Fusion of KLMS and Blob Based Pre-Screener for Buried Landmine Detection Using Ground Penetrating Radar

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ABSTRACT

In this paper, a decision level fusion using multiple pre-screener algorithms is proposed for the detection of buried landmines from Ground Penetrating Radar (GPR) data. The Kernel Least Mean Square (KLMS) and the Blob Filter pre-screeners are fused together to work in real time with less false alarms and higher true detection rates. The effect of the kernel variance is investigated for the KLMS algorithm. Also, the results of the KLMS and KLMS+Blob filter algorithms are compared to the LMS method in terms of processing time and false alarm rates. Proposed algorithm is tested on both simulated data and real data collected at the field of IPA Defence at METU, Ankara, Turkey.

Keywords — Landmine; IED; GPR; signal processing; adaptive signal processing.

I. INTRODUCTION

Buried landmines have been a major threat since their initial use in the 1800s. Nowadays, buried landmines consist not only of military landmines, but also of improvised explosive devices (IED) that are predominantly plastic and filled with mixtures of ammonium nitrate. The electromagnetic interference (EMI) detectors which have been used for a long time, fall short of detecting these IEDs since the amount of metal they include is very little if any. To remedy these problems, GPR has been actively used for buried target detection.

Since the start of the buried target detection solutions with GPR sensors, many methods have been proposed in the literature for processing the GPR data. In these landmine detection solutions, real time processing plays a crucial part. Therefore, processing is divided into two main parts, which are pre-screening and classification. In the pre-screening part possible threat locations are found; while in the classification part a final decision is made about whether the location is a threat or not. With this two phase processing, more complicated classification can be applied not to the whole data but only to the possible threat areas found by pre-screener. In other words, complex processing parts are decreased, so the real time processing is achieved.

As an adaptive pre-screening algorithm, LMS is the most widely used one in the literature [1]. Two dimensional LMS algorithm is applied through each depth bin with a window size of 9x7 (downtrack x crosstrack). Then, a threshold is applied to the filter result and a decision is made according to that threshold. Downtrack is the direction that the robot is going through while crosstrack is the direction in which the sensors are placed as shown on Figure 1. Some of the other pre-screener algorithms proposed in the literature include Constant False Alarm Rate (CFAR) [3], Robust Principal Analysis [5] and Q-Scan [6].

In this work, Kernel Least Mean Square, an adaptive and real time implementable method, is proposed. This work also includes the comparison of KLMS method results and LMS method results in terms of Process Time and False Alarm Rates.

