Buried metallic object identification by EMI sensor

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ABSTRACT

Electromagnetic Induction sensor (Metal Detector) has wide application areas for buried metallic object searching, such as detection of buried pipes, mine and mine like-targets, etc. In this paper, identification of buried metallic objects was studied. The distinctive features of the signal were obtained, than classification process was performed. Identification process was realized by utilizing k-Nearest neighbor and Neural Network Classifiers.

Keywords: Metal detector, identification, k-NN, neural network.

1. INTRODUCTION

Buried object detection and identification process is an important issue for real time searching applications [1]. Buried object can be a pipe, can or hazardous objects, such as landmine, UXO or IED. If the target is composed of ferromagnetic material, it can easily be detected by EMI (ElectroMagnetic Induction) sensor, if it is in the detection range. There are two approximations for searching method.

- One pass identification
- Two pass identification

In the first one, detection and identification are performed simultaneously in real time. Whereas, the second one has two stage, determination of suspicious region (detection) and then identification of the buried object utilizing different classification methods in quasi-real time. In this study two pass identification process is used. A typical search scenario is shown in Fig. 1, the operator walks through footpath by swinging EMI sensors in right and left sides.

![Fig. 1. Buried object search scenario](image-url)
Detection system obtains information of buried objects through a grid map given in the above figure. If any detection warning is occurred, it is localized precisely. In the second pass a new data is collected by centering suspicious region, then identification process is performed.

The simplest detection method of the buried metallic objects is based on ElectroMagnetic Induction (EMI) technique. In this method, two different coils are used, transmitter coil creates primary magnetic field and receiver coil takes inducted magnetic field. If there is a ferro-magnetic object in the region, receiver coil field is induced by small eddy currents originated by metallic objects, additionally. These additional currents are converted to voltage, utilizing appropriate circuits to produce warning signals. The conceptual diagram of EMI sensing method is shown in Fig. 2.

![Fig. 2. EMI sensor block diagram](image)

New generation metal detectors create digital information, depends on the metal density of the inspected area, instantaneously. Metal density information is created for high metallic targets. Also precision metal density information is useful for low-metallic object detection and identification stages. Due to these reasons, three channel EMI Sensor data were used. Precision metal density channel was split to the existence (E) channel and the precision density (P) channel. Relevant notation is given in the following.

\[
\begin{align*}
n & : \text{discrete time signal index} \\
K & : \text{dimension of EMI signal} \\
E(n) & : \text{metal existence channel of EMI Sensor } (n=1,\ldots,K) \\
P(n) & : \text{precision metal density channel of EMI Sensor } (n=1,\ldots,K) \\
M(n) & : \text{metal density channel of EMI Sensor } (n=1,\ldots,K) \\
\text{P}_{\text{sat}} & : \text{saturation value of the P channel} \\
\text{M}_{\text{sat}} & : \text{saturation value of the M channel} \\
\text{M}_{\text{steady}} & : \text{steady state value of the M channel} \\
\end{align*}
\]

E channel contains a logical information, it may be 0 or 1, depends on the detection. If the hardware produce a detection warning in inspected measurement point, \(E(n)\) value is 1, otherwise it is 0. P channel has a detailed information than the E channel, its value is in the range of \([0 \ldots \text{P}_{\text{sat}}]\), but smaller then the value of M channel.
The value of M channel is proportional with the metallic content of the inspected region in the range of \([M_{\text{steady}} \ldots M_{\text{sat}}]\). An example E, P and M channel graphics are shown in Fig. 3 (a), (b) and (c), respectively. In this figure, horizontal axis shows scanning position index. If a metal detection warning is created, E channel turns to dark on the graphical view and P value increases. M channel has a steady value \((M_{\text{steady}})\) in normal conditions, if there is a high metallic content in the region, its value rises up to \(M_{\text{sat}}\) value.

![Metal existence channel](image1.png)

(a) Metal existence channel

![Precision metal density channel](image2.png)

(b) Precision metal density channel

![Metal density channel](image3.png)

(c) Metal density channel

Fig. 3. Example metal detector signals
2. IDENTIFICATION METHODS

The solution of the buried object identification problem requires many of the pattern recognition issues [2]. In this study, two different classification methods were utilized and compared their results. The examined methods are k-Nearest Neighbor (k-NN) and Neural Network (NN) based classifiers.

The first step of the pattern recognition is feature selection. Suitable numerical features transform the input space to separable space for further classification process. Six convenient features have been defined dedicated to the EMI sensor data identification in the following section.

