DETECTION AND CLASSIFICATION OF BURIED RADIOACTIVE-METAL OBJECTS USING WIDEBAND EMI DATA

Anish C. Turlapaty, *Qian Du*, *Nicolas H. Younan*

Department of Electrical and Computer Engineering
Mississippi State University, MS 39762

ABSTRACT

Gamma-ray spectroscopy is frequently used for the detection of radioactive materials. As an alternative, we explore the use of electromagnetic induction (EMI) data for detection and classification of radioactive-metal objects, i.e., depleted uranium (DU), in this study. To reduce false alarms, a pattern recognition approach based on a decision tree structure is proposed. In an initial experiment, the DU rounds were placed in rows at three different depths in a rectangular field and EMI measurements are taken. The DU objects placed up to depth 30 cm below surface were successfully detected and identified along with the depth information. The algorithm also outperformed traditional threshold detection based method in terms of discriminating objects at 30cm depth.

Index Terms* — *Decision trees, Support vector machines, Clustering.

1. INTRODUCTION

Depleted uranium (DU) is the material leftover after the enrichment process of the natural uranium. The DU metal has several military applications such as armor piercing penetrator rounds because of its high density and pyrophoricity. Even though the DU metal is useful in several applications, it has some serious disadvantages. For instance, the DU rounds explode on impact with the target and the generated DU dust is chemically toxic and can be harmful if inhaled. These harmful effects warrant the need for efficient methods to detect the DU from a small scale such as the DU dust to large scale surveys of its distribution over land areas [1]. The existing methods for DU detection exploit its radiation properties and depend on counting either the beta particles or gamma photons [2-4]. There is a need for further research to test the scalability of these techniques for large scale land surveys.

A possible alternative is to use electromagnetic induction (EMI) spectroscopy for land surveys. The idea of using a library of signatures to detect the target metal was first introduced by Won *et al*. in [5]. However, the problem of variable orientation of the target object is not solved. Another approach for detection of subsurface metal objects is a combination of sophisticated EM modeling of vector magnetic potential observed by the GEM-3 sensor and optimal Bayesian detector [6]. A genuine statistical signal processing approach without the use of sophisticate EM models was developed in [7]. In this method probability distribution of data is assumed to be a bimodal Gaussian and the parameters are estimated from EMI data. This method outperformed dipole EM model based detectors in identifying unexploded ordnances. Application of modern pattern recognition methods for subsurface object detection is discussed in details in [8, 9].

The goal of this study is to evaluate the EMI based survey techniques for detection and classification of subsurface DU objects [10]. The EMI response data is obtained through the Geophex's GEM-3 that operates in a wide frequency band under 1 MHz. These EMI measurements are taken at seven widely separated frequencies from 330 Hz to 43.08 KHz. An unsupervised non-linear classification technique is developed, which can outperform existing methods in the literature.

2. METHODOLOGY

As illustrated in Figure 1, the target identification process can be divided into two steps: feature extraction and decision tree based classification. Later in the validation step, the signature of the objects that belong to each class is compared to the EMI response of the same object from the lab measurements. A given metal with known dimensions has a unique peak in the quadratic component of the EMI response. This EM property provides a theoretical foundation for the feature extraction and selection process. The measured spectral magnitudes of the quadratic component centered at its peak are considered as the components of the raw feature vector corresponding to each observation. At different stages of the classification, relevant features are either selected or constructed from this raw feature vector.

