Identification of metallic objects with various sizes and burial depths

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ABSTRACT

In this study, identification of the different metallic objects with various burial depths was considered. Metal Detector (MD) and Ground Penetrating Radar (GPR) were used to obtain metallic content and dielectric characteristic of the buried objects. Discriminative features were determined and calculated for data set. Six features were selected for metal detector and one for Ground Penetrating Radar. Twenty classification algorithms were examined to obtain the best classification method, for this data set. A Meta learner algorithm completed the classification process with 100 % performance.

Keywords: GPR, MD, classification, buried object.

1. INTRODUCTION

Buried object identification is an important topic in civil and military applications [1]. Generally, this process can be performed by using a sensor suit fixed to hand held or robotic system. There are two approaches for identification process: detection and then identification or online identification during scanning. First approach is more convenient than second one. Since all spatial sensor data is available in identification stage, rough size and shape of the buried object can be estimated depending on the sensors used in sensor suit.

Metal Detector (MD) and Ground Penetrating Radar (GPR) combination is usually convenient for most underground inspection applications. There are plenty of studies in the literature about identification of buried objects, one of them is given in [2]. In previous study [3] identification of the buried metallic objects at constant depth has been studied. However, the current study removes constant depth restriction and uses depth information obtained from complementary sensor, GPR.

The article was organized as follows; Section-2 gives problem definition and feature extraction methods including the classification methods used. Section-3 reports the experimental results and finally Section-4 gives conclusions.

2. THE PROPOSED IDENTIFICATION METHOD

Digital MD systems may provide metal density profile of the suspected region to the user. However, if the metallic content of the buried object is not high enough, there will be no remarkable change in metal density. In this case, more sensitive data channels are needed. The metal detector system used in this work has two channels, one of which is metal density ($M$) and other one is sensitive metal density ($S$) channel, can provide characteristic patterns for low metallic content objects.

GPR B-scan data shows the inspected region as an image, containing depth information proportional with dielectric properties of the soil. In the multi sensor case it is expected to obtain higher identification performance than single sensor case, generally.
Typical MD and GPR data are given in Fig.1 for medium size buried metallic object at shallow depth and relatively bigger size buried metallic object at deeper depth. It is shown that both MD data have almost the same information. The aim is to classify correctly this kind of buried object data, in various depths.

![Typical MD and GPR data](https://www.spiedigitallibrary.org/conference-proceedings-of-spie)

In order to correctly classify buried objects in different depths, discriminative features should be extracted. In the following section the selected features are explained briefly.

### 2.1 Feature extraction

The first step of identification is feature extraction and the second one is classification. The used notation and parameters are given in the following. Auxiliary information is also depicted in Fig.2, additionally.

- \( k \) : Discrete time signal indice in scanning direction (\( k=1\ldots K \))
- \( n \) : Discrete time signal indice of GPR image in depth (\( n=1\ldots N \))
- \( K \) : Length of EMI signal (at the same time number of A-Scans in GPR image)
- \( N \) : Length of A-Scan signals
- \( G(n,k) \) : GPR B-Scan image
- \( G_{BR}(n,k) \) : Background subtracted GPR image
- \( S(k) \) : Sensitive metal density channel of EMI Sensor
- \( M(k) \) : Metal density channel of EMI Sensor
- \( k_c \) : Cross points of directional correlation functions in scanning direction
- \( k_1 \) : Start indice of detection region in \( M \) channel
- \( k_2 \) : Stop indice of detection region in \( M \) channel
- \( k_3 \) : Start indice of saturation region in \( S \) channel
- \( k_4 \) : Stop indice of saturation region in \( S \) channel
- \( k_{\text{max}} \) : Indice of maximum value in \( M \) channel
- \( S_{\text{SATV}} \) : Saturation value of \( S \) channel
Feature-1: Detection length of metal density ($M$) channel:
This feature, calculates the length of metal detection duration, is useful in the discrimination of high or low metallic content objects. It also implicitly gives an idea for burial depth in conjunction with maximum value of metal density.

$$f_1 = M_{DETL} = k_2 - k_1$$ (1)

Feature-2: Maximum value of metal density ($M$) channel:
Maximum value of channel $M$ gives implicitly an idea for burial depth in conjunction with detection length in metal density channel.

$$f_2 = \max\{M(k)\}$$ (2)

Feature-3: Saturation length of sensitive metal density channel ($S$) during detection:
This feature is proportional with metal content of buried object and inversely proportional with burial depth.

$$f_3 = S_{SATL} = k_4 - k_3$$ (3)

Feature-4: Total area of metal density channel ($M$) during detection:
The area of metal density ($M$) channel between $k_1$ and $k_2$ gives information about the amount of heavy metal content of the buried object.

$$F_d = \sum_{k=k_1}^{k_2} M(k)$$ (4)
In order to obtain symmetry profile of metal density channel the following complementary features were defined.

