Adaptive identification of landmine class by evaluating the total degree of conformity of ring-CSOM weights in a ground penetrating radar system

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Abstract. In the world demining field, ground penetrating radar (GPR) systems are expected to visualize antipersonnel plastic landmines and distinguish them from iron fragments and soil clods. We previously proposed an adaptive texture-classification GPR based on a complex-valued self-organizing map (CSOM). In this paper, we propose a landmine-class identification method utilizing CSOM-space topology that reflects the total similarity of feature-vector values including the SOM-space structure constructed through self-organization. Experiments demonstrate that the proposed method can identify the landmine class to show where a landmine is buried even under a low-resolution and high-noise observation condition.

1 Introduction

Because of the noncontact and nondestructive manner of observation, ground penetrating radar (GPR) systems have wide application fields such as detection of buried objects, ruin surveillance, and groundwater investigation [1] [2]. Though GPRs can basically applicable to plastic landmine detection, there is still difficulty for practical use. Many research groups investigate to improve the performance [3] [4] [5] [6] [7] [8].

Metal detectors based on electromagnetic induction use low frequency electronics and, hence, the penetration is deep. They are widely used presently because most of plastic landmines contain small portion of metals at the detonator. Contrarily, GPRs using high-frequency radiation have a shorter penetration depth. However, they can acquire the features of scattering and reflection with a higher resolution. Therefore the combination of a metal detector and a GPR is expected to be powerful equipment in practical use, where the GPR takes charge of distinction of landmines from other metal scatterers or uneven ground-surface reflection. Such distinction ability has to be enhanced in GPRs.

We previously proposed adaptive frequency-stepped radar systems using complex-valued neural networks [9] [10]. We observe scattering and/or reflection three dimensionally (two-dimensionally in space by one-dimensionally in frequency) by coherent active imaging technique. Then we extract local textural features, just like our early vision does, from the complex-amplitude three-dimensional image data, and feed the result to a complex-valued self-organizing map (CSOM) to classify the local texture adaptively [11] [12]. The class labels are mapped backward to real space image in which where a landmine is buried, if any. In the system, we identified the landmine class by using tandem associative memories [13]. However, in the first (most prototype) system, we employed a mechanical scanning which required a long observation time.

Then the second system equipped with an electronically-scanned 12×12-element antenna array to reduce the observation time and to realize the portability [14] [15] [16] [17]. In the portable system, however, we found that, in some observation in difficult situation such as for wet laterite soil cases, we sometimes failed in the identification because of the low spatial resolution and the lower orthogonality among the feature vectors. Besides, we often required a long time for the identification because of the large number of combination arising from (the number of SOM classes) × (the number of teacher (sample) situations of observations).

In this paper, we propose a novel landmine-class identification method. It utilizes an advantage of the ring-CSOM we proposed before [16], that is, the topological fact that similar textural features belong to neighboring classes in the SOM space. In this method, we evaluate the degree of total similarity, or conformity, by comparing the whole the CSOM weights as well as the weights’ neighboring structure at once, instead of the tandem associative memories. We demonstrate in experiments that our proposed method can identify the landmine class more stably with a smaller calculation cost.

2 System construction and proposal

We first describe the overall signal processing in our GPR system, and review briefly the previous method to identify landmine class by using tandem associative memories. Then in Section 2.4 we propose our new method of identification based on the degree of conformity in the CSOM space. We also evaluate the calculation cost in Section 2.5.
2.1 Overall signal processing in our GPR system

Figure 1 is a rough flowchart showing the total processing conducted in our previous or novel GPR system. First we acquire the scattering / reflection image in three dimension, i.e., (two-dimension in space) \( \times \) (one-dimension in frequency), over a wide frequency band using coherent active imaging technique. Then we extract the textural features by calculating the correlations between pixel values in respective local areas in space and frequency domains. We feed the obtained feature vectors to a CSOM to classify adaptively the features, and obtain a segmented space image by projecting backward the classification result to the space image. In parallel, we identify the landmine class by using teacher (sample) data to visualize the landmine area [14] [15].

2.2 Brief review of adaptive classification of three-dimensional complex-valued textures by using the CSOM

A ring-CSOM [16] is used for the preprocessing to classify the texture in both of our previous and novel systems. We review the dynamics briefly. Figure 2 shows the ring structure of the ring-CSOM where we have 10 neurons for classification of features into 10 classes. In Fig.2, \( w_c \equiv [w_1, ..., w_N]^T \) denotes the \( N \)-dimensional weight vector representing the textural feature of class \( c \) (\( c = 1, ..., C \)), where \( [\cdot]^T \) stands for transpose, and \( C=10 \) in the present case.