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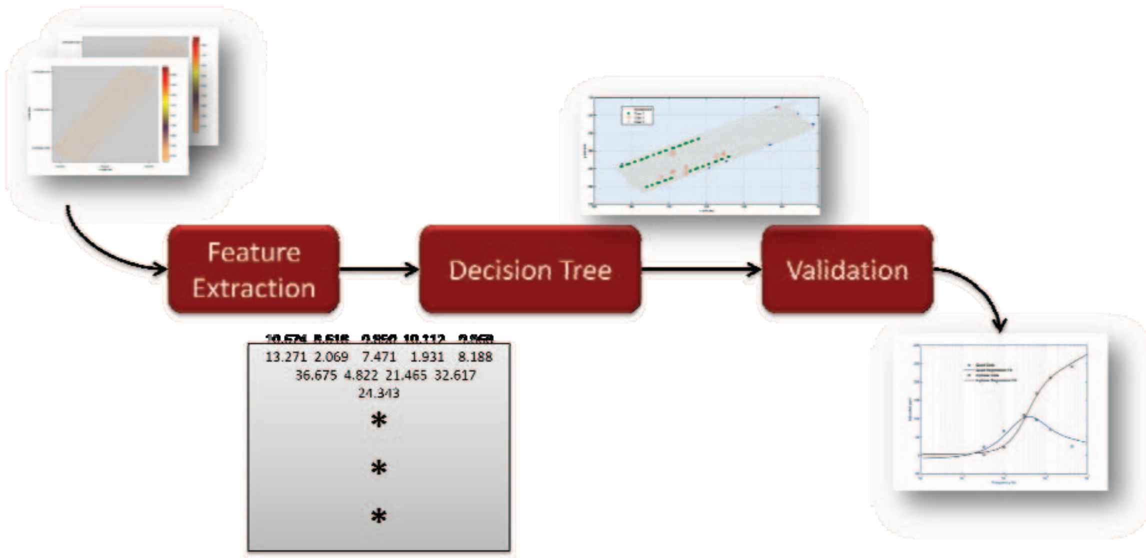


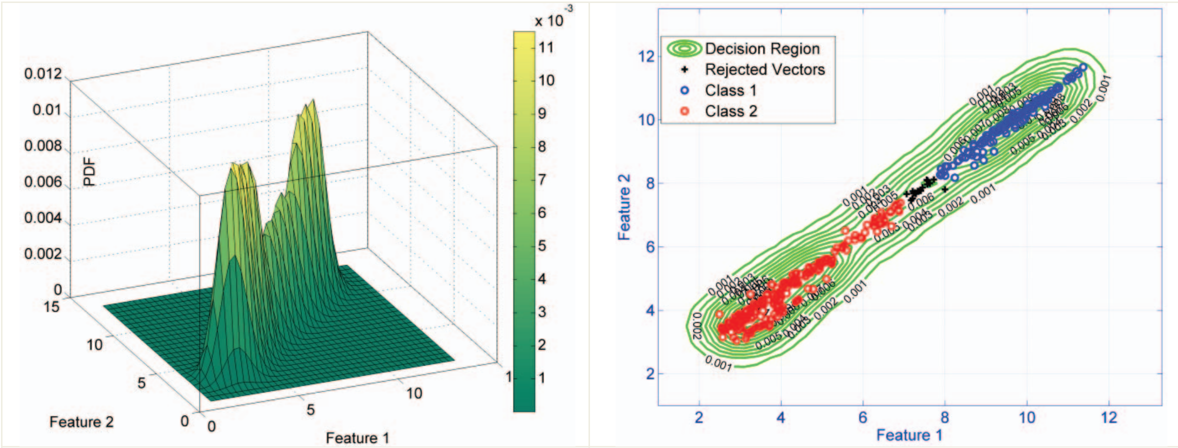
Figure 1: Block diagram of the target detection method using SVM.

The classification process is divided into three nodes of a decision tree and depends on the magnitude of the components in each feature vector. At node 1, the background observations are eliminated based on the magnitude of the EMI response. The EMI response of metal objects is usually significantly stronger compared to that of non-metals such as soil. Based on the magnitudes of the quadratic component the background observations are identified. Moreover, the EMI response of materials such as soil does not have a well defined peak. In this node, the central feature corresponding to the peak of target metal is used. In node 2, the metals that have a different signature than the target metal are separated based on the peak of the quadratic component. The peak of the quadrature component of the EMI response of metal objects tends to depend on its magnetic properties. For instance, the peak of the diamagnetic metals occur in the lower end of the EMI spectrum, the paramagnetic metals such as the DU have their peak in the middle of the log scale around few hundred Hz and finally the ferrous metals such as iron cluster at the higher end of the spectrum. Thus, based on the location of the peak, a diamagnetic metal can be separated from other types of metals such as iron. In this node, the three features around the central feature are used to determine the nature of the metal.