Feature-5: Left side area in M channel during detection:

\[
f_5 = \sum_{k=k_1}^{k_{\text{max}}} M(k)
\]  

(5)

Feature-6: Right side area in M channel during detection:

\[
f_6 = \sum_{k=k_1}^{k_{\text{max}}} M(k)
\]  

(6)

Feature-7: Maximum back reflection point of the buried object:

Depth information has a great importance in the classification of buried objects. In this study depth indicator has been calculated as maximum back reflection point of the buried object. In the first step, background removal was applied to GPR image as explained in [4], is a transform-domain adaptive filter scheme. Then directional correlation functions were calculated for left and right sides of the object region, is defined in the same study. Intersection point of two directional correlation functions gives position of the buried object center in scanning direction.

At this point, position of maximum value of background removed A-scan signal is found and assigned as depth indicator. A sample GPR image, background removed image and depth indicator are given in Fig.3.

\[
f_7 = D = \arg \max_n \{G_{\text{BR}}(n, k_c)\}
\]  

(7)

This feature mostly corresponds to distance between object and antenna of the GPR system. So, this parameter can be used as a depth indicator. In rare cases, double reflection obscures the first back-reflection and results in greater depth values.

![GPR images](https://example.com/gpr_images.png)

a) Original GPR image, \(G(n,k)\).

b) Background removed GPR image, \(G_{\text{BR}}(n,k)\).

Fig. 3. Typical GPR and background removed GPR images for a buried object.

2.1 Classification Methods

In the classification phase of the buried objects, the WEKA program has been used [5]. Three of the methods from WEKA, give the best classification results are explained below. These are type of Meta Learner, Bayes Classifier and Rule Based methods, respectively.
**Method-1:**
This method is named as DECORATE (Diverse Ensemble Creation by Oppositional Relabeling of Artificial Training Examples). DECORATE is a meta-learner and uses an existing strong learner, which is providing high accuracy on the training data, to build an effective different committee in a direct way [6]. The combination of the output of various classifiers is just useful when they differ on some inputs in an ensemble. The diversity of the ensemble is the measure of this difference and there are some procedures to measure ensemble diversity.

Main purpose of this algorithm is to produce ensembles iteratively, learning a classifier in each iteration and adding it to the current ensemble. Artificial training examples are produced from real data in each iteration and the number of these examples is stated as a fraction of the training data set size. Then the classifiers are trained on the original training data together with artificial data. A new classifier on the union of the original training data and the artificial data are trained. This classifier is rejected if addition of this new classifier to the current ensemble increases the ensemble training error. Otherwise, it is added to the current ensemble. When the desired ensemble size is reached or the maximum number of iterations is exceeded, this process ends.

\[ P_y(x) \] is the probability of example \( x \) belonging to class \( y \), is calculated as follows:

\[
P_y(x) = \frac{\sum_{c \in C^*} P_{C_i,y}(x)}{C^*}
\]

\( P_{C_i,y}(x) \) is the probability of example \( x \) belonging to class \( y \) according to the base classifier \( C_i \). The class membership probabilities for the entire ensemble are represented by \( C^* \). Most probable class is chosen for labeling \( x \).

In this study Quinlan algorithm [7] were used as the base learner for the ensemble methods of DECORATE classifier and each base classifier, \( C_i \), builds ensemble \( C^* \), where \( i \) is from 1 to 10 in our study. This means that ensemble consists of 10 distinct classification stages.

This classifier constructs a decision tree whose nodes denote discrimination rules about features. Classification is made according to top-down navigation. It is continued until the leaves in the model tree are reached. This means that the training instances at any leaf node should be permitted to be less than a certain minimum number. When that certain number is reached, the test node is taken away again, before finishing the tree. This is also called “pruning the tree”.

**Method-2:**
The second method is Naive Bayesian classifier. In this method, the Bayes’ rule is used to calculate the probability of each class when a test case \( x \) is supplied to be classified.

\[
p(Cl = c \mid X = x) = \frac{p(Cl = c)p(X = x \mid Cl = c)}{p(X = x)}
\]

Here, \( Cl \) and \( X \) stands for the class of an instance and the feature vector while \( c \) and \( x \) represent a particular class label and a particular feature vector, respectively. In this way, the most probable class can be predicted. \( X = x \) defines the event such that \( X_1 = x_1 \) and \( X_2 = x_2 \) and ... \( X_k = x_k \). Since an event is just union of feature values which are assumed to be conditionally independent according to naive Bayesian classifier theory, it can be obtained;

\[
p(X = x \mid C = c) = p(\wedge_{i=1}^{k} X_i = x_i \mid C = c) = \prod_{i} p(X_i = x_i \mid C = c)
\]

