typically low amplitude, seemingly random noise. Near a metallic target, there is a large increase in the magnitude of the response across most of the operating frequencies. This can be interpreted as a large low frequency component of the signal. If we consider the response across operating frequencies of the sensor, we can exploit a sinusoidal basis as well. Across operating frequencies, background noise tends to be less correlated than over a target. In the frequency domain, a DC signal will show up if all operating frequency responses are identical and nonzero. Other sinusoidal patterns are also present, but more complicated, such as damped ringing effects. A more detailed description of the method used and the specific theories associated are given below.

MI-ACE

The 2D Fourier features have a strong physical basis. However, modeling an expected 2D Fourier response and creating an ideal target signature with which to do detection is not trivial. Instead, we opt to automatically learn 2D Fourier target features from the data using a Multiple Instance dictionary learning method. The method used, known as Multiple Instance ACE (MIACE), has been specifically tailored for use with the ACE detector. This method was used because, unlike other MIL methods, it has a closed form solution.

Multiple Instance Learning (MIL) methods can learn target concepts from imprecisely-labeled data. In the context of landmine detection, data is often imprecisely labeled. In the case of the WEMI data investigated in this paper, ground truth centroid locations were provided for targets and clutter. However, given only centroids, it is difficult to assign accurate labels to every sample collected. A more intuitive labeling would be to say, somewhere near the ground truth point, there is likely to be a target. This more closely resembles multiple-instance models.

The Adaptive Coherence/Cosine Estimator (ACE) has been shown to be an effective detection statistic. ACE assumes that a target data sample can be modeled as a linear combination of a known target signature corrupted by random Gaussian noise. The WEMI sensor being investigated is likely to return data that closely matches this model. ACE uses an estimate of the background mean and background covariance to whiten the coordinate space before comparing a known target vector to a data sample using the cosine similarity measure. The ACE detector can be written as the following equation,

$$D_{ACE}(x_i, s) = \frac{s^T \Sigma_b^{-1} (x_i - \mu_b)}{\sqrt{s^T \Sigma_b^{-1} s} \sqrt{(x_i - \mu_b)^T \Sigma_b^{-1} (x_i - \mu_b)}}$$

where s is a known target signature and x_i is a feature vector. The background is assumed to be a Gaussian distribution parametrized by μ_b and Σ_b , which represent the mean and covariance, respectively. Geometrically, ACE can be interpreted as the square of the cosine of the angle between x_i and s , in a coordinate space whitened by the background estimation.

Following from the final ACE equation, an objective function and its updates have been derived to learn a target concept, s , from a set of training examples. The training examples are grouped into bags. Each bag is given either a positive or negative label. Positive bags contain at least one target instance. Negative bags contain only background instances. One of the primary advantages of MIACE over some other MIL algorithms is that it has a closed-form solution, allowing for relatively quick learning of new target concepts. Once a target concept is learned, it is then used with the ACE detector.

Previously, ACE and other detectors have been investigated for explosive hazard detection. These detectors have had considerable success using a dictionary generated from an electromagnetic model, known as the Discrete Spectrum of Relaxation Frequencies (DSRF). The DSRF generates the expected frequency response of the sensor to metallic objects, which is used as a target concept for a detector. The 2D Fourier features described above are not in the same domain as the DSRF dictionary. Therefore, a new target concept is needed to make use of these features. We combine the use of these 2D Fourier features with learning a target concept using MIACE in an algorithm we call FOMIACE. The 2D Fourier features and target concepts are vectorized to match the MIACE model.

FOMIACE operates as a prescreener with a sliding window with maximum spatial overlapping. Each window contains 51 spatial samples, each 21 dimensional. The magnitude of the 2D-FFT coefficients are computed and scaled between 0 and 1, after removal of the DC frequency components. The coefficients are vectorized, forming a single feature vector, x_i , for each window. For each lane, l , a target concept, s_l , was

learned using lane-based cross-validation. Each window's ACE confidence from the above equation is computed and assigned to the location of the window's spatial center.

Experimental Results

The following ROC curves were generated using scoring software provided with the WEMI data set. Multiple hits on the same target are not counted as false alarms, through a circular halo of radius 0.25m centered at the target. When hits are scored, polygonal convex hulls surrounding target centroids are computed, taking into account target size and the scoring radius. These polygonal ground truths were extracted from the scoring software by sending every instance in a data lane through scoring as if each point was an alarm. These ground truths were then processed to generate bag labels for each instance. Bag labels, along with the 2D Fourier features were fed into the MIACE algorithm to learn a target Fourier concept. A cross-validation scheme was used whereby 1 subset was left out and tested on, using the other 13 to learn the target concept. These target concepts were used with ACE for detection. Results are compared to ACE with a global background estimate, ran on the sine-filtered data using a 100 element DSRF dictionary. The ROCs of running lane-based cross-validation FOMIACE on the EMI test set are shown in Figure III-1.