In the third node, the feature vectors are classified into two classes of the target metal. As a first step, two composite features are constructed by summation of the logarithms of the two neighboring spectral magnitudes to log the peak magnitude. These composite feature vectors are used as the input vectors to the one class SVM algorithm with the Gaussian kernel. The SVM algorithm used in this study consists of three steps. In step one, a convex optimization problem is solved using quadratic programming on the selected feature vectors and a set of support vectors is generated. The optimization approach basically consists of reformulating the SVM problem in terms of Lagrange multipliers. The feature vectors are extracted from the initial EMI measurements through log-transformation. In step two, these support vectors are used to estimate the probability density function (PDF) of the target metal in the new feature space. In the final step, the PDF is used to separate the target metals into two classes each corresponding to objects at different depths. The PDF has two distinct Gaussian peaks that correspond to the centers of two Gaussian distributions and thus two clusters. Individual feature vectors are classified to one of these two clusters based on their distance to the two centers. A threshold value is used to reject vectors that do not belong to either cluster.

3. IMPLEMENTATION

Initially, the EMI response of several metals including the DU is measured in a controlled setting. The raw EMI data in ppm is converted to adjusted ppm by performing background corrections. Since the goal of this study is to detect buried DU metal, we consider the EMI response of a 1-inch diameter DU round. Its quadratic component has a peak at approximately 3.5 KHz. The relation between peak value and the values from its neighboring channels can be very useful for characterizing DU metal of same radii. The closest values to the peak in the field data are near 3.03 KHz and 5 KHz respectively. A model is fit to the discrete valued EMI response and is used as a reference for comparing with the field measurements.



(a) Visualization of the PDF

(b) Class separation based on the PDF

Figure 2: Estimated PDF of the DU objects in feature space.

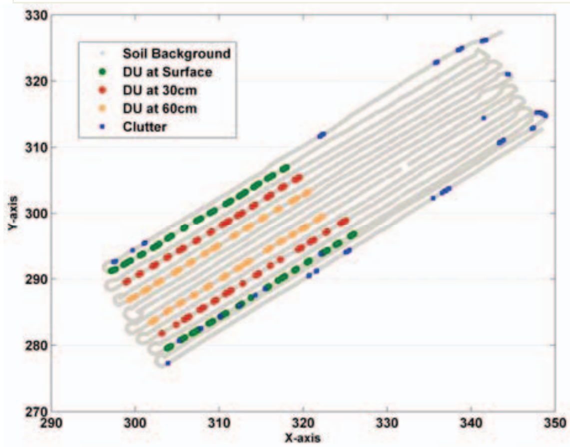


Figure 3. Ground truth of DU objects

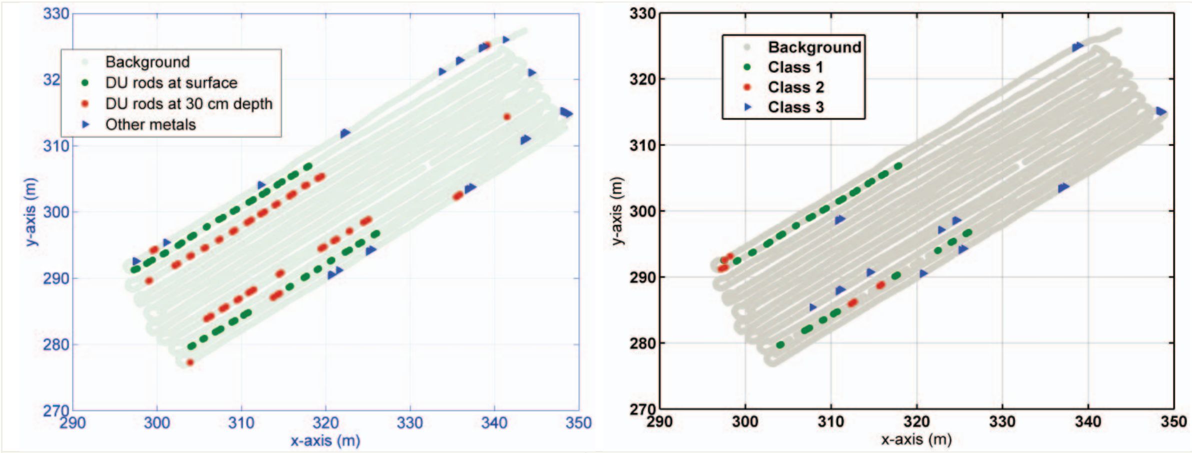
In the first two nodes of the decision tree, the background measurements corresponding to the soil and the signatures of other metals are classified as described in methodology section. In the third node, the classification is performed as follows. The Class 1 represents the DU objects close to the surface and the Class 2 represents the deeper DU objects. This classification is achieved based on the probability distribution function approximated by the one-class support vector machines (OCSVM). For the OCSVM learning, the three spectral peaks surrounding the theoretical peak were used to construct the feature vector for each observation point. The results from the decision tree methodology are validated by comparing the signatures of the target objects of each class with laboratory EMI measurements of the corresponding metals. Figure 2a shows the PDF approximation from the SVM learning and the Figure 2b shows the separation between Classes 1 and 2 using the PDF as explained in the previous section. In this study we have three rows of DU objects placed in two sets of three parallel rows as presented in Figure 3. DU rounds are placed at the surface in the first row shown in green, 30cm depth in the middle rows shown in red, and 60cm depth in the inner rows shown in brown respectively.

