On the Use of Log-Gabor Features for Subsurface Object Detection using Ground Penetrating Radar

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ABSTRACT

Handheld ground penetrating radar (GPR) enables the detection of subsurface objects under different terrains or over regions with significant amount of metal debris. The challenge for the handheld GPR 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.

Keywords: Ground penetrating radar, subsurface object detection, log-Gabor, support vector machine

1. INTRODUCTION

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.

Once data have been collected, they must be algorithmically analyzed in order to determine the presence or absence of a subsurface object. A common strategy is to first apply a prescreening algorithm to the sensor data. The goal of a prescreener is to scan the incoming data for anomalies and report any alarm locations that may contain a target. The alarm locations can then be further analyzed by more sophisticated algorithms in order to lower the false alarm rate (FAR)[1-3].

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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.

In this paper, we propose the use of log-Gabor features in conjunction with a support vector machine (SVM) to improve the detection rate of an existing anomaly detection algorithm. 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.

The paper is organized as follows. Section 2 describes the hand-held GPR data and prescreener alarm generation. Section 3 details the log-Gabor feature extraction method. Section 4 explains the SVM classification and confidence value generation. Section 5 describes the experimental setup and results. Section 6 concludes the paper.

2. DATA DESCRIPTION

Two different GPRs are used in this study. The first is an impulse radar, which emits a wideband pulse that propagates into the soil. The second is a step-frequency radar. Both radars contain three spatially separated receivers. A hand-held GPR is carried by a robotic arm, which sweeps the GPR back and forth while advancing forward. This provides a sequence of GPR data. The GPR data is regularized with a spatial sampling interval of 1 cm.

The experimental hand held demonstrator GPR data is processed by an anomaly detection algorithm[4] in a causal manner. This algorithm acts as a prescreener and relies on the Mahalanobis distance measure[5] to generate a real-valued confidence at each spatially sampled location. Locations that have confidence values above a certain threshold are labeled "alarm locations" for further analysis. The data sets used in this study consist of the B-scans at these alarm locations and the corresponding confidence values from the prescreener.

3. LOG-GABOR FEATURE EXTRACTION

The log-Gabor filter[6-7] 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_0 and θ_0 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. These 36 log-Gabor filters cover the entire frequency plane with three different bandwidths and 12 orientations. 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 1 illustrates this feature extraction method performed on a particular B-scan.