So, the probability of feature vector to which class they belong can be easily calculated, in test cases. According to training data results, feature value vector can be assigned to a class. Continuous probability distribution over the range of that feature’s values is assigned to each numeric feature. It is assumed that the values of numeric features are normally distributed within each class. Therefore, mean and standard deviation values can define this distribution and this causes the probability of an observed value from such estimates to be easily calculated. While a continuous valued feature is
assigned to a class, the mean and standard deviation of the feature should be estimated. It is assumed that numeric feature has Gaussian distribution in Naive Bayes type of classification [8].

\[ X = x \] represents our feature values vector and each vector consists of seven elements, comprising features. \[ C = c \] denotes our classes which is totally 16.

Method-3:
The third method is a rule based classifier, is called Non-Nested Generalized Exemplars (NNGE). Firstly, it learns incrementally by classifying. Then each new example is generalized. NNGE uses hyper-rectangles to define each class and there are maximum and minimum feature-values denoting each class borders for continuous features [9]. Appending an example to the hyper-rectangle for continuous feature, overlap of the bounds should be avoided causing to stretch the feature bounds by increasing the maximum value or decreasing the minimum value.

In NNGE algorithm, numeric ranges of features are adjusted for each class. If there are two different feature ranges for a class then two hyper-rectangle are created. Modified Euclidean distance function, which permits the correct calculation of distances from hyper-rectangles for classifying new examples, is applied to generate hyper-rectangles, exemplar and feature weights. The difference between two continuous points is called as distance, divided by the range of possible values to normalize. An example lying within a hyper-rectangle’s bounds is defined as having a distance of zero. However, when the distance of related exemplar is equal to the minimum distance for that exemplar’s class, single generalized exemplar is created instead of two different ranges for features. These processes are repeated for all the exemplar in the set. Then model is adjusted by pruning over generalized hyper-rectangle if exemplar falls inside a hyper-rectangle of another class. After the adjustment, generalization process begins. If nearest neighbor is a hyper-rectangle, then each feature range is extended to include the new example. Yet, hyper-rectangle is returned back to original size and new example is stored verbatim if extended hyper-rectangle still includes conflicting examples. Else modifications are processed in hyper-rectangle and example is thrown away. In the case of nearest neighbor that it is a single example, a hyper-rectangle is created covering two examples. If this rectangle covers conflicting examples, new hyper-rectangle is thrown away and new example is stored verbatim. If this is not the case, new hyper-rectangle is kept and example is thrown away.

The rules of NNGE in our classification were defined by maximum and minimum values of the features. Finally, NNGE classifies all the instances to related classes by checking these rules. These rules can be generated by determining which range of values of features defines first class definition and second class definition, etc.

3. RESULTS

In this study, identification of four different buried objects was studied in various burial depths. The data has been collected by a robotic system, moves with 20 cm/sec scanning velocity. Height of sensors from soil surface is approximately 5 cm. The buried objects have been almost emplaced in the center of scanning line. The buried objects are four different sized metallic discs emplaced in different burial depths. The metallic discs have 3 cm of height and 5, 10, 15 and 20 cm of diameters. These metallic objects were buried in the soil with the burial depths of 5, 10, 15 and 20 cm. Twenty data for each metallic discs were collected, thus 320 data were acquired. Sixty percent of this set was separated as the training and the rest for the test. The training set was formed from 192 randomly chosen examples and the rest of them (128 examples) constituted the test set.

In the identification stage, first the features were extracted as explained in Section 2.1 and the feature vectors were obtained. In the second step these vectors were classified into 16 classes where each class corresponds to a different sized discs buried in different depth. The used feature vectors were formed by concatenating above mentioned seven features; \[ f_1, f_2, ..., f_7 \]. The distributions of features were given in Fig.4. In the figure, each row contains distributions of different buried objects, namely, MD5, MD10, M15 and MD20. For each subfigure, the horizontal axis gives the data number and the vertical axis gives it’s value. There are two columns in each row, first one contains the feature distributions having small values and second one contains the feature distributions having large values. In each distribution, the dashed lines are used to separate the depth of the buried objects. In other words, burial depths of the objects are aligned from 5cm to 20 cm, with four dashed lines, respectively.
Identification performance depends on both the discriminative properties of the features and performance of the used classification method. For this reason, twenty different methods of WEKA were examined in the classification step. As mentioned in Section 2-1, DECORATE, Naive Bayes and NNGE methods gave the best classification performances. The performance results of the above mentioned three classification methods are given in Table.1 for all seven features. Here, MDX_Y represents the disc with radius X at burial depth Y.
Table 1. Classification performance of the used methods for seven features

