Use of an Application-Specific Dictionary for Matching Pursuits Discrimination of Landmines and Clutter

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Abstract—The HSTAMIDS handheld landmine detection system has been used in a number of humanitarian demining activities. Existing algorithms used with this system to assist human in discrimination process do a better job than the operator alone. However, they are unable to model mine and clutter signatures completely, leading to inaccurate mine confidence assignment. This paper presents a matching pursuits (MP) based landmine detection system using an application-specific dictionary. Prototypes for mine and clutter classes are built using MP decomposition of class members. A fuzzy K-nearest neighbor rule is used to assign confidence values for mine and clutter discrimination. The proposed algorithm is demonstrated on data acquired from three different landmines test sites.

Keywords—Landmines detection, matching pursuits, fuzzy K-nearest neighbors

I. INTRODUCTION

Landmines are unique among weapons of war as they continue to kill long after the conflict has ended. It is estimated that more than 100 million landmines are buried in more than 80 countries around the world. Each year, 26,000 people are either killed or maimed by a landmine [1,2]. Landmines specifically designed to cause damage to people are known as anti-personnel (AP) mines. They are small in size and weight and are buried at shallow depths so that they can be triggered by the pressure of a footstep. The process of clearing a minefield of AP mines is known as humanitarian demining. The goal of humanitarian demining is to remove lingering remnants of war and to make sure that the land is safe for civilian use.

The HSTAMIDS handheld landmine detection system has been used in a number of humanitarian demining activities [3]. It employs frequency-swept continuous wave radar antennae and a Minelab F1A4 electromagnetic induction (EMI) metal detector (MD) to locate landmines and to help discriminate them from clutter [4]. The EMI output signal is presented to human operators as an audible signal. Expert operators can distinguish landmines from many types of clutter using only the metal detector’s audible signal.

A Feed-forward Order-Weighted Average (FOWA) Network originally designed for use in the robotic landmines detection system [5], has been adopted to work well with the handheld system [6,7]. One-dimensional metal detector (MD) and ground penetrating radar (GPR) signals are used to compute features like average intensity, width of signal, etc. Features from various sweeps are combined using order-weighted averaging before presenting to a feed-forward neural network for classification. This approach has been shown to perform better than an expert human operator [6,8]. However, mines usually have distinct metal signatures that stay consistent across various sweeps and mine samples, while random metallic clutter can have random signatures. Classification algorithms based on discrimination surfaces, such as FOWA, can potentially produce high values for random inputs. In addition, mine and clutter objects with different metal signatures can have similar features leading to similar confidence value assignment by FOWA.

This paper proposes an algorithm for handheld landmine detection based on the matching pursuits (MP) technique. It tries to provide robust performance by building prototypes based on shapes of mine and clutter objects using MP. MP is a greedy technique that finds approximations of signals by iteratively projecting them onto a set of predefined signals, called the dictionary. First, an application specific dictionary is generated by segmenting training signals, with known ground truth, to extract their significant shapes. Then matching pursuits is used to find approximations of training signals by projecting them onto this dictionary. Candidate prototypes for each class are built by normalizing the MP approximations of its class members. Class representatives are chosen from these candidates based on maximum similarity to the rest of the members. Fuzzy memberships are assigned to the representatives to capture the degree of sharing among the mine and clutter classes. A fuzzy K-nearest-neighbor-based rule is used to assign confidence values to test samples.

The rest of the paper is organized as follows: Section II gives an overview of the Matching Pursuits algorithm. Section III describes the proposed detection system. Experimental results are presented in section IV and conclusions are drawn in section V.

II. MATCHING PURSUITS

Let \( H \) be a Hilbert space, \( \Gamma \) a set of indices, and \( D = \{ g_\gamma; \gamma \in \Gamma \} \) a family of functions in \( H \) such that \( \| g_\gamma \| = 1 \).
The family \( D \) is referred to as a dictionary. Given a signal \( f \in H \), the aim is to represent it as a linear combination of atoms \( g_n \) selected from \( D \). Matching pursuits is a greedy technique that makes this selection by successive approximations of \( f \). The algorithm starts by setting residue \( R_0 \) equal to the original signal \( f \). At each step, the corresponding residue is decomposed by projecting it on the dictionary atom that matches the residue best, i.e., the dictionary element that gives the largest projection of residue. Let \( R_i \) be the \( i \)th order residue and \( g_y \) the index for which the corresponding dictionary atom \( g_{y_i} \) yields a maximal value of inner product:

\[
\langle g_y, R_i \rangle = \sup_{j \neq y} \langle g_j, R_i \rangle \quad (1)
\]

Starting with an initial residue \( R_i = 0 \) the algorithm evolves by subdecomposing the \( i \)th order residue into

\[
R_i = \left\langle g_y, R_i \right\rangle g_y + R_{i+1} \quad (2)
\]

which defines the residue at order \( n+1 \). Since \( R_{n+1} \) is orthogonal to \( g_y \):

\[
\| R_i \|^2 = \| R_i \|^2 + \| R_{i+1} \|^2 \quad (3)
\]

From (2) it follows that at iteration \( n \) the MP algorithm results in an intermediate representation of the form

\[
f = f_m + R_{m+1} \\
f_m = \sum_{n=1}^{m} \left\langle g_y, R_n \right\rangle g_y \quad (4)
\]

If the dictionary \( D \) is complete, it has been shown in [9] that \( f_m \) converges to \( f \) when \( n \to \infty \). Nevertheless, if the approximation is stopped at iteration \( n \), the function \( f_m \) gives an approximation of \( f \) with an error equal to \( R_{m+1} \). The choice of the dictionary \( D \) for the matching pursuits algorithm plays an important role in approximation capabilities of the algorithm.