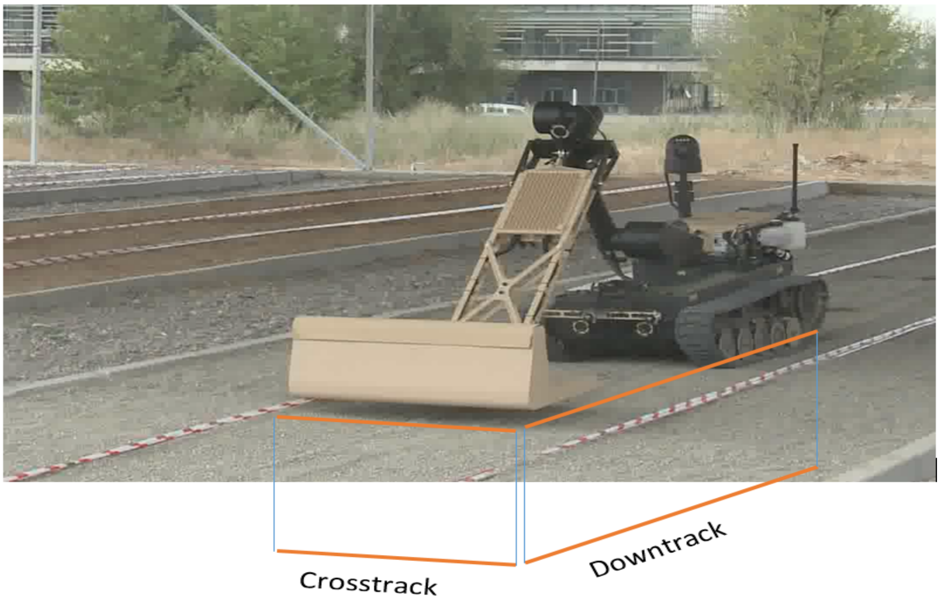

Figure 1. NIITEK GPR Panel integrated to the robot

II. Pre-Processing

Before the GPR data can be input to the pre-screener, a series of steps are applied to the data. The first one is called Ground Bounce Removal. In this step, the ground reflections on the signal are found and shifted so that each data column has the ground bounce at the same depth. To achieve this, we modified the algorithm proposed in [3] as given below, to increase the robustness for the cases of the mines that are buried closer to the surface. First for each downtrack plane, every column's maximum value is found and their positions are averaged.

$$Find, maxpos(j) = k_j \;\; such\ that \left| I(j,k_j) \right| > |I(j,l)| \quad \forall_{\substack{l=1,2\ldots N \\ l \neq k_j}}$$

$$if \;\; |k_j - k_{j-1}| > 10$$

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$$Find, max_2pos(j) = m_j \;\; such\ that \left| I(j,k_j) \right| > \left| I(j,m_j) \right| > |I(j,l)| \quad \forall_{\substack{l=k_j-5,k_j-4,\ldots,k_j+4,k_j+5 \\ l \neq k_j}}$$

$$if \; \frac{\left| I(j,m_j) \right|}{\left| I(j,k_j) \right|} > 0.6 \,, g_j = m_j$$

$$else \; g_j = k_j$$

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$$else \; g_j = k_j$$

$$\Delta j = g_j - \frac{1}{M} \sum_{j=1}^{M} g_j$$

$$\tilde{I}(j,k) = I(j, k - \Delta j)$$

where $\tilde{I}(j,k)$ is the shifted data, $I(j,k)$ is the original data, j is downtrack coordinate, k is the depth coordinate and g is the depth of ground estimation on $I(j,k)$. Figure 2 shows the original data $I(j,k)$ while Figure 3 shows the shifted data $\tilde{I}(j,k)$.