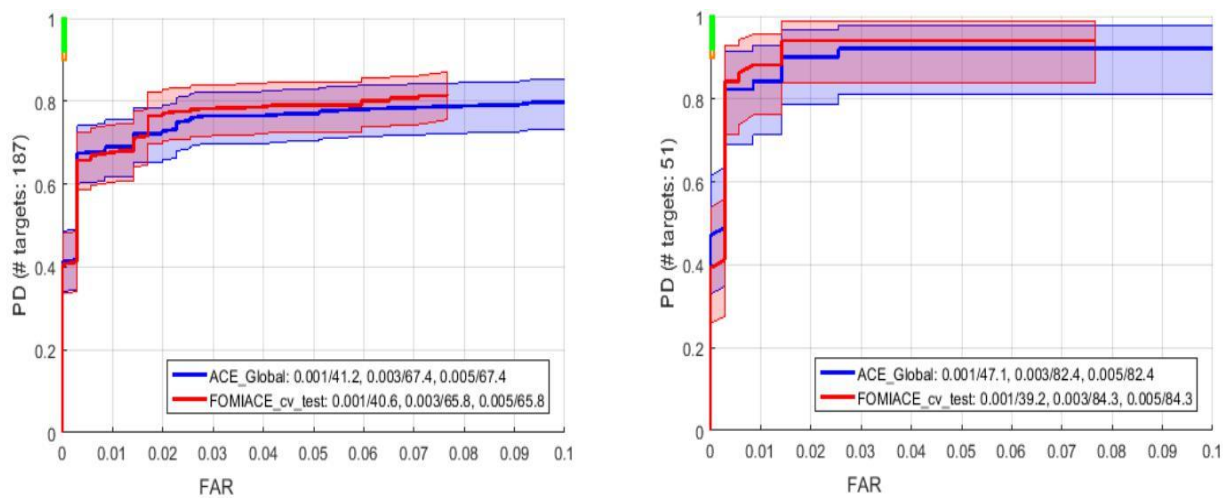


Figure III-1. Receiver operator curves comparing FOMIACE to ACE Global over fourteen lanes of WEMI data. Scored on targets up to a depth of 8" with a halo radius of 0.25m.

Hits on clutter are ignored. Left, scored on all targets. Right, scored on low-metal AP targets only.

Conclusions

The results of the 2D Fourier features look promising. The FOMIACE algorithm, introduced herein, provides a slight increase in ROC performance. A qualitative comparison between an ACE confidence map and a FOMIACE confidence map show that FOMIACE, likely due to its inherent windowing, is smoothed a little spatially. This may help to increase signal to noise ratio. It should be noted that ACE is using the 100 element DSRF dictionary, while FOMIACE is only using a single target concept, yet performance is comparable. In addition, should hardware changes be made to the sensor which affect the accuracy of the DSRF dictionary, new target concepts can quickly be learned from new data using MIACE. Further investigation into higher-dimensional Fourier features, which take into account multiple spatial dimensions, in addition to operating frequencies, could yield further benefits. Likewise, an extension to learn multiple target concepts for both detection and discrimination may improve results.

IV. Log-Gabor Feature

The challenge for GPR subsurface explosive detection is to reduce the false alarm rate and limit the undesirable human operator effect. This paper proposes the use of log-Gabor features to improve the detection performance. In particular, we apply 36 log-Gabor filters to the B-scan of the GPR data in the time domain for the purpose to extract the edge behaviors of a prescreener alarm. The 36 log-Gabor filters cover the entire frequency plane with different bandwidths and orientations. The energy of each filter output forms an element of the feature vector and an SVM is trained to perform target vs non-target classification. Experimental results using the experimental hand held demonstrator data collected at a government site supports the increase in detection performance by using the log-Gabor features.

Background

Landmines and other subsurface explosives pose a significant threat to people worldwide. Although these weapons are usually buried during times of war, they can remain active far after hostilities have ceased. This can render entire plots of land permanently unusable for civilian activity. As a result, a significant amount of research has been dedicated toward developing subsurface object detection systems that are capable of combating this type of weaponry.

Subsurface object detection systems typically utilize one or more physical sensors to gather a digital image of an underground area. Electromagnetic induction (EMI) sensors, commonly known as metal detectors, have traditionally been used for this purpose. These sensors have been shown to be quite effective, but they are only capable of detecting objects with high metal content. Unlike EMI sensors, ground penetrating radar (GPR) sensors can detect objects with little or no metal content. As a result, GPR has become a popular choice for both vehicle mounted and hand-held platforms.

Vehicle mounted systems move at a fairly rigorous pace and generally focus on detecting anti-tank (AT) targets. Since the sensors are attached to some type of rolling vehicle, these systems can only be effectively used on terrain that is traversable by the vehicle. Hand-held systems, on the other hand, require a human operator to sweep the detector back and forth over the ground. This results in a significantly slower rate of movement but allows for operation on more difficult terrain. Unfortunately, it is not always feasible for human operators to sweep the detector with a high level of precision. Even small variations in the height or speed of a sweep may drastically affect the data being collected, which can make it more difficult to achieve a high detection rate.

If enough labeled GPR data are available for analysis, achieving a reduced FAR may be viewed as a supervised learning task. In this case, some method must be defined to extract meaningful features from the GPR data at each alarm location. The resulting set of feature vectors is then used to train a supervised learning model to perform either classification or regression. Once the model is trained, its generalizability is typically gauged by testing its performance on data that was not used during training. A successful model should be able to perform its classification or regression task on unseen data with a high degree of accuracy.

We developed the use of log-Gabor features in conjunction with a SVM to improve the detection rate of an existing anomaly detection algorithm, for both vehicle-mounted and hand-held GPR. A set of 36 two-dimensional log-Gabor filters with different bandwidths and orientations is designed that covers the entire frequency domain. Each filter is applied to the B-scan at an alarm location whose output forms a feature. The collection of the 36 features yields a feature vector for SVM for target vs non-target detection.

Log-Gabor Filters and Features

The log-Gabor filter is defined in the frequency domain through the polar coordinate. Let ρ be the radius from the center and θ the angle from the x-axis. The log-Gabor filter response in the frequency domain is

$$G_L(\rho, \theta) = \exp \left\{ -\frac{1}{2[\log(\sigma_\rho)]^2} \left[\log \left(\frac{\rho}{\rho_o} \right) \right]^2 \right\} \bullet \exp \left\{ -\frac{1}{2\sigma_\theta^2} (\theta - \theta_o)^2 \right\}.$$

The parameters ρ_o and θ_o control the bandwidth and the orientation of the filter response, and σ_ρ and σ_θ determine the spreading factor in the radius and angle.

At each alarm location, 36 log-Gabor filters are applied to the B-scan of the GPR data. For the hand-held system, these 36 log-Gabor filters cover the entire frequency plane with three different bandwidths and twelve orientations.

