# A Novel Algorithm of Landmine Detection

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**Abstract**— A novel algorithm which exploits aspectual invariance and local contrast to discriminate landmines from other man-made targets and natural clutter in Synthetic Aperture Radar (SAR) image is proposed in this paper. Firstly, Azimuth Scattering Entropy (ASE), which measures the characteristic of aspectual invariance, is extracted as a detection feature. The detection threshold is then acquired from the histogram of the ASE image with an auto-adaptation method. The ultimate detection result is obtained by fusing results from aspectual invariance detection and Constant False Alarm Rate (CFAR) detection of the full aperture image. The algorithm concerns with the use of prior information of the to-be-detected targets and provides new thinking for detection scheme in SAR image. The results of experimental data demonstrate the effectiveness and practicability of the proposed algorithm.

## 1. INTRODUCTION

Landmines left after war are difficult to clear, which threatens humans life and hinders the development of social economy. Landmine clearance is a task which brooks no delay. However, landmine detection is a worldwide problem [1], primarily due to: 1) landmines are usually of small size, which demands high resolution in imaging and detection and complicates the implementation of radar system. 2) Landmines have small Radar Cross Section (RCS) and low signal-to-clutter ratio (SCR) in SAR image. As a result, landmine detection is a typical weak and dim target detection problem in complex environments.

Recently, many detection techniques have been investigated. The Lincoln Laboratory Automatic Target Recognition (ATR) algorithm [2] is a typical procedure of ATR in SAR image due to its clear thinking and reasonable structure. The subsequent improved algorithms mainly improve on each stage (prescreening, discrimination and classification) of the Lincoln Laboratory ATR algorithm. In these methods, target characteristics are usually used in the discrimination stage, other than the prescreening stage, i.e., the detection stage. Assume that we bring forward target's prior information. That is to say, target characteristics, which might be used in the discrimination and classification stage, are included in the prescreening stage. Thus, the prescreening becomes more specific and its accuracy increases. Although new detection features involved in the prescreening stage increase the calculation amount of prescreening, the false alarm of the extracted Region of Interest (ROI) decreases, and this will eventually decrease the calculation amount of the discrimination and classification stage. In consequence, the calculation amount of the whole ATR scheme decreases.

This paper takes the background of detecting metal anti-tank mines with Airship Mounted Ultra-wide Band SAR (AMUSAR) [3], and is organized as follows. Section 2 gives full introduction to the fusion detection algorithm, and experimental result is given in Section 3 followed by conclusion in Section 4.

## 2. FUSION DETECTION ALGORITHM

### 2.1. Basics of Fusion Detection Algorithm

Common landmine detection features involve scattering intensity, double-hump [4], morphological feature, etc.. These features perform well in landmine detection, but operators usually ignore the aspect-frequency dependence of targets in the discrimination and classification stage. Landmine is a typical body-of-revolution (BOR) target [5] and aspectual invariance is the most significant and the most robust characteristic, while most man-made targets and natural clutter show inconspicuous aspectual invariance. Therefore, aspectual invariance is a promising discrimination feature of BOR targets and non-rotary body targets.

Fusion detection takes full advantage of multiple features of targets, which can efficiently increase detection rate and decrease false alarm rate. From the abstract level, fusion can be divided into: pixel-level fusion, feature-level fusion and decision-level fusion. As can be seen from the analysis above, detection based on aspectual scattering characteristic can distinguish BOR target and non-rotary body target effectively, but is not able to eliminate clutters with high aspectual invariance.

CFAR detection can detect strong scattering targets, but cannot distinguish BOR target and strong scattering clutters. If we fuse the detection results based on the two features, clutters with strong aspectual invariance and scattering can be eliminated effectively, which will decrease the false alarm rate of landmine detection.

### 2.2. Azimuth Scattering Entropy

In order to use aspectual invariance to detect landmines, appropriate measurement is needed. Assume that $I_{i,j}^n$ $(n = 1, \dots, N)$ is the amplitude of pixel $(i, j)$ corresponding to aspect angle $\theta_n$, where $N$ denotes the number of sub-apertures and $i$, $j$ represents the pixel index along the range and azimuth directions, respectively. Let $p_{i,j}^n$ denotes the proportion of $I_{i,j}^n$

$$p_{i,j}^n = I_{i,j}^n / \sum_{n=1}^{N} I_{i,j}^n, \quad n = 1, \dots, N \tag{1}$$

Azimuth scattering entropy, the measurement of aspectual invariance is given as

$$E_{i,j} = -\sum_{n=1}^{N} p_{i,j}^n \ln\left(p_{i,j}^n\right) \tag{2}$$

In order to enhance the distinguish degree of measurement, (2) is modified as (3) through nonlinear transform.

$$E_{i,j} = 1 / \left[\ln(N) + \sum_{n=1}^{N} p_{i,j}^n \ln(p_{i,j}^n)\right] \tag{3}$$

### 2.3. ASE Detector and Determination of Threshold

The detector is defined by the rule

$$\begin{cases} E_{i,j} > T_{ASE} & \text{presence of a target pixel} \\ E_{i,j} < T_{ASE} & \text{presence of a clutter pixel} \end{cases} \tag{4}$$

where $E_{i,j}$ is the azimuth scattering entropy of pixel $(i, j)$ and $T_{ASE}$ is the global threshold of ASE.