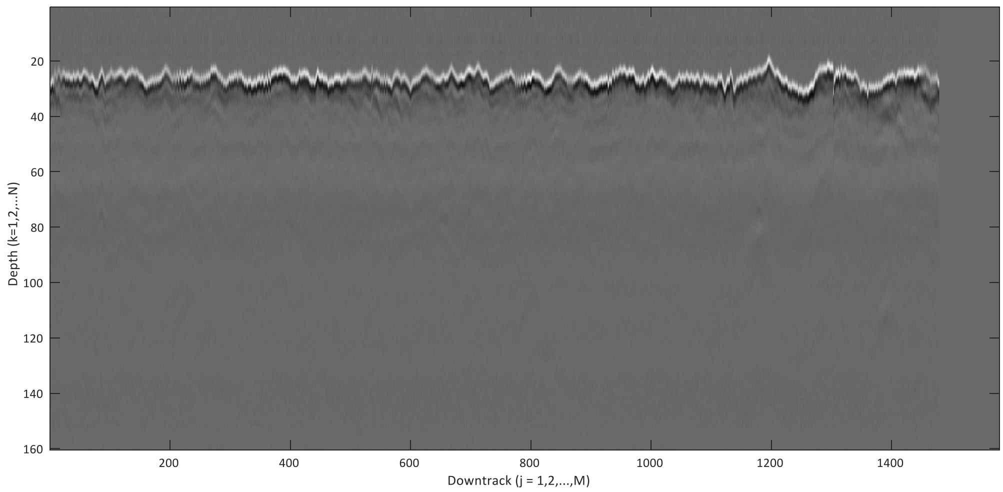

Figure 2. $I(j,k)$: Original data before shifting according to the ground bounce

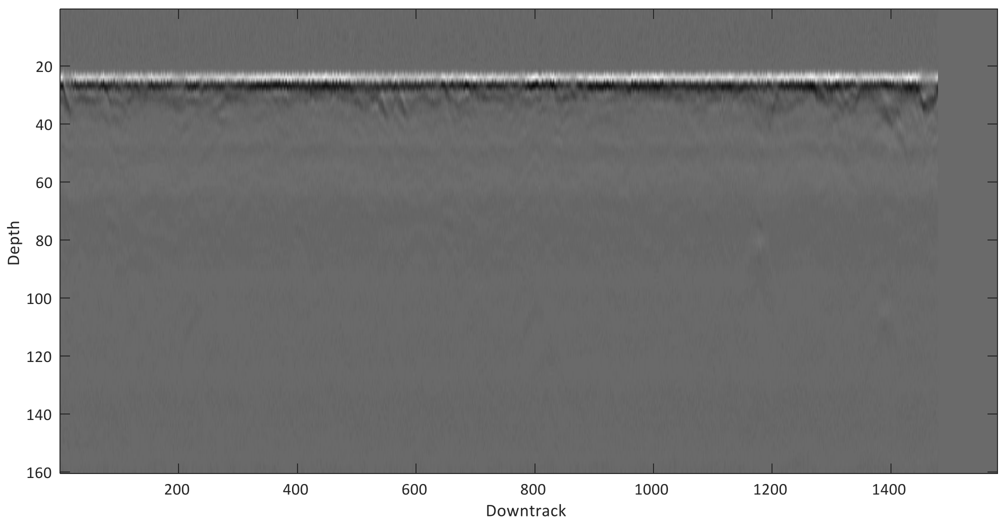

Figure 3. $\tilde{I}(j,k)$: The shifted data

Once $\tilde{I}(j,k)$ is found, the data above that ground bounce is omitted since it does not contain any valuable information, i.e.

$$\tilde{I}(j,k) = 0\,, if\ k < g$$

After ground bounce removal, the second preprocessing step, whitening, is applied to compensate the effect of the power loss of the signal due to the penetration through the ground. For whitening, the mean and the standard deviation of signal power is found for each depth. Then the mean is subtracted from the values at that depth and the result is divided by the standard deviation.

$$\tilde{I}(j,k) = \frac{\left(\tilde{I}(j,k) - \frac{1}{M}\sum_{x=1}^{M}\tilde{I}(x,k)\right)}{\sqrt{var\left(\tilde{I}(l,k)\right)}}\ , \qquad l = 1,2,\ldots M$$

This method achieves normalizing the data at each depth and avoiding the effect of signal dissipation. After these two steps, proposed pre-screener algorithm is applied on the filtered data.

III. KERNEL LEAST MEAN SQUARE BASED PRE-SCREENER

In this work, KLMS method is proposed as a pre-screener. KLMS is an improvement over the LMS algorithm, which is an adaptive solution. The only difference is that instead of using the signal value directly, KLMS uses the value that corresponds to the signal in the kernel space. The most widely used kernels are the polynomial kernel (3) and the Gaussian kernel (4).

Mathematical expression of KLMS algorithm's a-priori error is given at (1). The input ($\tilde{u}$) – output ($\tilde{y}$) relation after N step training is given at (2).

$$\boldsymbol{e_n^a = y_n - \mu \sum_{i=1}^{n-1} e_i^a K(u_i, u_n)} \qquad (1)$$

$$\boldsymbol{\tilde{y} = \mu \sum_{i=1}^{N} e_i^a K(u_i, \tilde{u})} \qquad (2)$$

$K(u_i, u_j)$ represents the kernel at (1) and (2). For the proposed study, the kernel is chosen as the Gaussian kernel (3). The polynomial kernel shown on (4) can also be tested.

$$K(u_i, u_j) = \exp\left(-a\left\|u_i - u_j\right\|^2\right) \qquad (3)$$

$$K(u_i, u_j) = ({u_i}^T u_j + 1)^p \qquad (4)$$

where a is the kernel variance and p is the polynomial degree of the polynomial kernel.

A. Blob Based Pre-Screener

The buried landmines have a blob like shape when observed on C-Scans, i.e. when a single depth layer is taken into account. The blob based pre-screener proposed in this work detects blob like shaped object by applying an asymmetric 2D Gaussian shaped filter to each depth layer. Then a threshold is applied to the results.