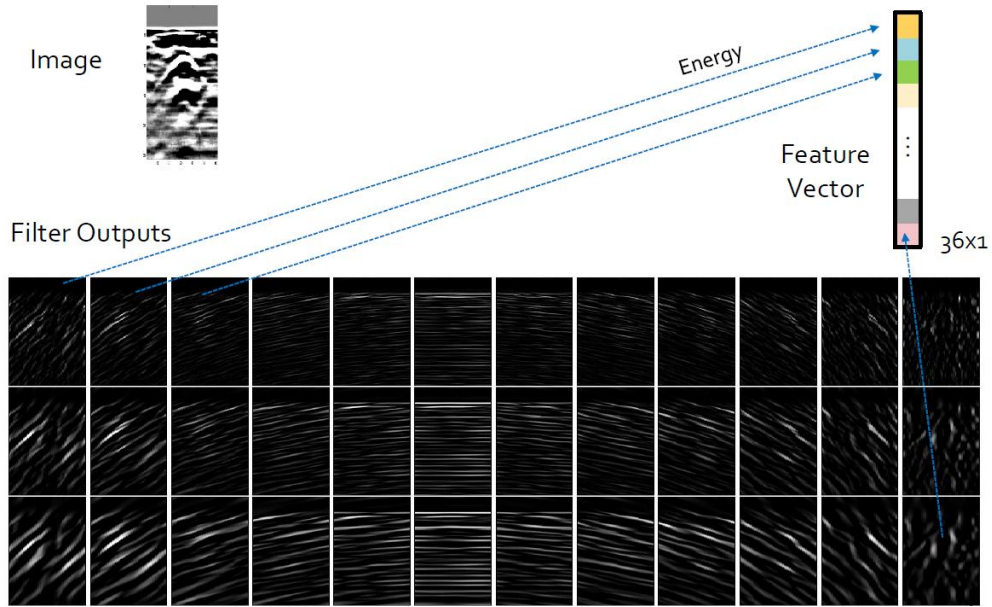


Figure IV-1. The total energy from each filtered B-scan region forms an element of the feature vector. This process is repeated for each of the three spatial regions, resulting in 108 features for each alarm location.

Each filtered B-scan is then separated into three overlapping spatial regions, left, middle and right. The total energy in each spatial region is computed and used as an element of the feature vector. The result is a vector of 108 features for each alarm location. Figure IV-1 illustrates this feature extraction method performed on a particular B-scan.

Using the same filtered B-scan, a second feature vector is also computed for each alarm location. Once again, each GPR B-scan is separated into the same three spatial regions. Then, each spatial region is partitioned into 6 depth regions. The total energy is computed in each depth region, and the maximum energy is used as the feature value. Thus, another 108 features are generated for each alarm location. The two feature vectors are concatenated, resulting in a total of 216 features for each alarm location.

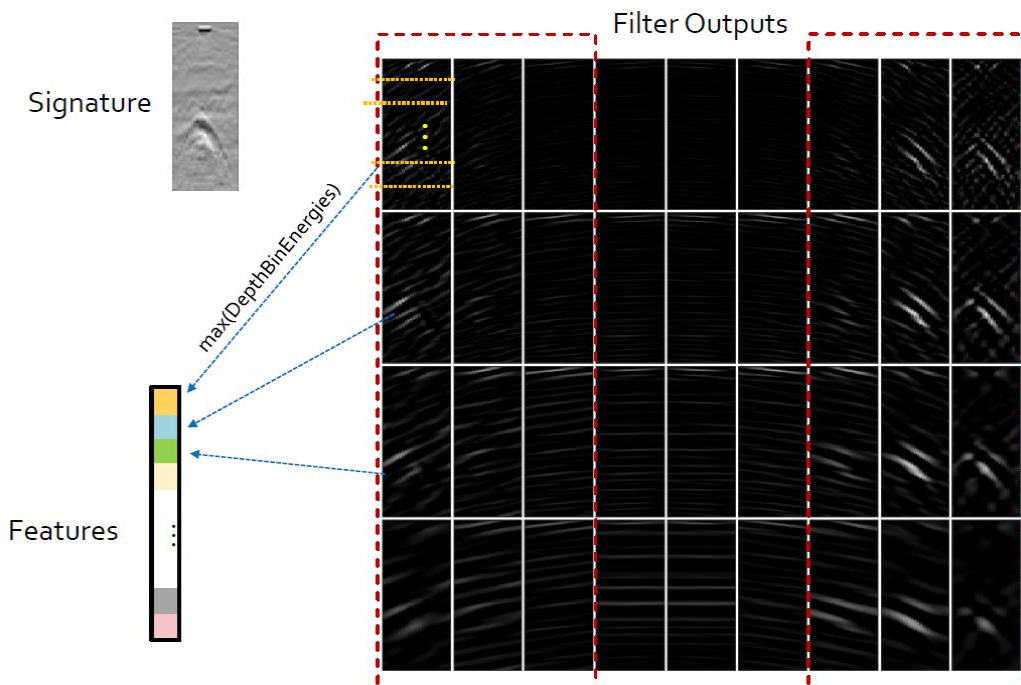


Figure IV-2. Log-Gabor filter outputs of a target B-scan image and the generation of features.

For the vehicle-mounted GPR system, we also use 36 log-Gabor filters. However, the number of scales is four and that of orientation is nine. The features are the maximum

energy in a depth bin for a given log-Gabor filter output. Figure IV-2 gives an example for the processing in the vehicle-mounted GPR data. The processing is repeated for the cross-track, diagonal and anti-diagonal slices. As a result, the length of the feature vector is 144.

Experimental Results

A. Hand-held System

We have also tested the developed log-Gabor filter bank on the handheld-based system. The radar is a step-frequency radar, with a bandwidth up to about 3 GHz. The prescreener is MH. Figure IV-3 gives the results over all targets, Figure IV-4 the results when excluding the anti-personnel and wire targets, and Figure IV-5 the results when excluding only the anti-personnel targets. Overall, the developed log-Gabor feature based classifier shows good and consistent performance.