2.1 Feature extraction

In order to obtain satisfactory classification performance in the EMI sensor data, different features were studied and the following six features were selected.

**Warning length of metal detection:**
This feature calculates the length of detection warning, useful in the discrimination of the high or low metallic objects itself.

\[ f_1 = \text{length} \{ E_{\text{dark}} \} = M_{\text{stop}} - M_{\text{start}} \]  

(1)

**Maximum value of metallic density channel (M):**
Maximum value of channel M shows the peak metal density.

\[ f_2 = \max \{ M(n) \} \]  

(2)

**Left side detection area of metallic density channel (M), bounded by maximum position’s of LFC and 10 data neighbors**
This one corresponds to metallic region integral of channel M bounded by \( M_{c-10} \) and \( M_{c} \) (see Fig. 4)

\[ f_3 = \text{area}_{\text{left,10}} \{ M(n) \} \]  

(3)

**Right side detection area of metallic density channel (M) bounded by maximum position’s of LFC and 10 data neighbors**
This one corresponds to metallic region integral of channel M bounded by \( M_{c} \) and \( M_{c+10} \)

\[ f_4 = \text{area}_{\text{right,10}} \{ M(n) \} \]  

(4)

\( f_3 \) and \( f_4 \) features indicate a kind of symmetry of channel M, roughly.

**Total area of metallic density channel (M) within ± 10 data neighbors of \( M_{c} \):**
This feature corresponds to integral of channel M bounded by \( M_{c-10} \) and \( M_{c+10} \), also corresponds to metallic density of the inspected area.

\[ f_5 = \text{area}_{20} \{ M \} = f_3 + f_4 \]  

(5)

**Maximum value of precision metal density channel P:**
Maximum value of precision metal density channel may help to increase identification rate especially for low density metallic objects.

\[ f_6 = \max \{ P \} \]  

(6)
The above mentioned feature calculation point parameter $M_c$ corresponds to indices of maximum of LFC function, shown in Fig. 4 (a) and (b). That value directly affects the feature values of $f_3$, $f_4$, and $f_5$. Due to the $M(n)$ signal may have asymmetric or spiky shapes, the location of maximum value of M channel may not correspond to good separation point for feature extraction process. For this reason, calculation of $M_c$ was realized by taking the FFT transform of M channel and then by finding the location of maximum value of the low frequency portion of $M(n)$ signal. Actually, LFC function construction is realized by taking the lower 4 bins of digital frequencies and than taking inverse FFT.

Example results of this process are shown in Fig. 4, for the data of two different objects. As it is shown in the figures that the metal density channel M may have different forms, single mode or multimode. The advantage of the above mentioned calculation way of $M_c$ is to make its performance independent from the noise and spikes in M channel.

![Fig. 4. Example LFC functions and corresponding $M_c$ positions.](image)

The feature distributions of selected class-2 and class-3 objects are also shown in Fig. 5, these are not easily separable. Where, the horizontal axis corresponds to the test data and vertical axis corresponds to the feature values (class-2 objects are represented by diamond and class-3 objects are represented by square). As it can be seen in the Fig. 5, that the classification of these objects requires complex decision boundaries.

### 2.2 Classification with k-NN

One of the instance-based learning methods is the k-Nearest Neighbor algorithm which is widely used for classification. Simply, the unclassified pattern is compared to the stored known pattern to assign the new pattern to the most k similar class [3].

First, the known class samples and their labels are stored. The parameters of the algorithm are distance function and number of neighbors, namely k. The most common distance function is Euclidean distance. The Euclidean distance between two data set $x_i$ and $y_i$ in the multidimensional (R) space is given in (8)
The distances between unclassified pattern and stored patterns are computed utilizing this distance function. The nearest k neighbors determine the class of the unknown pattern. Generally, the voting procedure is applied to establish the class. In some cases, the distances are weighted during the voting procedure. In this work, the Euclidean distance is used and the voting procedure is applied with k=3 (no weighting).

\[ d_e = \sqrt{\sum_{i=1}^{R} (x_i - y_i)^2} \]  

Fig. 5. Feature distributions of two selected hardly separable Class-2 and class-3 objects set
2.3 Classification with neural network

In this part of the study, multi layer perceptron with one hidden layer [4] is used in the classification stage, alternatively to the k-NN method. The structure of the classifier is given in Fig. 6. The back propagation algorithm and sigmoidal neuron transfer function are used.

The input layer has six input neurons since the dimension of the input vector is six. The dimension of the output is 3 since the classes are coded in three digits (100: Class-1, 010: Class-2, 001: Class-3). Different number of hidden neurons and learning rate values were examined and discussed results in the conclusion section.