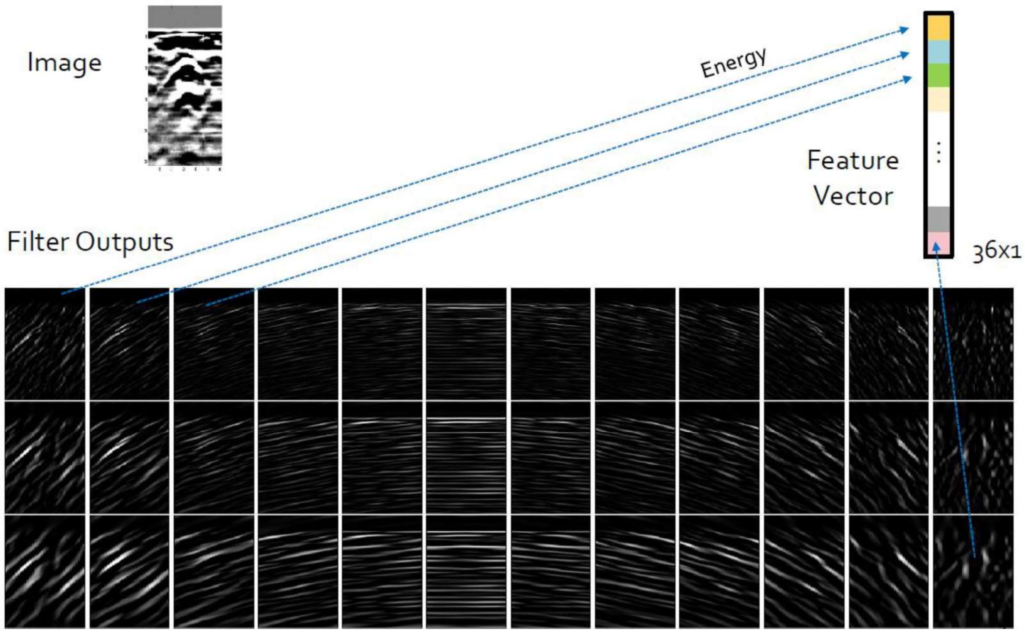

Figure 1. The total energy from each filtered B-scan region forms an element of the feature vector. This process is repeated for each of the three spatial regions, resulting in 108 features for each alarm location.

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.

4. CLASSIFICATION & CONFIDENCE

4.1 Classification

The mean and standard deviation of each feature in the anti-tank (AT) target sample distribution is computed. Each log-Gabor feature is normalized by subtracting the computed mean and dividing by the standard deviation. A linear kernel SVM is then trained to perform target vs. non-target classification on the normalized log-Gabor features. Once training is complete, the SVM model is used to perform feature selection.

In general, an SVM seeks to learn the hyperplane $wx + b = 0$ which maximizes the margin between two classes of data. The weight vector *w*, which is the normal to the learned hyperplane, is of particular interest. Once an SVM has been trained, this weight vector gives an indication of which features most heavily influence the model's predictions. Features corresponding to small absolute values in the weight vector have little effect on the SVM predictions, while features corresponding to large absolute values in the weight vector are very important. In the linear kernel case, the weight vector *w* can be directly computed and used to perform feature selection[8].

By analyzing the SVM weight vector, a subset of the most heavily weighted log-Gabor features are selected. The linear kernel SVM is then re-trained using the reduced feature set.

4.2 Confidence

Confidence values are assigned to each alarm location by computing the signed distance from the normalized, log-Gabor feature vector to the SVM hyperplane. A negative value indicates a non-target prediction, while a positive value indicates a target prediction. A large value indicates a very confident prediction, while a small value implies an uncertain prediction.

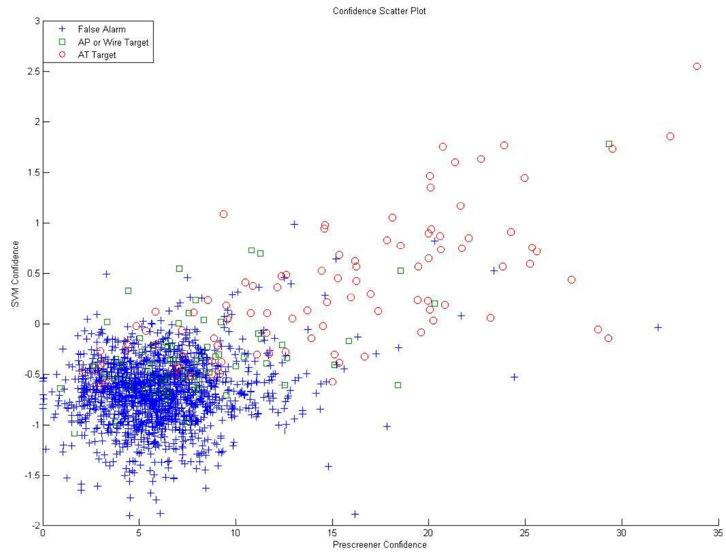

Figure 2. Each point represents the log-Gabor SVM classifier confidence and the prescreener confidence of an alarm location in a particular data set. Compared to the prescreener, the SVM assigns a higher confidence to some targets and a lower confidence to many false alarms.