In general conditions, BOR targets have much bigger ASE than non-rotary body targets and clutters, so we can use an empirical value as the global threshold according to typical ASE values of different targets. However, the descent of SCR will reduce the estimation accuracy of ASE [6], and the calculated ASE of BOR targets is usually smaller than typical values. False alarms will emerge if empirical value by simulation data is used as the global threshold. To solve that problem, we determine global threshold with adaptive method. BOR targets are usually with bigger ASE, and the pixels of BOR targets stay in the tailing part of the histogram of ASE image.

Assume that random variable $E$ denotes ASE of corresponding pixel. Given that the confidence coefficient of BOR target pixel is $1 - \varphi$, global threshold $T_{ASE}$ is then determined by

$$P\{E > T_{ASE}\} = 1 - \varphi \tag{5}$$

where $P$ denotes probability distribution of ASE histogram, and $\varphi \in [0, 1]$ is empirical value which is referred to as the proportion of non-rotary body target in the whole ASE image. If the cumulative distribution function (CDF) of ASE image is $F$, (5) is rewrite as

$$1 - F(T_{ASE}) = 1 - \varphi \tag{6}$$

### 2.4. Fusion Detection Algorithm

The scheme of our fusion detection algorithm is shown as Fig. 1. The local judgment of each part is ‘hard judgment’, and the fusion rule in decision fusion centre is ‘and’, which decreases false alarm, but demands 100% detection rate in each local detection. Low threshold is set in each local detection to guarantee high local detection rate.

As can been seen from the scheme, the introduction of new detection feature increases the calculation amount. However, the extra calculation amount won’t add up the whole runtime of landmine detection, primly due to: 1) parallel fusion algorithm, 2) utilization of ‘multi-GPU and multi-CPU’ real-time processing framework [7] in engineering application. The primary added runtime stays on the decision fusion stage, and it is negligible to the reduced runtime in the subsequent discrimination stage due to the decrease of false alarm.

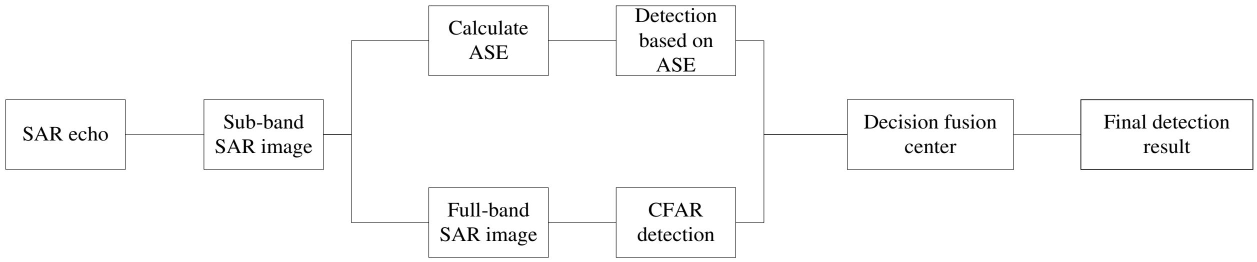



Figure 1: Framework of fusion detection algorithm.

## 3. EXPERIMENTAL RESULTS

Data used in this paper is collected by AMUSAR system, which adopts step frequency signal system and achieves resolution of 0.1 meter in range and azimuth directions. The system adopts Archimedean Spiral Antenna and has main beam angle wider than 60 degrees.

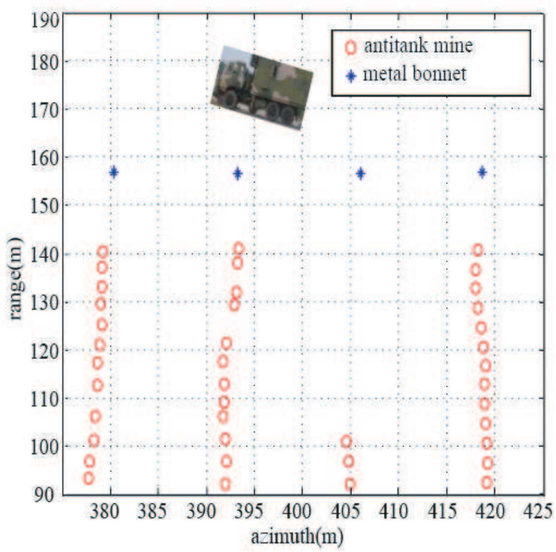



Figure 2: Sketch map of minefield.

