TEXTURE FEATURE SELECTION FOR BURIED MINE DETECTION IN AIRBORNE MULTISPECTRAL IMAGERY

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ABSTRACT

In recent years, airborne minefield detection has increasingly been explored, due to its capability for low-risk standoff detection and quick turnaround time. In this paper, a methodology for buried mine detection in airborne multi-spectral imagery, based on color texture information of the mine signatures, is explored. This methodology is based on utilizing the color texture information in the buried mine signatures, which is extracted via the cross co-occurrence texture features. A systematic approach is developed for the selection of a small subset of co-occurrence texture features that are useful for detection. Bhattacharya coefficient-based analysis is used for the initial selection of discriminatory texture features, followed by principal feature analysis to identify the features with mutually uncorrelated information. Finally, detection performance results for actual airborne data are presented. The performances are compiled for four different feature-based detectors, and compared with the conventional multi-band RX anomaly detector, to validate the proposed feature selection method.

1. INTRODUCTION

Detection of buried landmines in airborne multispectral imagery is a challenging problem. The baseline detector for buried mines in several airborne detection systems is the popular RX anomaly detector [1]. Several techniques for improvement over the RX detector have been proposed in the past; however, most of these methods have focused on the detection of surface mines [2, 3], and few algorithms have been proposed specifically for buried mine detection [4]. As a result, notable success has been reported for surface mine detection, but results for buried mine detection are far from satisfactory. In this paper, a methodology, based on co-occurrence texture features, is explored for effective detection of buried mines in airborne multispectral imagery. A systematic two-step procedure for selection of suitable texture features is presented.

The primary challenge in using electro-optical multispectral data for buried mine detection comes from the fact that the spectral signature of the mine area is very similar to the spectral signature of the background constituents. Any technique that works directly with the intensities of the pixels, like anomaly detection or linear unmixing, is rendered ineffective, due to the substantial overlap of the spectral subspaces defined by the mine pixels and the background. However, the particle compositions of the long exposed and recently disturbed surfaces show distinct spectral/spatial variations due to difference in particle size, and variations in the thermal signature of the mine area due to small shadows. The methodology explored in this paper is based on exploiting this fact by utilizing features based on intensity variations through texture features, instead of the pixel intensities directly.

2. OVERVIEW OF METHODOLOGY

The detection methodology uses co-occurrence texture features to capture the information in the spatial distribution of the spectral vectors in the airborne imagery. First, the cross co-occurrence matrices (CCM) [5] based texture features are extracted for each pixel in the multispectral image. CCMs are the extension of the popular Gray-Level Co-occurrence Matrix (GLCM) [6] texture features to color images. Then, seven popular co-occurrence features namely, Maximum Probability, Energy, Contrast, Inverse Difference Contrast, Correlation, Variance and Entropy, are extracted for various cross-band combinations. A novel eighth feature, called the Normalized Color Index (NCI), is also introduced and extracted. A total of 240 raw CCM features per pixel are obtained. Since this number is large, a technique for selecting a subset of discriminatory features is needed. For this a two-stage methodology for feature selection is used. The first step is to identify texture features with relatively high discriminatory information, in terms of their ability to separate false alarms from the mine signatures. This is done by obtaining sample distributions for each feature over the training set of mine and background patches, using Kernel Density Estimation with Gaussian kernel. Bhattacharya coefficients, based on the density estimates, are used to quantify the discriminatory information in the features. In the second step, a few features are short listed from this subset, using a technique for critical variable selection, called Principal Feature Analysis (PFA) [7]. PFA takes the interdependencies amongst the short listed features into account, and eliminates redundant features. Using the two-step process, the number of features per pixel is reduced to three. One of these selected features is NCI between red and near infrared channels representing the popular Normalized Difference Vegetation Index (NDVI) [8], used in remote sensing to identify live vegetation.

To demonstrate the efficacy of the feature selection process, detection performance results of four different feature-based detectors, which use the selected features, are compared. The four detectors are: the Matched Filter, AND Fusion, Spatially Weighted Kernel-RX (SW-KRX), and the Vegetation Mask detector. While the Matched Filter and AND Fusion detectors are supervised and semi-supervised in nature, respectively, the SW-KRX and Vegetation Mask detectors are completely unsupervised. The Matched Filter, AND Fusion, and SW-KRX detectors are the extensions of similar standard detectors to the feature images. However, the Vegetation Mask detector is more heuristically based and is motivated by the empirical observations that the region with true buried mines signature typically has low value of NCI feature.

3. RESULTS

The buried mine detection performance results of the four feature-based detectors and the multi-band RX detector are compared based on two large airborne multispectral image datasets, collected at different times, and under different terrain conditions. It is observed that all the feature-based detectors achieve a significant improvement in detection performance over the RX detector. The results point toward the possible improvement in performance by using the selected features, and confirm the efficacy of the feature selection process in identifying features with significant discriminatory information, exploitable for effective buried mine detection. It is also observed that similar texture features are selected under different terrain conditions, which suggests the usefulness of these features for the buried mine detection problem in general.

4. KEY CONTRIBUTIONS

A feature selection methodology is presented, as part of the algorithm for buried mine detection. The methodology is one of the first to exploit color texture information in airborne multispectral images, using CCM texture features. Although CCM features have been proposed in the past, they have not been used extensively, and are relatively less explored. A novel CCM feature, termed Normalized Color Index, is proposed, which extends generality of the definition and scope of the popular NDVI [8] feature. A unique two-stage scheme, using Bhattacharya coefficients and Principal Feature Analysis, is presented for discriminatory feature selection. Four different feature-based detectors are also presented. Finally, detection performance results are compiled for the feature-based detectors and the multiband RX detector, which demonstrate the effective extraction of texture information via the CCM features, and the efficacy of the feature selection process.

5. REFERENCES

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