The SVM confidence values are then coupled with the prescreener confidence values. Figure 2 illustrates the relationship between the two on a particular data set. In general, the SVM predictions become more reliable as the SVM confidence increases. However, the SVM predictions become significantly poorer as the feature vectors become close to the learned hyperplane. Thus, the SVM and prescreener confidences are coupled by

$$fused\_conf = \log(prescreen\_conf) * (SVM\_conf + 2)$$

The $+2$ term acts to shift the SVM confidence values above zero. The log function is used to compress the effect of the prescreener confidence on alarm locations that are easily classified by the SVM. Alarm locations whose log-Gabor feature vectors fall near the hyperplane will all be assigned similar confidence values by the SVM. Thus, the fused confidence for these locations will be influenced more heavily by the prescreener.

4.3 Sequential Backward Elimination

The features selected by analyzing the SVM weight vector all have some degree of influence over the SVM predictions. However, some of the selected features may not help to improve the final, fused confidence values. To determine if any such features are present, sequential backward feature elimination is performed on the previously selected feature set. The performance of the fused confidence values is scored at each iteration. Features are sequentially eliminated until no increase in performance is observed.

5. EXPERIMENTAL SETUP & RESULTS

5.1 Setup

The following training and testing scheme was repeated for both data sets used in this study. First, the log-Gabor feature vectors for the AT targets and false alarms were randomly partitioned into 10 subsamples of approximately equal size and nearly equal target to non-target ratios. 10 data folds were defined, with 9 subsamples used as training data and the 1 remaining subsample used as test data for each fold. Anti-personnel (AP) targets, wire targets, and clutter objects were then randomly partitioned into 10 subsets and divided among the 10 test sets. This way, only the AT targets and false alarms were used for training, each alarm location was tested exactly once, and the training and test sets for each fold were disjoint.

For each fold, the mean and standard deviation of each log-Gabor feature was computed over the AT targets in the training set. Then, each log-Gabor feature in both the training and test set was normalized by subtracting the computed mean and dividing by the standard deviation. The normalized training data was used to train a linear kernel SVM to perform binary, target vs. non-target classification. The SVM was implemented using the MATLAB LibSVM package[9]. Each alarm location was assigned an SVM confidence value by computing the distance from the trained SVM hyperplane to the log-Gabor feature vector in the corresponding test set.

The SVM weight vector was computed for each data fold. The features were then ordered from highest to lowest average influence across all 10 folds. A script was written to exhaustively test each subset of the k most heavily weighted features, with k incremented from 2 features up to the total number of features. The subset corresponding to the highest detection rate, measured as the area under the receiver operator characteristic (ROC) curve, was selected. Finally, sequential backward elimination was performed to remove any remaining features that were not important to the fused confidence value distribution. Again, performance at each iteration was judged by computing the area beneath the ROC curve.

5.2 Results

For the impulse radar, all 216 log-Gabor features were initially used to train the SVM. By analyzing the weight vector, a total of 95 of these features were selected. Sequential backward elimination removed another 10 features, resulting in a total of 85 selected features. Figure 3 shows the experimental results when all targets in the dataset are included in scoring. Figure 4 shows the results when AP & wire targets are excluded from scoring. Figure 5 shows the results when only AP targets and false alarms are scored. In all cases, the proposed method shows improvement over the prescreener alone.

For the step-frequency radar, it was found that the second log-Gabor feature vector did not improve detection performance. Therefore, only the first 108 log-Gabor features were used to train the initial SVM. A total of 64 of these features were selected by analyzing the SVM weight vector. Sequential backward elimination removed another 12 features, resulting in 52 selected features. Figure 6 shows the results of all targets scoring for this data set. Figure 7 shows the results when AP & wire targets are excluded. Figure 8 shows the results when only AP targets and false alarms are scored. Once again, each result indicates improved performance over the prescreener alone.

6. CONCLUSION

We have proposed the use of log-Gabor features to improve the detection performance of a hand-held GPR system. A linear kernel SVM was trained to perform target vs. non-target classification using the features. Confidence values were extracted from the trained SVM and coupled with the prescreener confidence values. The proposed method was tested on two data sets collected from two different GPRs. For both data sets, the use of log-Gabor features yielded improved performance over the prescreener alone.