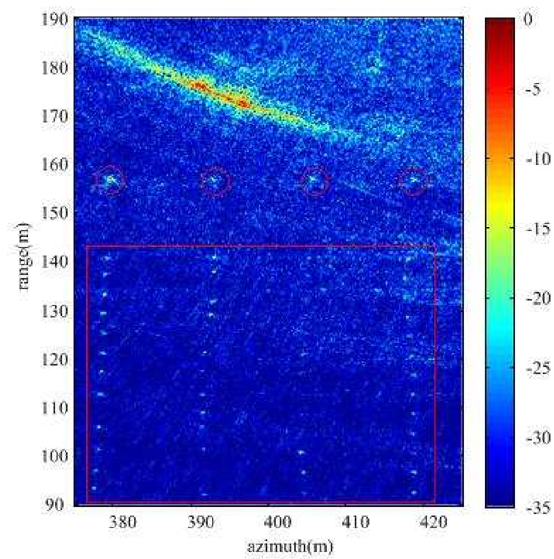
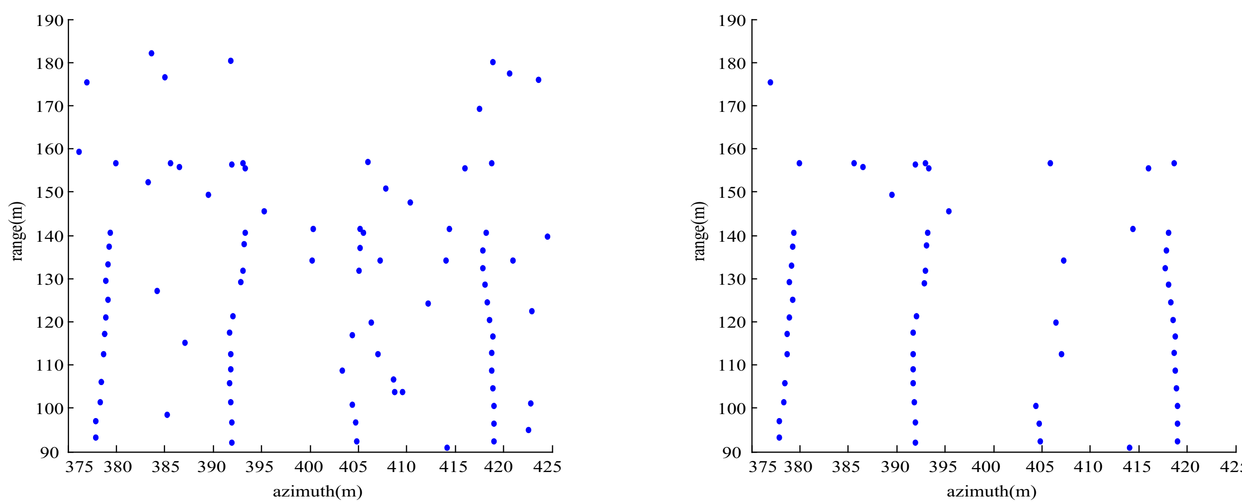



Figure 3: Full aperture SAR image.




(a) (b)

Figure 4: Detection result when the parameter of false alarm rate in CFAR detector is 0.005. (a) The CFAR detection result. (b) The fusion detection result.

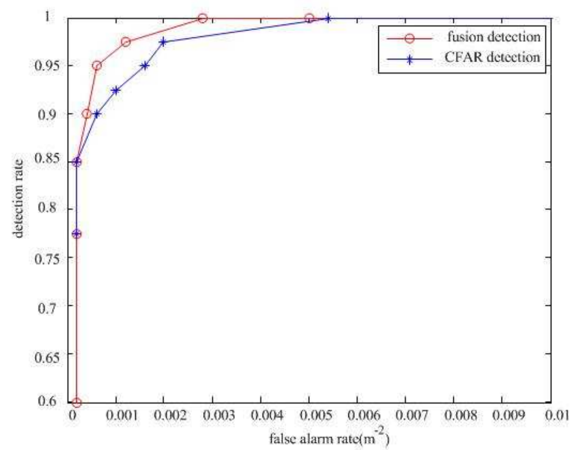



Figure 5: ROC curves.

The experimental layout is shown as in Fig. 2. The soil moisture in our experimental site is between 5% and 10%. There are 40 anti-tank mines with diameter of 30 cm and a truck in the minefield. Four metal bonnets with diameter of 30 cm and height of 30 cm are also placed as calibration objects.

Figure 3 is the full aperture SAR image obtained by BP imaging algorithm, in which the rectangular box and the circle represent the minefield and metal bonnet, respectively. CFAR detection result and fusion detection result are shown in Fig. 4. It can be seen that there are fewer false alarms in fusion detection. In order to acquire more accurate conclusion, the receiver operator characteristic (ROC) is adopted, as is shown in Fig. 5. Compared with single feature detection, fusion detection decreases false alarm rate while guaranteeing high detection rate.

## 4. CONCLUSION

In this paper, a fusion detection algorithm based on aspectual scattering characteristic and local contrast is proposed. Compared with traditional methods, this method takes full advantage of aspectual invariance of BOR targets and achieves lower false alarm rate and higher detection rate. Further research could include the utilization of sub-band information. And it would be of interest to see how well two-dimension prior information (sub-band and sub-aperture information) performs in landmine detection.

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