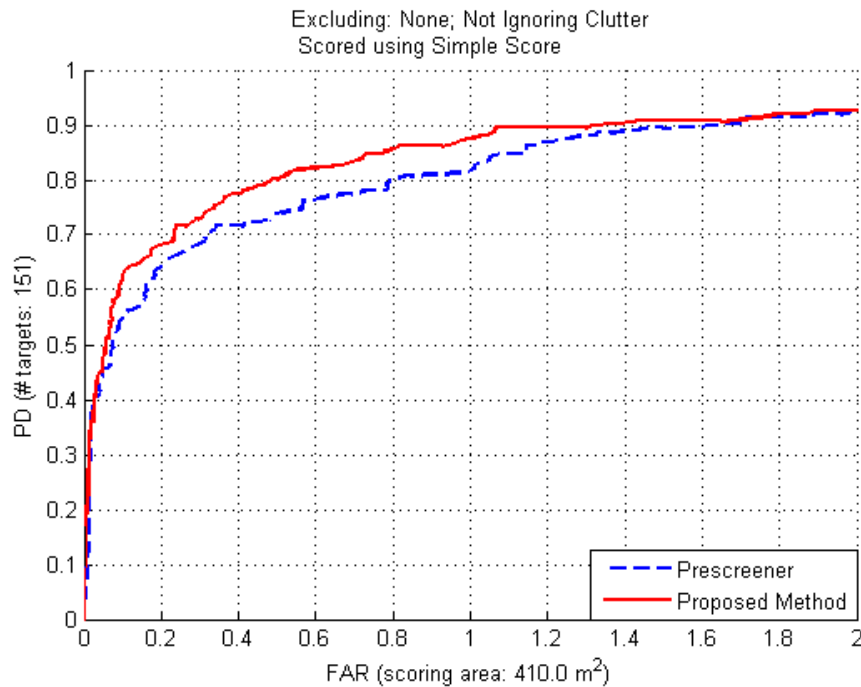


Figure IV-3. Performance of the proposed log-Gabor algorithm for all targets.

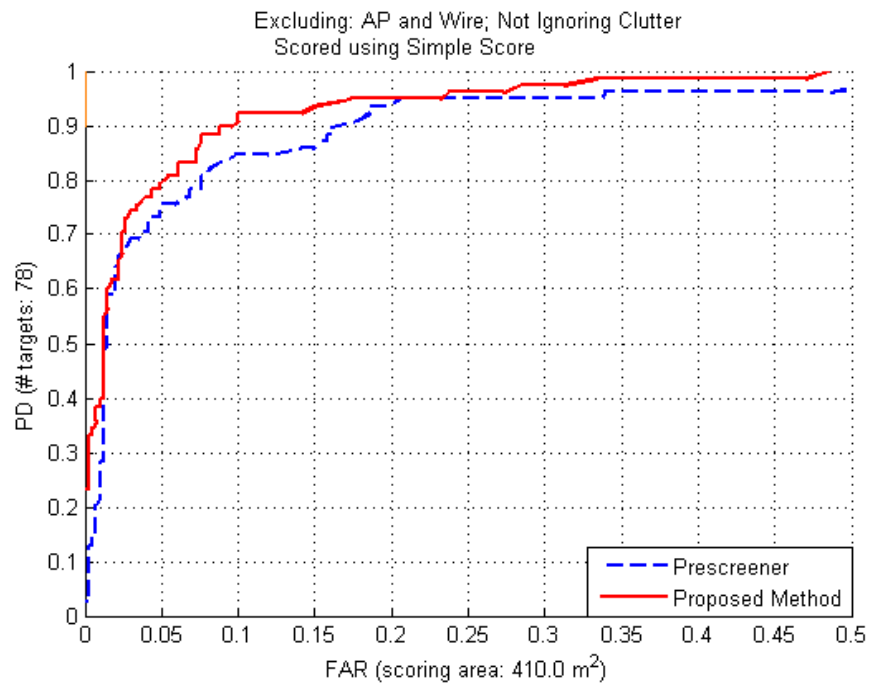


Figure IV-4. Performance of the developed log-Gabor algorithm for anti-tank targets.

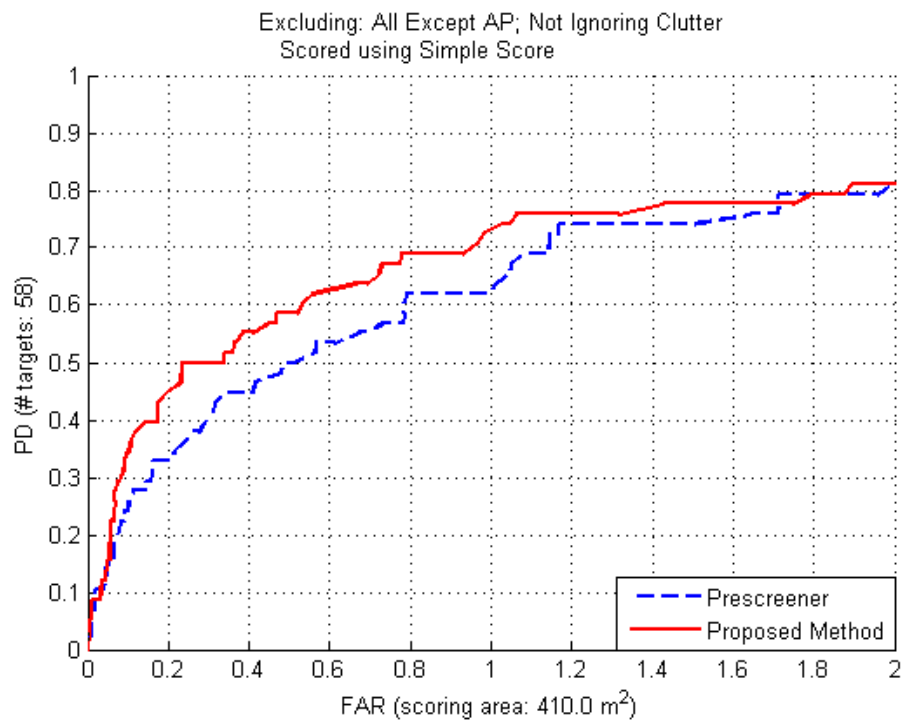


Figure IV-5. Performance of the developed log-Gabor algorithm for anti-tank and wire targets.