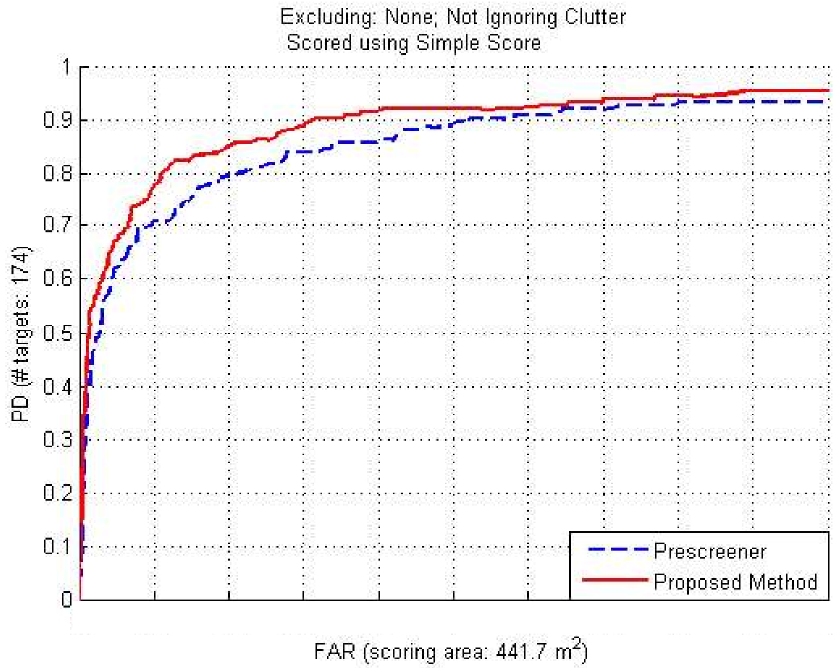

Figure 3. All targets scoring on the impulse radar data set.

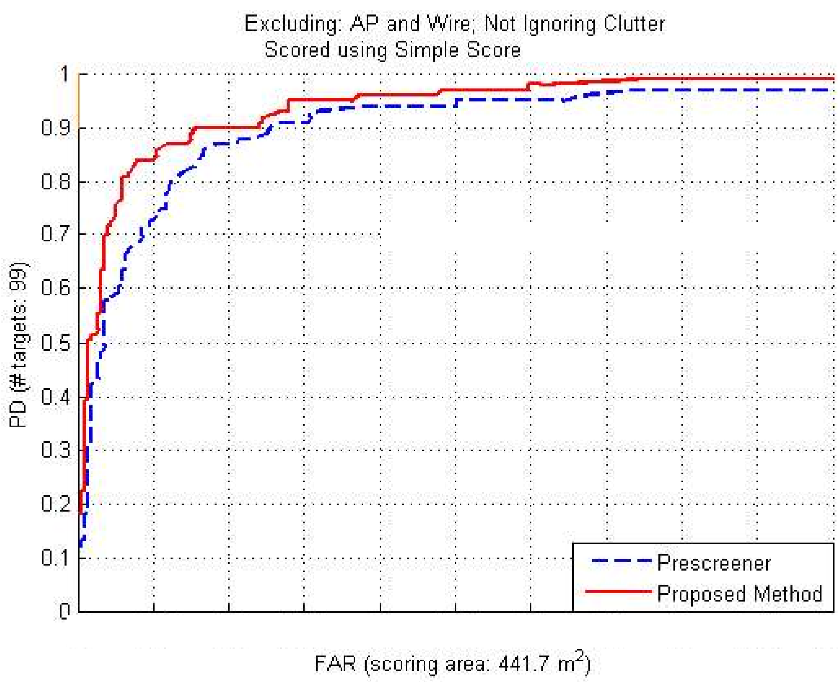

Figure 4. Excluding AP and wire targets on the impulse radar data set.