<table>
<thead>
<tr>
<th>Classification Method</th>
<th>Performance (%)</th>
<th>Misclassified objects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Method-1 (DECORATE)</td>
<td>100</td>
<td>-</td>
</tr>
<tr>
<td>Method-2 (NNGE)</td>
<td>96.88</td>
<td>MD5_10, MD15_15, MD20_20</td>
</tr>
<tr>
<td>Method-3 (Naive Bayes)</td>
<td>96.09</td>
<td>MD15_15 (two samples), MD10_20, MD15_20</td>
</tr>
</tbody>
</table>

In DECORATE classifier, the number of leaves created was 79 and the size of the tree was 157. The overall classification performance of DECORATE method is 100%. In other words, all of 128 examples classified correctly. This also means that the extracted features give exact information to discriminate the objects fully, with different burial depths.

As for NNGE classifier, total 18 exemplars including 17 hyper-rectangles and one single exemplar were created. The classification performance of the NNGE classifier is 96.88%. This method correctly classifies the 124 of the 128 example of the test set.

In Naive Bayesian classifier, all feature vectors are normal distributed with varying standard deviation and mean values. Moreover, each class has prior probability of 0.06. The classification performance of the Naive Bayes method is 96.09%. This method correctly classifies 123 of 128 example of the test set.

In order to examine the discriminative property of the features, we excluded some features and tried for classification. When the feature vectors consist of five features, namely \( f_1, f_2, f_3, f_4, f_7 \) the performance of the algorithm decreased. The classification performance of DECORATE method was 97.65%. In this case three of the 128 test vectors were not classified correctly. The performance of the Naive Bayes algorithm (96.88%) did not change. Only the misclassified objects changed. The performance of the Naive Bayes classifier decreased to 94.53%.

Table 2. Classification performance of the used methods for five features

<table>
<thead>
<tr>
<th>Classification Method</th>
<th>Performance (%)</th>
<th>Misclassified objects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Method-1 (DECORATE)</td>
<td>97.65</td>
<td>MD20_15, MD20_20, MD15_20</td>
</tr>
<tr>
<td>Method-2 (NNGE)</td>
<td>96.88</td>
<td>MD10_10, MD15_15, MD15_20, MD20_20</td>
</tr>
<tr>
<td>Method-3 (Naive Bayes)</td>
<td>94.53</td>
<td>MD5_10, MD10_10 (two samples), MD15_15, MD20_15, MD10_20, MD15_20</td>
</tr>
</tbody>
</table>

In addition to the exclusion of features \( f_5 \) and \( f_6 \), the feature obtained by GPR (\( f_7 \)) was also excluded. In this situation the scores decreased compared to the case of five features. This case corresponds to use of only metallic features. The identification performance of the methods decreased to 92.97%, 89.84%, and 93.75%, respectively for DECORATE, NNGE and Naive Bayes classifiers. These results indicate that determined seven features constitute the minimum feature set for 100% correct classification, for this data set.

Table 3. Classification performance of the used methods for four features (only MD features)

<table>
<thead>
<tr>
<th>Classification Method</th>
<th>Performance (%)</th>
<th>Misclassified objects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Method-1 (DECORATE)</td>
<td>92.97</td>
<td>MD20_15 (seven samples), MD10_20, MD15_20</td>
</tr>
<tr>
<td>Method-2 (NNGE)</td>
<td>89.84</td>
<td>MD10_10, MD10_10, MD10_20, MD15_15, MD20_15 (seven samples), MD15_20, MD20_20</td>
</tr>
<tr>
<td>Method-3 (Naive Bayes)</td>
<td>93.75</td>
<td>MD5_10, MD10_10 (two samples), MD15_15, MD20_15, MD10_20, MD15_20, MD20_20</td>
</tr>
</tbody>
</table>
4. CONCLUSIONS

In this study identification of metallic buried object was studied. The classification results of several burial depths of the same object and several objects buried at the same depth were obtained. Objects were buried in four depths. Since depth of a target is unknown in real environment, identification algorithms would be failed. So, estimation of the burial depth of the object is required. In previous study [3] there was a constant depth restriction, but in this study it was removed and GPR was added as additional sensor to obtain burial depth.

Discriminative features were obtained from MD and GPR sensors. Six features selected from MD, one from GPR and the feature vectors were formed. Totally 320 data were collected and separated into the 16 classes. In order to assess the identification performance, 60% of the collected data utilized for training and the rest for testing.

Twenty classification methods were tested to obtain the best one. The performance of a Meta learner algorithm named as DECORATE [6] reached classification performance of 100%. The results show that when a buried object can be identified in a constant depth, it may be identified in different depths if its depth was accurately determined, generally. Since in real applications, the buried objects do not have always the same shape with different sizes, one step improvement of this study could be, the identification of the objects with different shapes.

5. REFERENCES