The dynamics of the self-organization in the CSOM is expressed as follows.

\[
\begin{align*}
\mathbf{w}_c(t + 1) &= \mathbf{w}_c(t) + \alpha(t)(\mathbf{x} - \mathbf{w}_c(t)) \\
\mathbf{w}_{c \pm 1}(t + 1) &= \mathbf{w}_{c \pm 1}(t) + \beta(t)(\mathbf{x} - \mathbf{w}_{c \pm 1}(t))
\end{align*}
\]

\[
\alpha(t) = \alpha(0) \left( 1 - \frac{t}{T} \right) \tag{3}
\]

\[
\beta(t) = \beta(0) \left( 1 - \frac{t}{T} \right) \tag{4}
\]

\( \mathbf{w}_c(t) \): reference vector of the winner class \( \hat{c} \)
\( \mathbf{w}_{c \pm 1}(t) \): reference vector of the neighbor class \( \hat{c} \pm 1 \)
\( \mathbf{x} \): input feature vector
\( t \): iteration number in self-organization
\( T \): maximum iteration number
\( \alpha(t) \): self-organization coefficient for the winner
\( \beta(t) \): self-organization coefficient for the neighbors
\( C \): number of the neurons in the CSOM

Since the total neuron number is small (\( C=10 \)), we define the neighbors of the winner class \( \hat{c} \) as the nearest ones \( \hat{c} \pm 1 \). Unlike the K-means algorithm which we employed in our early works, the CSOM including the
neighbors’ self-organization improves the classification performance. At the same time, the dynamics places the reference vectors \( w_c \) in the order that reflects the similarity among the features, i.e., in such a manner that similar features belong to neighbor classes. We intend to utilize this ring-shaped similarity in the CSOM space to evaluate the landmine class identification.

### 2.3 Previous method: Identification of landmine class by using tandem associative memories

In the previous system, we employed tandem associative memories [13], explained in this section, for the identification of the landmine class. With pre-experiments of data acquisition for known landmine areas, we prepared a set of sample (teacher) data before we process an unknown data set. Then, first we chose a data in which the observation situation as a whole was most similar to that of the unknown data. Afterwards we examined the similarity of classes of the unknown data by comparing the classes in the most similar data including a known landmine class. That is, we had double stages of evaluations of (i) the data-set similarity including circumstances such as soil and burial situations and (ii) the class similarity in the most similar set of data, resulting in a large calculation cost. In addition, the results sometimes suffer from the low resolution and low orthogonality caused by the array antenna of the portable system.

### 2.4 Proposal: Identification of landmine class based on the degree of conformity in the CSOM space

Our new proposal solves the above problems by utilizing the order of the weight sequence in the CSOM space so that we can evaluate the class similarity at one time. We propose a method to evaluate the likelihood that a class represents a landmine by calculating the degree of conformity of the CSOM neuron weights (reference vectors) in the CSOM result for the sample signal sets \( W_s \equiv [w_1, ..., w_C], \quad (s = 1, ..., S) \) (sample weight sets) and that for the unknown signal set under test \( W \equiv [w_1, ..., w_C] \) (unknown weight set) in which landmines should be visualized, if any.

For the sample signal sets, we know beforehand which class or classes indicate a landmine. In the following description, we assume a landmine class as \( c_0 \) for respective sample signal sets. Figure 3 illustrates how we calculate the degree of conformity. First we calculate the covariance \( R_s(r) \) between a \( s \)-th sample CSOM weights and the unknown CSOM weights rotated by \( r \)-steps in the CSOM space as

\[
R_s(r) = \text{Re} (\text{Tr}(W(r) W_s^*) - < \text{Tr}(W(r) W_s^*) >_r) \tag{5}
\]
Table 1. Parameters of the target and the system

<table>
<thead>
<tr>
<th></th>
<th>Target (Plastic landmine)</th>
<th>System</th>
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<tbody>
<tr>
<td>Size</td>
<td>φ 78mm, 40mm high</td>
<td>Antenna height 2 ~ 3 cm above ground</td>
</tr>
<tr>
<td>Burial depth</td>
<td>2 ~ 3 cm</td>
<td>Number of feature classes C = 10</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Initial self-organization coefficients α(0) = 0.4</td>
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<td></td>
<td></td>
<td>β(0) = 0.1</td>
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<tr>
<td></td>
<td></td>
<td>Maximum self-organization iteration T = 10</td>
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<td></td>
<td></td>
<td>Sample (teacher) signal number S = 5</td>
</tr>
</tbody>
</table>

where $\text{Re}(\cdot)$ and $\text{Tr}(\cdot)$ stand for real part and trace, respectively,

$$<\text{Tr}(W(r)W_s^*)>_s \equiv \frac{1}{C} \sum_{r=0}^{C-1} \text{Tr}(W(r)W_s^*)$$

and

$W(r)$: matrix consisting of vectors of CSOM weights $w_c$, r-step rotated in the CSOM space, obtained for the unknown signal set