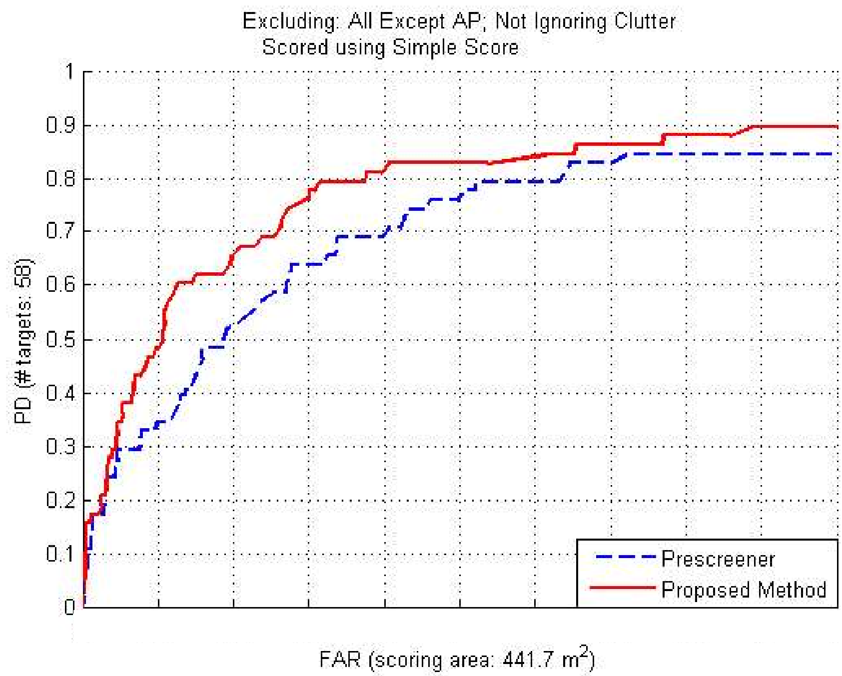

Figure 5. Excluding all except AP targets on the impulse radar data set.

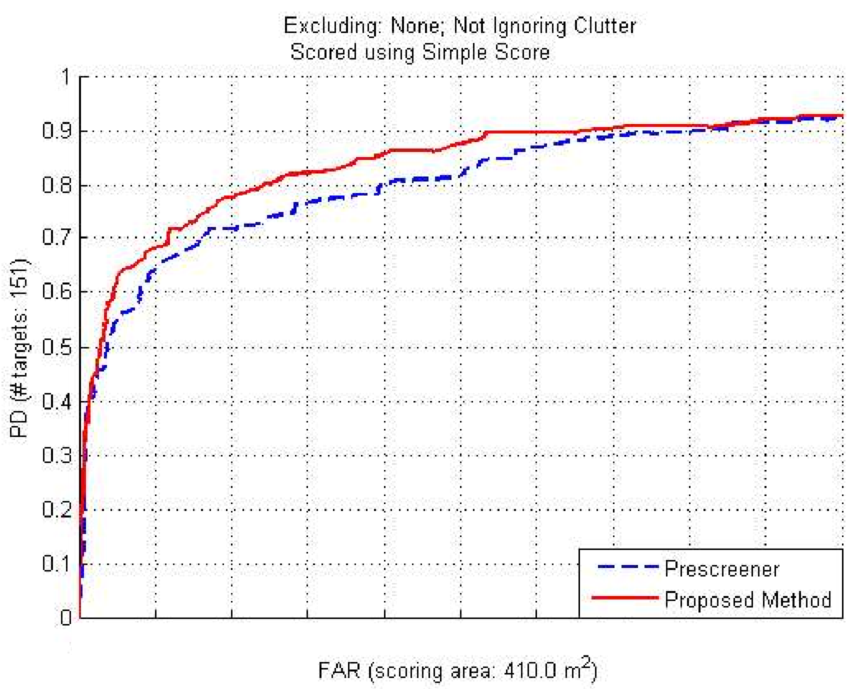

Figure 6. All targets scoring on the step-frequency radar data set.