III. MATCHING PURSUITS BASED LANDMINES DETECTION

Let \( X = \{x_1, x_2, \ldots, x_X\} \) and \( Y = \{y_1, y_2, \ldots, y_Y\} \) be set of \( N \) input patterns and their corresponding class labels. \( y_i \) can be a Mine(M)/Non-Mine(NM) label or it can be label of their subclasses i.e.

\[
y_i \in \{M_1, \ldots, M_M, NM_1, \ldots, NM_{NM}\}
\]

Also let \( T = \{t_1, t_2, \ldots, t_T\} \) be \( N_T \) test patterns with unknown labels. Then the matching pursuits based landmine classification process can be defined by the following five steps:

A. Data Extraction

The AN/PSS-14 system is used to collect data over target object in an abbreviated region (AR) sweep pattern as described in [6]. The AR sweep pattern involves two sweeps away from the target to establish the zero output level of metal detector and ten sweeps in the crosstrack direction over the target. The metal detector provides two signal outputs for every sweep referred to as channels \( M_1 \) and \( M_2 \). Each \( M_i \) is median filtered to remove noise and is linearly resampled to a standard length \( n_m \). Centroid \( C_i \) for each \( M_i \) is calculated as:

\[
C_i = \sum_{j=1}^{n_m} jM_i(j) \quad (5)
\]

Each \( M_i \) is clipped around \( C_i \) with a window size \( n_w \) to give \( M_{i,w} \) where \( i = 1,2 \). Therefore, each input pattern \( x_j \) is given by:

\[
x_j = \{M_{i,w}, M_{i_w}^{1}, \ldots, M_{i_w}^{SN}: i = 1,2,SN = 1,2,\ldots,10\}
\]

i.e. \( x_j \) has ten crosstrack sweeps, each having two channels. Therefore, every input pattern \( x_j \) comprises of a total of 20 vectors of length \( [1 \times n_w] \).

B. Dictionary Design

Choice of the dictionary \( D \) for the matching pursuits algorithm plays an important role in determining the magnitude of the approximation error \( R_{n+1} \) and the number of dictionary atoms \( m \) required for the approximation. If atoms in the dictionary are similar to the signal \( f \), fewer atoms will be required to achieve smaller error and vice versa. Therefore, the choice of dictionary is usually application dependent [10,11]. In our application, the dictionary is built from training data by segmenting channel signals \( M_n \) of all crosstrack sweeps. Segmentation is done based on zero crossings in the signal. The dictionary obtained in this manner may have many elements of similar shape with different displacements. Therefore, we need to prune the dictionary to make it concise. A two-threshold sequential clustering algorithmic scheme (TTSAS) [12] is used to prune the dictionary by clustering similar elements together. Clustering is made invariant to signal displacement by clustering the power spectra of signals using Euclidean norm. Cluster centers of all clusters are then used as atoms \( g_i \) of the dictionary \( D \).

C. Matching Pursuits

The matching pursuits step is critical to the process as it is the precursor of building mine and nonmine prototypes for classification. Here all the sweeps from \( X \) are treated independently. Before the MP step, for each sweep, data from both channels are concatenated together to form vectors of length \([1 \times 2n_w]\) i.e.

\[
S = \{M_j^i \ s.t. i = 1\ldots N, j = 1,\ldots,SN\}
\]

where \( M \) is the concatenation of channels \( M_{1,w} \) and \( M_{2,w} \) with superscript \( j \) denoting its sweep number while subscript \( i \) denoting the input pattern number.

Each element \( s_i \) in \( S \) is iteratively projected onto dictionary elements by the MP algorithm as described in section II. However, the elements of dictionary \( D \) do not have displacement information because of shift invariant clustering. Therefore, in every iteration of matching pursuits, we not only need to find the dictionary element \( g_y \) that gives the biggest projection onto residue signal \( R_i \) but we also need to find its best displacement. Displacement is found by finding cepstrum of \( R_i \) and \( g_{y_i} \) concatenated together. The cepstrum of a signal is defined as the Fourier transform of the logarithm of its power spectrum. In [13] it has been used to find disparity between two

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stereo images. In our context, it will identify the amount \( d \) by which \( g \) needs to be shifted to give best projection \( R_n \) onto \( g \):

\[
\text{sig} = [R_n | g] \\
\text{ceps} = F(\log|F(\text{sig})|) \\
d = \arg \max_c \text{ceps}
\]

(7)

where \(|.|\) denotes magnitude of spectrum of signal, \( F \) denotes its Fourier Transform and \( n_e \) is one half the length of signal \( R_n \).