$W_s$: matrix consisting of vectors of CSOM weights $w_c$ obtained for s-th sample signal set

We calculate the covariance values for all the possible rotation steps $r$ for the unknown data set in which we want to identify the landmine class. When we have 10 classes ($C=10$), we have 0 through 9 possible rotation steps.

After calculating the covariance $R_s(r)$ for all the $S$ sample sets, we obtain an averaged covariance $R(r)$ as

$$R(r) = <R_s(r)>_s = \frac{1}{S} \sum_{s=1}^{S} R_s(r)$$

Finally, we regard the landmine likelihood of the $\{(c_0 - r) \mod 10\}$-th class of the unknown signal set as the value of $R(r)$ with r-step rotation, and we color (in grayscale) the CSOM-segmented real-space image with $R(r)$ values to indicate the landmine area. For example, when the landmine class in a sample signal set is $c_0 = 3$, then we assign to the class 6 of the unknown signal set the value $R(7)$.

This treatment realizes the average of the suggestions obtained by respective sample signal sets. At the same time, if there are some sample data sets that does not show significant indication, their effect is reduced in the summation process. This mechanism works well to indicate the landmine class likelihood.

2.5 Calculation cost

The calculation in Section 2.4 requires a calculation cost of only $O(SC)$. Contrarily, the conventional method (tandem associative memory) [13] requires $O(lSC!)$ where $l$ denotes the average iteration number required for convergence in the associative memories. It is found that the calculation cost of the proposed method is smaller than that of the conventional one.

3 Experiment

We present typical results obtained in a series of experiments in a heavily wet laterite-soil landmine field. Here we prepared 6 signal sets corresponding to observations of land area including a single plastic landmine TYPE 72. We regard one signal set as unknown data, while other 5 as sample signal sets. Table 1 lists the parameters of the target and our proposed visualization system. Among the parameters, we determined the initial self-organization coefficients $\alpha(0)$ and $\beta(0)$ empirically. We buried a plastic landmine for every observation, almost at the center, so that the soil condition including clods and stones, as well as the burial angle, are changing observation by observation. The roughness of the ground surface is about 2cm peak-to-peak in the height.

Figure 4 shows one of the six signal sets, which we assume unknown signal set here. Each color indicates a class, as shown in the color bar. Neighboring classes suggest similar features. In this case, class 1 (red) shows the landmine class area. We regard other five signal sets as sample signal sets.
Figure 5 shows the covariance $R_s(r)$ obtained for the signal set shown in Fig.4 with other five sample signal sets $s=1$ – 5. We assigned an identical landmine-class number to all the sample sets in such a way that their landmine class corresponds to the landmine class in the unknown test signal set when $r = 5$.

In Fig.5, we find that we have a peak at $r = 5$, or $r = 4$ or 6 for any samples. As a whole, we can see the tendency to have the maximum at $r = 5$, though it may not always exact. In other words, the covariance $R_s(r)$ become mostly the maximum when the landmine class in the sample signal set faces to the landmine class in the unknown signal set in the rotation in the CSOM space. The result suggests that the similar features of the weights neighboring in the CSOM space cooperate to indicate a high correlation as a whole. By averaging $R_s(r)$ over all the sample data sets, we obtain the average covariance $R(r)$ in (7).

Figure 6 is the result of the averaged covariance $R(r)$ mapped to the segmented image in Fig.4 in grayscale. The brightness is expected to suggest the landmine likelihood. Actually, the landmine is buried at the center, which corresponds to the brightest region. The experiment demonstrates good identification of the landmine class even in such a bad observation conditions with a small calculation cost.

4 Summary

This paper proposed a method to identify the landmine class based on the degree of conformity of the total CSOM weights. With this method, the similar features of the weights neighboring in the CSOM space cooperate to indicate a high correlation of the whole signal set, even if the signal sets have been obtained in low-resolution and low-orthogonality conditions, resulting in a correct, stable identification of the landmine area. The calculation cost is smaller than that of our previous tandem associative-memory method.

References