![Neural network structure](image)

Fig. 6. Neural network structure

3. EXPERIMENTAL RESULTS

Identification of three class data was studied in the EMI sensor data set. Most of the buried objects were cylindrical form but some of them were rectangular prism. The data set is composed of two different sets, which were taken with one week delay. Totally 168 training data and 110 test data were used.

All the test objects have high metallic contents, so the metal density channel (M) increases considerable when detection warning signal is created. Three different performance tables are given in the following:

Case: 1 Training with 84 data from data set-1 and test with 57 data from data set-1

During the neural network trials, we used different parameter values for learning rate, the number of neurons and stop criteria (epoch number or error value) for the back propagation algorithm. After some trials, we decided to use 40 hidden
neurons. First we chose the learning rate was 0.03125 and stopped the algorithm at 25,000 epochs. In this case, the performance were % 92.9. We increased the epoch number to 125,000 then the performance increased to % 94.7. In similar way, we tested different learning rate values and also error values to finish the algorithm, in order to get more satisfactory results. We got % 96.49 classification performance when we used the learning rate=0.025 and error=0.084. The method classified two class-3 objects as class-2.

<table>
<thead>
<tr>
<th>Methods</th>
<th>Classification performance</th>
</tr>
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<tbody>
<tr>
<td>k-Nearest Neighbour (k=3)</td>
<td>55/57 = %96.49</td>
</tr>
<tr>
<td>Neural Network (h=40)</td>
<td>55/57 = %96.49</td>
</tr>
</tbody>
</table>

**Case:2** Training with 84 data from data set-2 and test with 55 data from data set-2

We obtained % 94.5 classification performance in 55 test data, when we selected the learning rate as 0.0125 and error value as 0.09, 0.08, 0.07 and 0.05. The classification performance increased up to the % 100, when we chose the error value as 0.04.

<table>
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<tr>
<td>k-Nearest Neighbour (k=3)</td>
<td>55/55 = %100</td>
</tr>
<tr>
<td>Neural Network (h=40)</td>
<td>55/55 = %100</td>
</tr>
</tbody>
</table>

**Case:3** Training with 168 data from data set-1 and data set-2, then test with 112 data from data set-1 and data set-2

In this case we merged the training sets of Case 1 and Case 2, in order to create the training set of Case 3. We obtained the test set in the same way. We selected the learning rate as 0.0125 for trials and we faced % 95.5 classification performance when the error = 0.09. The performance was % 96.4 when the error = 0.085. The algorithm classified two class-2 objects as class-3 when the error was 0.08, in other words the classification performance was %98.2

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<tr>
<td>k-Nearest Neighbour (k=3)</td>
<td>110/112 = %98.21</td>
</tr>
<tr>
<td>Neural Network (h=40)</td>
<td>110/112 = %98.21</td>
</tr>
</tbody>
</table>

The reason of the misclassifications may be understood from Fig. 7. As shown in Fig. 7 (b) and (d), M signals may be similar to each other for Class-2 and Class-3 data. Moreover the other signal channels does not give any distinctive information. In this case, use of $f_3$ and $f_4$, increases the identification performance.

4. CONCLUSIONS

The obtained results showed that the realized two methods gave the same performance for the same data. In the k-NN method all the known pattern are stored and the new one is compared with them. The storage of all patterns requires the high storage capacity, if the number of patterns is high. On the other hand, in the neural network paradigm, only the weight values are stored. The dimension of the weights is smaller than the k-NN pattern storage. So, the trade of between performance and storage capacity determines the selection of the methods.

However, the neural network approach requires so many trials than the k-NN method. The learning rate, the number of hidden neurons and error value/epoch numbers are tried with different values and also the algorithm should be run more than one times since the initial values of weights are also important. All these trials require effort and time. Whereas, one run is enough to get the best performance from k-NN method, when the k value is determined.
The data set used in this study were collected with a specified burial depths. In other words, different burial depths of each object wasn’t studied. In real environment, depth of the target is unknown, so it is needed to obtain burial depth by other sensors such as GPR, acoustic, laser, etc. Otherwise, an object features of a specific depth may be interfered with another object features of different depth. So, the performance of the methods would be worst. However, the proposed methods give satisfactory results as it is considered in their specified sub-space. Use of depth information as a parameter would make it to preserve its performance.

5. REFERENCES

2. C.M. Bishop, “Pattern Recognition and Machine Learning”, 2006