4. RESULTS & DISCUSSION

The final classification of all the metals and the DU at different depths is presented in Figure 4a. The proposed method successfully detected 25 out of 26 objects at surface and 21 out of 26 objects at 30cm depth. However, none of the objects at 60cm depth were detected. This can be explained based on sensitivity of GEM-3 sensor to distance from the target. For comparison purpose, a classification is also performed using multiple threshold based class separation [5] and is illustrated in Figure 4b. This method could not separate the Class 2 objects from other non-DU metals. Validation method: The Quadratic components of the EMI responses of the same object measured under different conditions should have high correlation given by $Quad_{field}(f) = a \times Quad_{lab}(f)$. Magnitude of EMI response from field measurements depends on the depth of the target under the surface. The magnitude of H field inversely depends on square of the distance. Thus, objects of Class 1 have higher magnitude as they are on the surface. Class 2 objects are much deeper at 30cm from surface thus show relatively weaker signal strength [6]. The close agreement of the target signatures of Classes 1 and 2 with the quadrature component of EMIR from lab based measurements is illustrated in Figure 5.

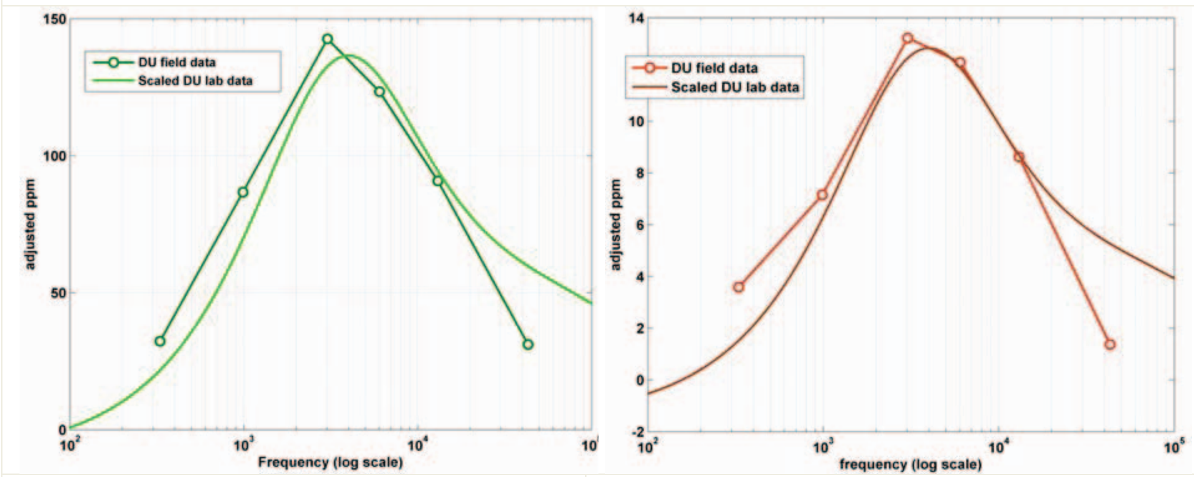
5. CONCLUSION

We evaluated the possible application of GEM-3 derived EMI data for subsurface DU metal objects. The unique properties related to paramagnetic nature of DU metal is exploited in feature extraction and discrimination of these objects. A SVM based clustering approach is presented for separating the DU-objects at different depths. The detection algorithm is tested on an EMI dataset. A likely extension of this work is testing the detection/discrimination algorithm in the presence of substantial clutter and variable sized DU objects



(a) The proposed decision tree method (b) Threshold detection method in [2]

Figure 4: Classification map of the different metal objects from the field measurements.



Class 1: DU objects close to the surface Class 2: DU objects deep under the surface

Figure 5: Validation of the DU metal objects with lab measurements.

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