IV. EXPERIMENTAL RESULTS

The real data that the algorithms were applied on are collected using NIITEK's GPR panel with 12 sensors at the field of IPA Defence at METU, Ankara, Turkey. The field is 15 meters long, and consists of 4 different lanes with different types of soil. The GPR panel integrated to the robot is shown on Figure 1.

Also, simulation data have been generated using gprMax [7] simulation program. In the program, the radar properties are chosen close to the NIITEK GPR panel properties. On the other hand, since simulation of one sensor scanning of a domain with sizes Crosstrack=0.5 m, Downtrack=1 m, depth=0.65 m lasts about 24 hours when the PC is dedicated to the simulation, only one sensor, as opposed to 12 sensors, has been simulated. Several simulations with different material types with basic geometrical shapes (sphere, rectangular prism, circular prism) buried underground at different depths have been made.

For KLMS, the dictionary size is chosen as 144 or 96 according to the tests carried out. It corresponds to 12 or 8 downtrack values for each sensor. μ is chosen as 0.01 according to the experiments carried out. For a, several values were tested between 1 and 5. As it is stated at [2], selecting too high or too low values for a can affect the algorithm performance. Likewise, [4] states that μ should be chosen carefully as it may result in a divergence. In our experiments, after the training, dictionary is refreshed whenever new data with high error is found. When the learning rate is too small, the convergence speed is slow. On the other hand, when the learning rate is too big, the data estimation may start to diverge. Thus, learning rate is chosen accordingly.

For the blob based pre-screener, the size of the blobs range from 8 x 4 (Downtrack x Crosstrack) to 20 x 12 (Downtrack x Crosstrack).

KLMS vs LMS	KLMS (Dictionary Size=96)		KLMS (Dictionary Size=144)		LMS (9x7 window)	
	False Alarm	True Positive	False Alarm	True Positive	False Alarm	True Positive
Heterogeneous Soil	40	205	41	205	35	205
Average Processing Time	0.014 Seconds/Crosstrack layer		0.015 Seconds/Crosstrack layer		0.075 Seconds/Crosstrack layer	

Table 1. KLMS algorithm compared with LMS algorithm in terms of FAR and processing time

Effects of KLMS Kernel Variance	KLMS (Dictionary Size =96)		KLMS (Dictionary Size =144)	
a	False Alarm	True Positive	False Alarm	True Positive
$a =$ 1.25	79	205	71	205
$a =$ 2.5	55	205	59	205
$a =$ 5	40	205	41	205

Table 2. Results obtained with different variance values

The false alarm and true positive rates of KLMS and LMS algorithms run on the same data sets are given in Table 1. Both algorithms have only one true negative on the sample data set, which shows that the algorithm has %99 detection rate. However, false alarm rates are high. As it is seen in Table 1, application of LMS algorithm on one Crosstrack plane takes about 0.075 seconds according to the measurements made. On the other hand, application of KLMS algorithm on one Crosstrack plane takes about 0.014 seconds. These processing times do not include pre-processing times. Possible target areas detected by the KLMS algorithm are shown on Figure 4 with the areas surrounded by a red rectangle.

After the KLMS is applied, the result of blob based pre-screener is multiplied with the result of the KLMS. It decreases the number of false alarms. Figure 4 shows the result of KLMS itself while Figure 5 shows the result of KLMS and blob based detector combined. Figure 6 shows the bird's-eye-view of both KLMS only and combined results.