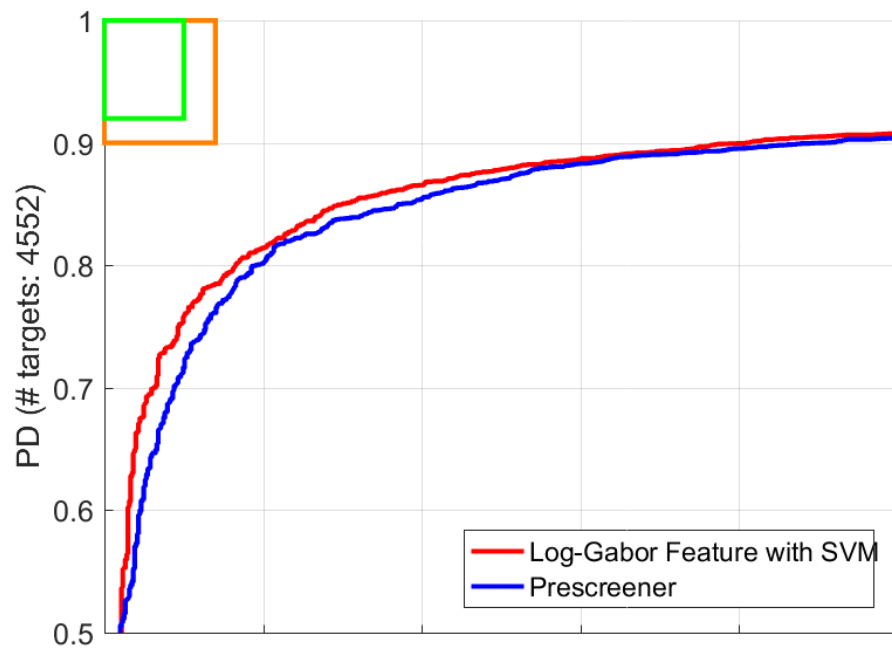


Figure IV-6. ROC performance of the log-Gabor detection algorithm for all targets.

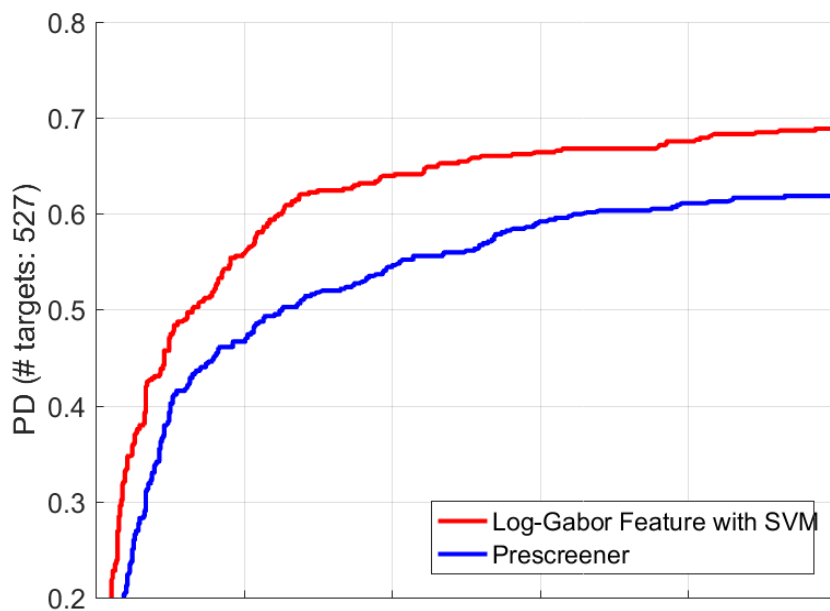


Figure IV-7. ROC performance of the log-Gabor detection algorithm for deep targets.

B. Vehicle-Mounted System

The experimental dataset was collected at two geographically well separated US government test sites in 2016. It contains a mix of metal, low-metal and non-metal anti-tank targets, buried at various depths. There were seven lanes from the first site and six lanes from the second. Each lane has multiple passes. The area coverage for the data collection is over 120,000 m². The total number of target encounters in the entire data set is 4552, in which 527 are deeply buried targets.

The prescreener used is the F2CCY, which is indeed a fusion for the F2 and CCY prescreeners. Lane-based 13-fold cross validations were applied to obtain the ROC curves. Figure IV-6 illustrates the results for all the targets, where the blue curve is from the prescreener and the red curve from the proposed log-Gabor feature based classifier. The proposed algorithm gives better results than the prescreener. When we fuse the two together, there is a significant performance improvement.

The benefit of the proposed method appears when we look at the detection performance of the deeply buried targets. It is apparent in Figure IV-7 that the improvement in detection at a given false alarm rate can be as high as 10%.

Conclusions

We have developed the log-Gabor features, which can be applied to both the hand-held and the vehicle-mounted GPR system. The log-Gabor features are not only able to maintain the extraction of edge behavior of the GPR echo return in the spatial domain, but also the frequency domain characteristics of the return for better distinction of targets with false alarms. The features appear to be particularly useful in the vehicle-mounted system for the detection of deeply buried targets and no-metal targets.

V. Target Tracking by Random Finite Set Statistics

Introduction

Target tracking is an important component to monitor a moving target and predict its trajectory. Target tracking improves the detection of weak target and eliminates false alarms. We have developed and investigated the performance of a target tracker based on the random finite set statistics (FSST). The tracker is capable of handling the tracking of multiple targets simultaneously. It operates on the decision level where the observation is the alarm coordinates from an image. Over different frames in a video sequence, the tracker follows the alarm locations along different frames in a video sequence, by fitting the alarm locations to a dynamic motion model of a target. The net results are multiple tracks for different targets.

Compared to other tracker, FSST is particularly effective in handling cross-over target tracks to avoid incorrect track association. It also reduces track lost when alarm detection misses, and minimizes the accidental creation of false tracks.

Target Tracking

The purpose of target tracking is to improve target detection and obtain the target trajectory based on some attributes collected from a target. Figure V-1 illustrates the target tracking problem. We have a video sequence composes of a collection of frames. Each frame has multiple targets. We first apply a detector to generate the alarm locations. The alarm locations from a detector, and maybe together with features at the alarm locations as well, form the input to the tracker.