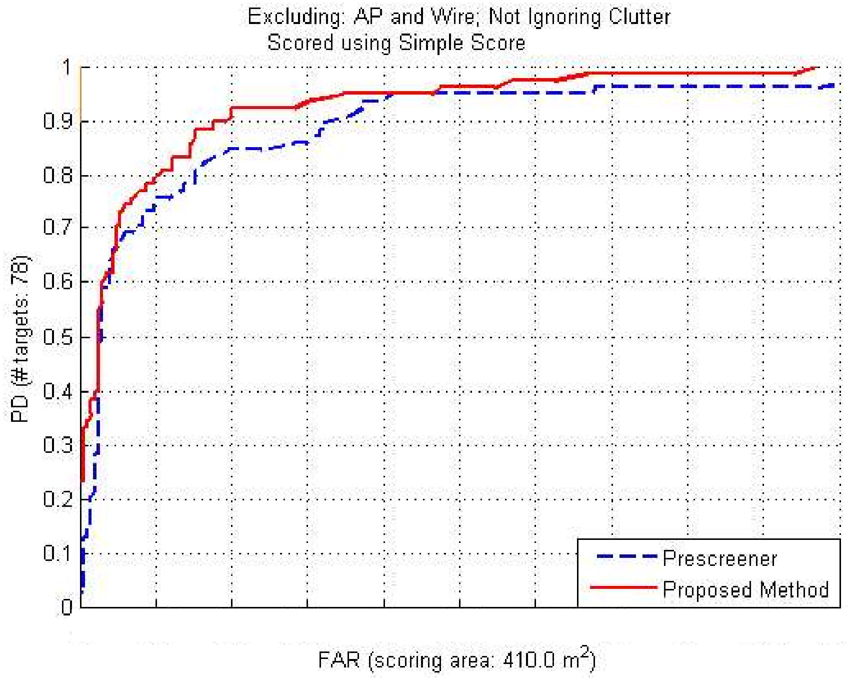

Figure 7. Excluding AP and wire targets on the step-frequency radar data set.

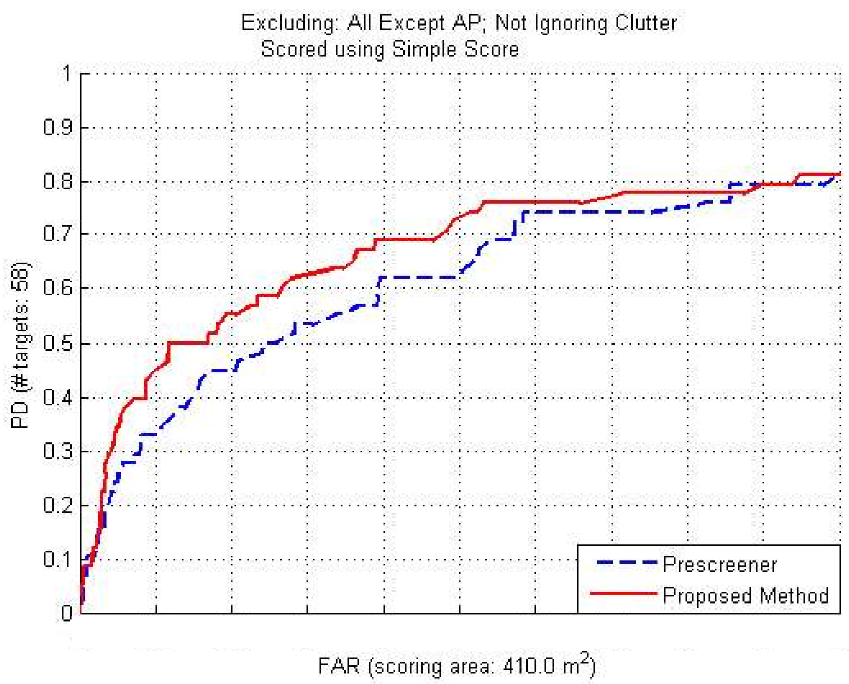

Figure 8. Excluding all except AP targets on the step-frequency radar data set.

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