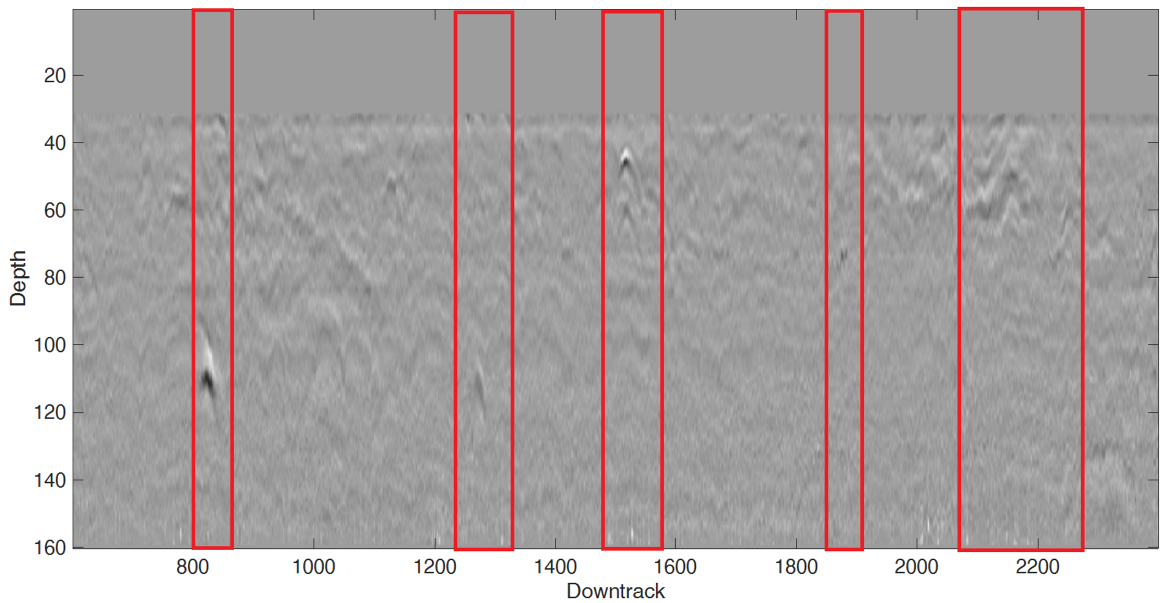

Figure 4. The threats found (shown in red rectangles) as a result of KLMS method before the blob based filter is applied

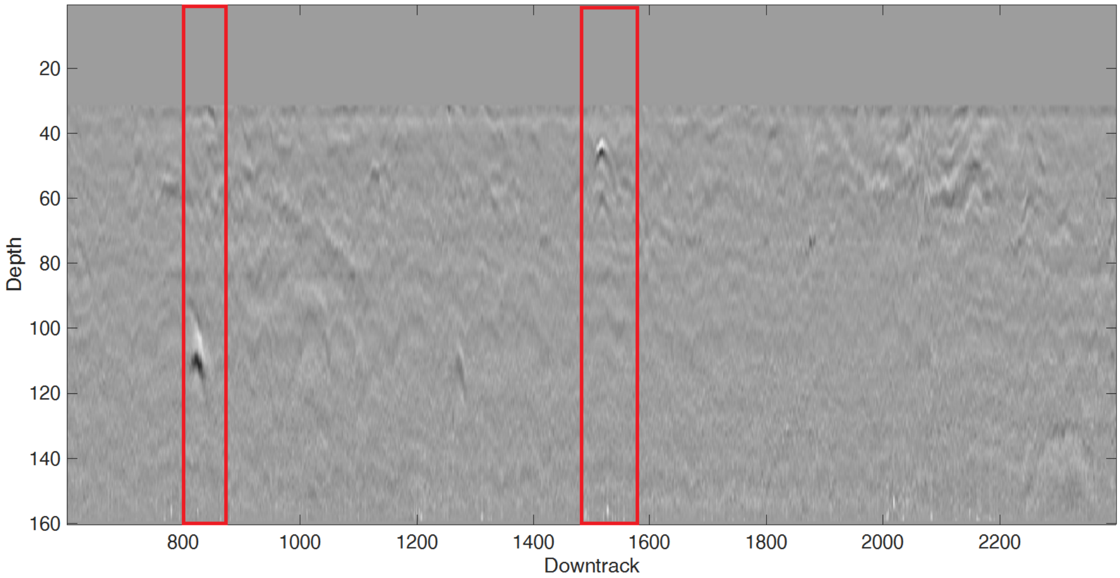

Figure 5. The threats found (shown in red rectangles) after the blob based filter is applied