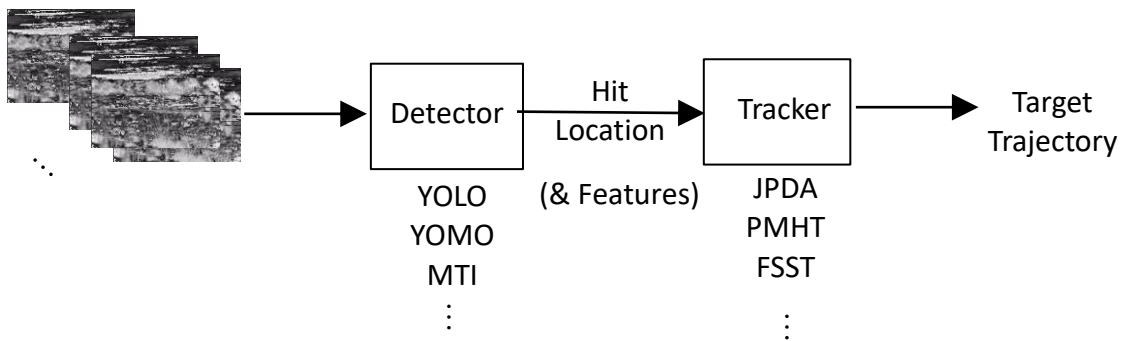


Figure V-1. Target tracking problem

The detector can be a sophisticated detector such as the convolutional neural network (CNN) based detector that includes YOLO and YOMO, or a simple detector such as the moving target indicator (MTI). Typical tracker includes the Joint Probability Data Association (JPDA) and Probabilistic Multiple Hypothesis Tracker (PMHT). The output of a tracker is the target tracks. Figure V-2 illustrates a typical tracker output, where the dots are the alarms from the entire video sequence, and the two curves are the tracks obtained from a tracker for two separate targets.

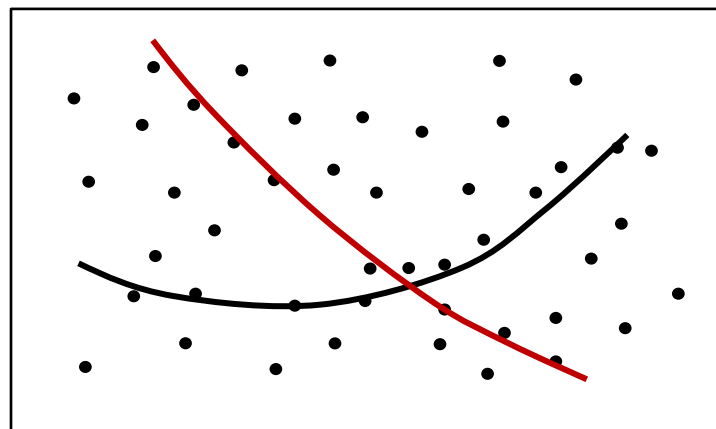


Figure V-2. Tracker output

Statistical Tracker Formulation

Let us define a target state vector as

$$\mathbf{x}_k = (x_k, y_k, v_{x,k}, v_{y,k})$$

where k is the discrete time index, (x_k, y_k) and $(v_{x,k}, v_{y,k})$ are the target position and velocity at time k . A statistical tracker has two components. One is the target dynamic model described by

$$\mathbf{x}_{k+1} = \varphi(\mathbf{x}_k) + \mathbf{u}_k$$

The other is the observation model represented as

$$\mathbf{z}_k = (\tilde{x}_k, \tilde{y}_k)$$

$(\tilde{x}_k, \tilde{y}_k)$ is the observed noisy position of a target. The objective of target tracking is to estimate the target state at time k given all the past and current observations $\mathbf{z}_1, \mathbf{z}_1, \dots, \mathbf{z}_k$.

The motivation for statistical tracking includes the followings:

- Presence of false and miss detections (false positive and true negative)
- Multiple targets of same type
- Track before confirmation for weak targets
- Trajectory prediction

Traditional tracker, including JPDA and PMHT, uses the measurement to track association for tracking of multiple targets. Such a tracking approach has the limitation that the estimated tracks are prone to be incorrect if the measurement to track association is wrong at the beginning. The FSST tracker is a tracking technique that does not require measurement to track association, and thereby has the potential to improve tracking performance.

FSST Tracker

Different from JPDA and PMHT which belong to the measurement to track association approach, the FSST tracker is an association free multi-target tracker. It is first proposed and developed by Ronald Mahler [1]. The FSST tracker uses the FSST to transform multiple-sensor Multiple-Target problem into a mathematical Single-Sensor Single-Target equivalence. Figure V-3 shows such a concept.

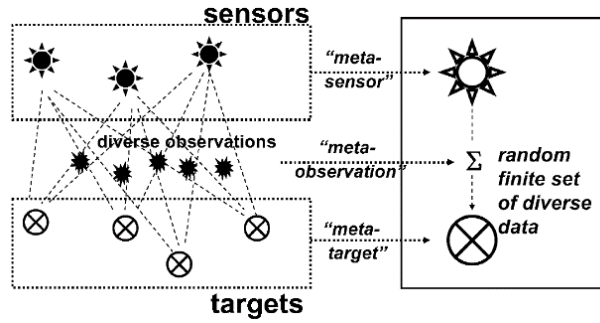


Figure V-3. FSST tracker concept^[1]

Tracking by FSST is formulated as follows:

- Bundle states of all n targets together into a random finite set (RFS):

$$\begin{aligned} X &= \{ \mathbf{x}_{(1)}, \mathbf{x}_{(2)}, \dots, \mathbf{x}_{(n)} \} \\ &\equiv \{ \mathbf{x}_{(2)}, \mathbf{x}_{(n)}, \dots, \mathbf{x}_{(1)} \} \quad \text{order independent} \end{aligned}$$

- Group all sensor measurements (detections) at frame k as Z_k
- Collect all measurements up to frame k as

$$Z^{(k)} = \{ Z_1, Z_2, \dots, Z_k \}$$

- The tracking problem is to estimate all n target state vector X given $Z^{(k)}$.

For further details regarding the FSST tracker, please refer to [1].