The approximation process stops when either the residual error (RE) falls below a fixed error-threshold \( R_{\text{max}} \), or iteration number \( m \) reaches maximum allowable iterations \( m_{\text{max}} \). At any iteration \( n \), residual error is defined as normalized residue \( R_{n+1} \). Mathematically:

\[
RE = \left( \frac{\{f - f_n(f, f_n)\}}{\{f, f_n\}} \right)^2 \times 100
\]

where \( RE \) is used as stopping criteria instead of \( R_{n+1} \), because residue can have a large or small value depending on absolute maximum intensity of \( f \). Normalizing \( R_{n+1} \) by original signal \( f \) eliminates the magnitude of residue, thus giving a uniform maximum intensity of \( f \).

Since the matching pursuit algorithm chooses the dictionary element with maximal projection \( c_m \), all the coefficients \( c_n \) in \( s_{kn} \) are sorted in descending order of magnitude. Normalize all coefficients by \( c_j \):

\[
s_{kn} = \sum_{n=1}^{m} c_n \frac{g}{d_{kn}}
\]

(9)

For further processing, each prototype \( R_i \) is assigned a fuzzy membership in the class of mines, \( u^m(R_i) \) and a fuzzy memberships in class of clutter \( u^c(R_i) \). The minimum distance and Fuzzy C-Means based approach of Frigui and Gader [14] is used for this labeling. For each \( R_i \), the closest mine prototype \( R^m_i \) (any mine subclass) and the closest clutter prototype \( R^c_i \) (any nonmine subclass) is identified. Labeling is assigned as

\[
u^m(R_i) = \frac{1}{\text{dist}(R_i, R^m_i)} + \frac{1}{\text{dist}(R_i, R^c_i)}
\]

(13)

E. Fuzzy K-NN based confidence assignment

Using an approach similar to Frigui and Gader [14], each test point \( t_i \) is assigned a confidence value as follows: For each of the ten sweeps, concatenate together channels \( M_1 \) and \( M_2 \) to give \( tM_i \) after clipping them around their respective centroids. For each pattern \( tM_i \), find K most similar prototypes \( P_1,..,P_K \) where similarity is defined by (12). Based on these K prototypes, \( tM_i \) is assigned confidence as follows:

\[
\text{Conf}(tM_i) = \frac{1}{\text{dist}(tM_i, P_1)} \sum_{i=1}^{K} \frac{1}{\text{dist}(tM_i, P_k)}
\]

(14)

To further reduce confidence value of non-metallic clutter and blanks, \( \text{Conf}(tM_i) \) may be thresholded based on maximum intensity of the sweep \( j \). Similar thresholding can also be employed for FOWA outputs. Finally \( t_i \) is assigned confidence by taking the mean value of the top \( i \) confidence values of its sweeps.

IV. EXPERIMENTAL RESULTS

The MP-based discrimination algorithm was developed and tested on MD data collected from three sites. Site 1 has a total of 224 targets with 44 mines, 147 clutter and 33 blank signatures. Site 2 has 280 targets with 120 mines, 22 clutter objects and 138 blanks, while site 3 has 267 targets with 108 mines, 97 clutter and 62 blanks.

Data from site 1 was chosen for training i.e. to build prototypes for mine and non mine classes. Then sites 2 and 3 were classified using these prototypes. 10 nearest prototypes

![Figure 1. Modified Matching Pursuits Algorithm](image-url)
were used to assign confidence value to each target using (14). To compare performance of the two algorithms, FOWA was also trained on site 1 and tested on sites 2 and 3. Figures 2 and 3 show the receiver operating characteristic (ROC) curves for discrimination of mines from blanks and mines from non-mines (blanks and clutter) respectively. The horizontal axis is the percentage of false alarm (PFA) and vertical axis is percentage of detection (PD) of mines. Test results for site 1 are reported as the outcome of 10-fold crossvalidation for both FOWA and the proposed algorithm (MP).

Experimental results show that MP (using MD data alone) performs comparably to or better than FOWA (which fuses MD and GPR features) on all three sites. FOWA features are based on signal intensity range for each class type, while MP models the characteristic signal shapes of each class. If signal strength of a target is different from usual, due to different burial depth, etc., FOWA will misclassify the object, but MP will assign it to the correct class due to its shape based classification mechanism.

V. CONCLUSION

In this paper we proposed a new algorithm for landmine detection. It models characteristic shapes of each class by building prototypes using matching pursuits and assigns confidence using fuzzy K-NN. Experimental results show that on an average, at 90% PD, MP shows a 24% decrease in PFA against non-mines and 71% decrease against blanks when compared to FOWA. Also, at 95% PD, the performance for both is similar. Therefore, the new algorithm can be used independently, or in conjunction with FOWA to achieve more reliable humanitarian landmine detection.

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