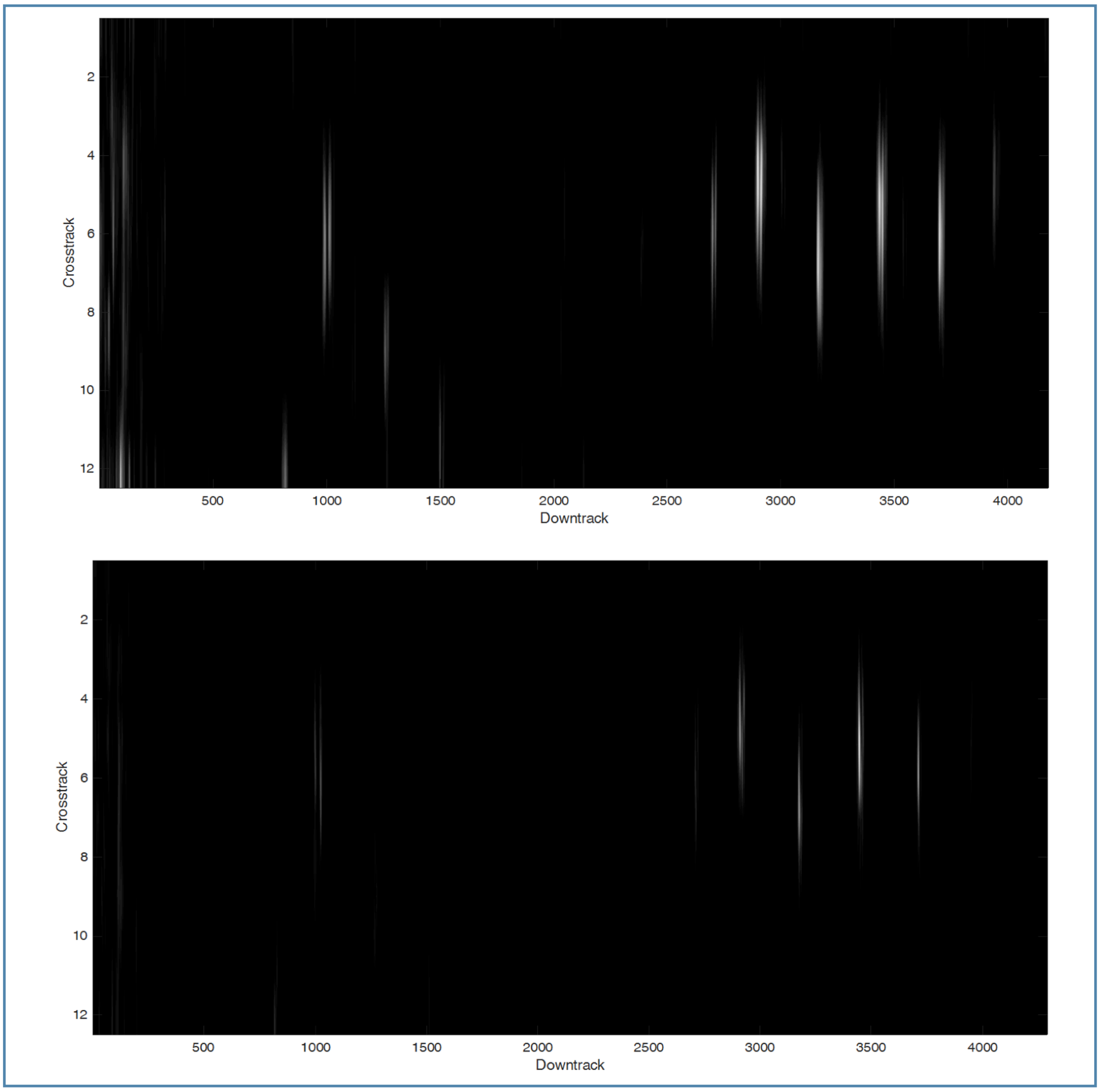

Figure 6. The bird's-eye-view of the field where the white areas represent possible threats. The upper figure shows the KLMS only result. The below figure shows the KLMS and blob based pre-screener combined.

V. CONCLUSION AND FUTURE WORK

KLMS algorithm is an adaptive algorithm of which real time processing is possible. According to the results of this work, KLMS can be an alternative to the LMS method for pre-screening of GPR data. Further, if it is combined with blob based pre-screener, the performance can be increased. For future work, polynomial kernel will be tested and weighted fusion using pre-screener algorithms will be applied.

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