[1] R. P. S. Mahler, "Statistics 101 for multisensory, multitarget data fusion," *IEEE Aerosp. Electron. Syst. Mag.*, vol. 19, no. 1, pp. 53-64.

FSST Tracking Results

The FSST tracker used is based on the implementation from [2].

A. Single Target

Figure V-4 shows the result of a single target that is a vehicle circling around in a road. The x- and y-coordinates of the alarm locations that form the input to the tracker are indicated by the cross-symbols. The solid lines are the target tracks from the tracker. At the beginning the FSST tracker assumes there are two tracks. One track terminates quickly at around 400 frames. The track remains is the actual track from the vehicle. The estimated tracks follow the alarm locations well.

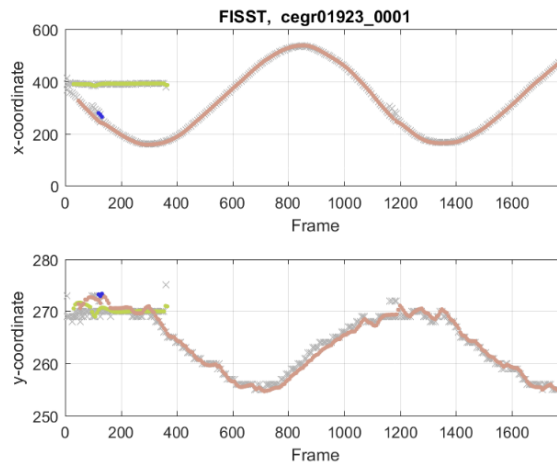


Figure V-4. Result of the FSST tracker, single target

Figure V-5 illustrates the comparison results of the FSST tracker with the JPDA and PMHT trackers. The FSST tracker has similar performance with the JPDA tracker, and it behaves better than the PMHT tracker as the PMHT tracker terminates the actual track and initiates new tracks often.

[2] B.-N. Vo, B.-T. Vo, and H. G. Hoang, "An efficient implementation of the generalized labeled multi-Bernoulli filter," *IEEE Trans. Signal Process.*, vol. 65, no. 8, pp. 1975-1987, Apr. 2017.

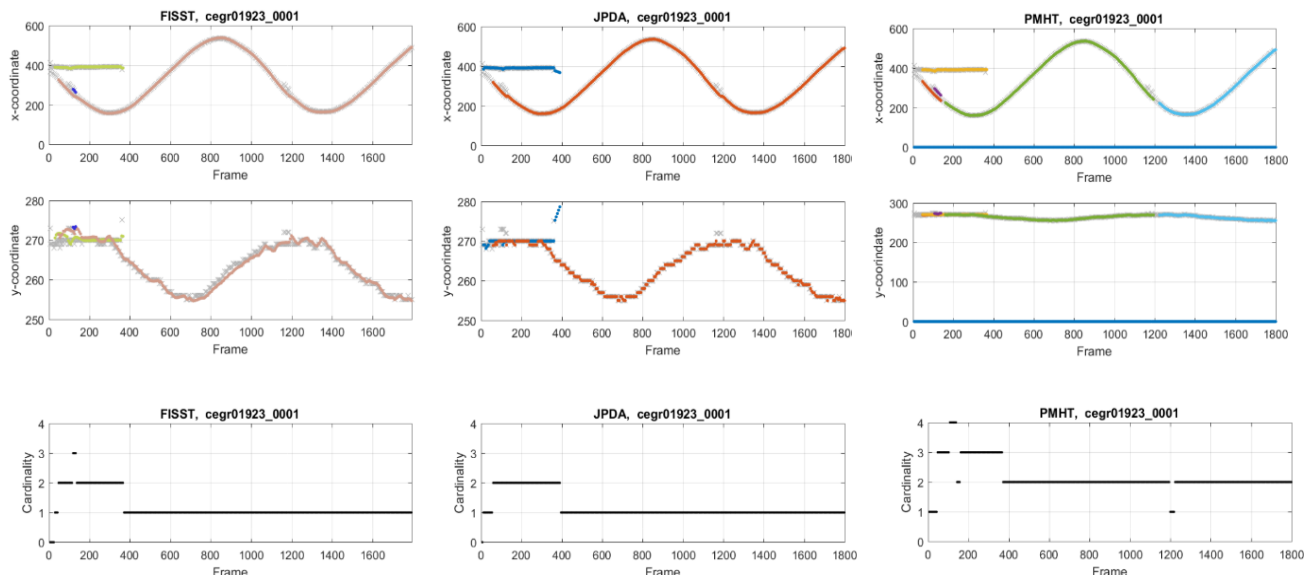


Figure V-5. Tracking result comparison for the FSST, JPDA and PMHT trackers

B. Multiple Targets

Figure V-6 presents the tracking results of two targets. Both targets are persons. While walking back and forth, they also cross each other. This is a challenging tracking scenario. The good performance of FSST stands out clearly in this experiment. At the beginning FSST needs some time to build the correct tracks and eliminate the unnecessary ones. After frame number 500, the tracker follows very well the two trajectories of the targets. The FSST tracker does not have false track association when the two targets cross each other at about frames 1100 and 1700.

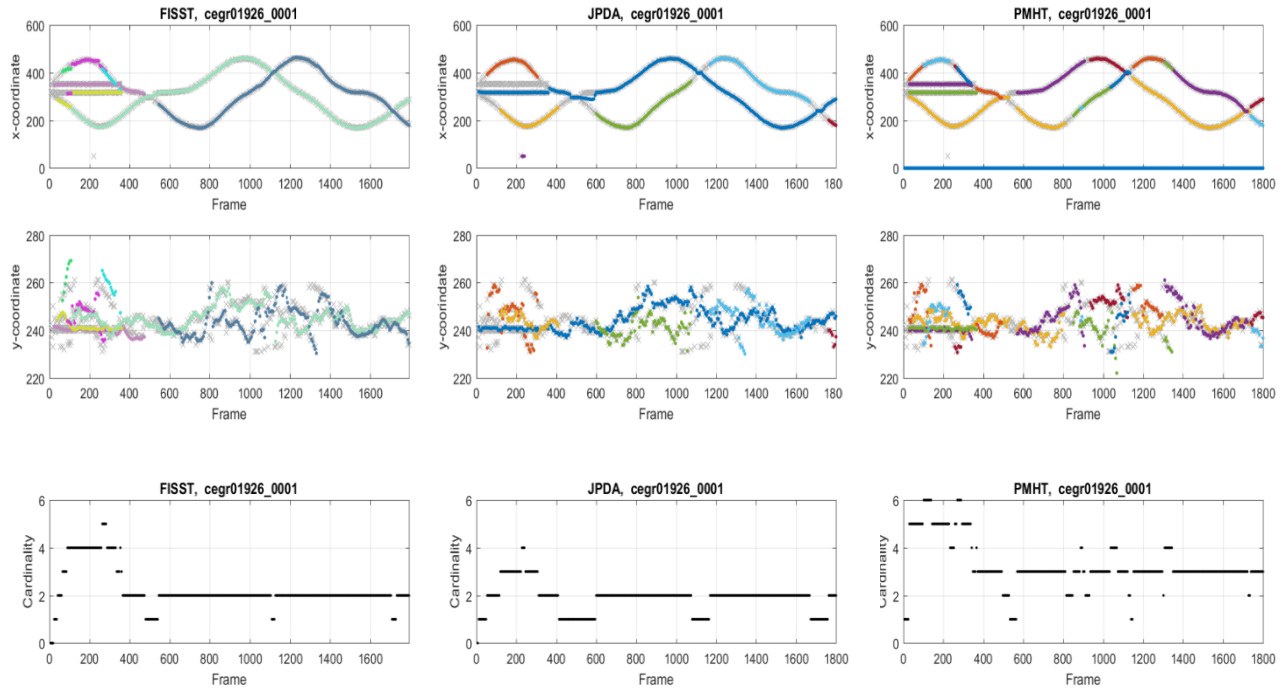


Figure V- 6. Tracking result comparison for the FSST, JPDA and PMHT trackers, two targets of walking persons

JPDA, on the other hand, terminates one track with the persons cross over at both instances. It takes some time to rebuild another track again. PMHT terminates and breaks correct tracks often and restarts new ones. It cannot follow at least one track when the two persons cross over at both instances.

C. Multiple Close Targets

To further examine the performance under even more challenging situation, we tested the scenario when two targets of persons are moving close to each other. Figure V-7 shows the results. The superiority performance of JSST compared to JPDA and PMHT is very clear. JPDA falsely terminates the track of one target and restarts as new tracks often. PMHT does these for both targets. Wrong track association also occurs in both when the targets cross over.

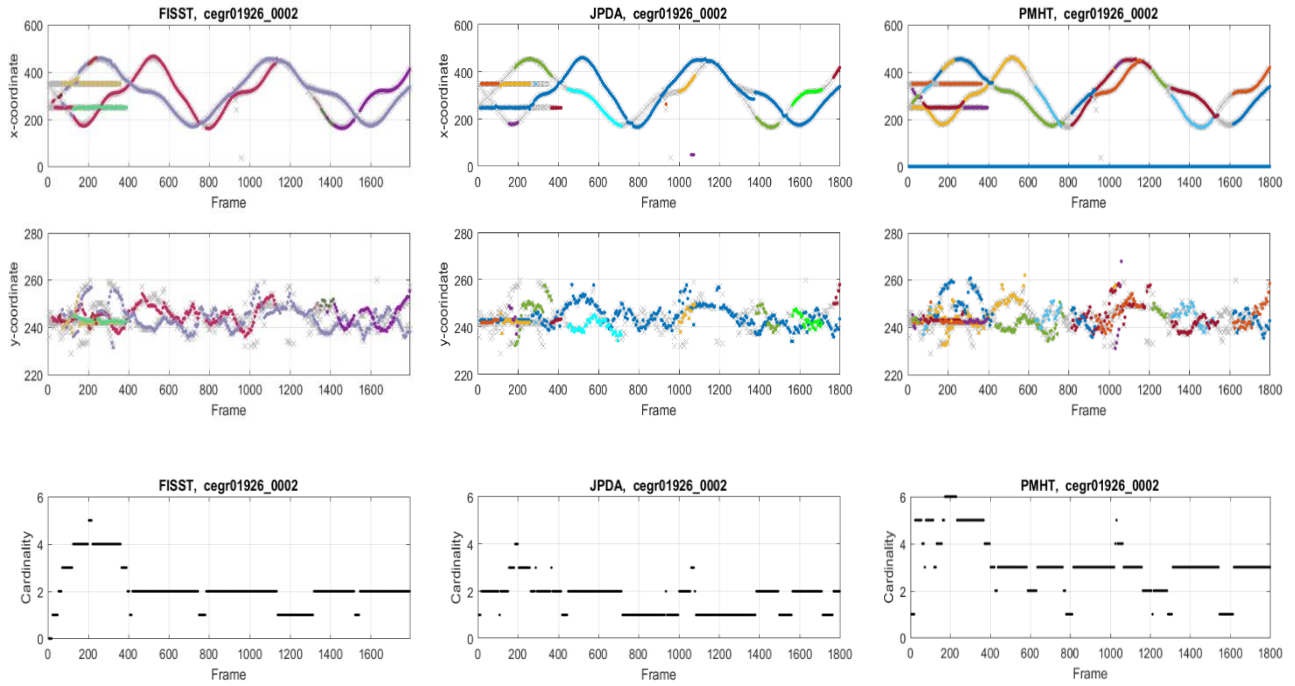


Figure V-7. Tracking result comparison for the FSST, JPDA and PMHT trackers, a challenging scenario with two targets of walking persons close to each other

Conclusions

Tracking of a number of moving targets is a complicated and difficult problem. While many techniques such as JPDA and PMHT have been developed, their performance is insufficient when the target tracks cross over or close to one another.

We have proposed to develop the new tracker based on finite set statistics, without requiring measurement to track association for the tracking of multiple targets. The mathematics behind is a little involved. The performance, however, appears to be superior to the traditional techniques JPDA and PMHT. We plan to develop the FSST tracker further to improve performance.