INFRARED LAND MINE DETECTION BY PARAMETRIC MODELING

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ABSTRACT

A parametric model for the infrared signature caused by a buried land mine is presented. Further, a detector is calculated for the case where the background noise can be described by an autoregressive process. The detector separately estimates the parameters of the mine and the noise in an alternating fashion. The estimates are then used in the likelihood ratio test. Simulations show that significant gains in performance can be achieved as compared to the standard detector used, which correlates the infrared image with the known mine shape and thresholds the square of the output.

1. INTRODUCTION

Detection of land mines recently has gained considerable interest in the research community. The quest for removal of buried mines is driven by the fact that most victims are innocent people suffering long after the battles have ended. Traditional techniques are both dangerous and time consuming, urging the need for more effective methods. Techniques such as Ground Penetrating Radar(GPR), advanced metal detectors, acoustic sensing, have among others been investigated for this task. A description of different evolving methods can be found in [1]. One of the techniques that has gained the most interest is the use of optical sensing. Detection of buried land mines using optical methods is possible principally by using the infrared wavelengths.

In short, the thermal contrast appearing on the surface due to a buried land mine is caused mainly by three phenomena. First, the mine and soil have different thermodynamical properties. Thus, as the soil is heated up in the morning, or cooled down in the afternoon, the soil and the mine will react differently. Secondly, the presence of the mine interferes with the heat flow constantly moving up and down down through the soil as the surface is either heated up by solar radiation, or is cooled down due to the lack of solar radiation. Thirdly, the presence of the mine prevents the natural moisture flow in the soil. For instance if it has been raining, the soil above the mine contains more moisture than the soil in the surroundings, changing the thermal properties of the soil above the mine. For a thorough description of the physical processes that govern the mine signature, see [5]. Problems occur when designing a detector, since the signature of a buried land mine varies significantly depending on external parameters such as weather, soil moisture, solar radiation, burial depth, and time of burial, among others.

In this paper we present a way of circumventing this problem by modeling the variety of mine signatures in a parametric way. Subsequently, the paper presents a test that detects the proposed signature model, if it is embedded in spatially colored noise. To enable implementation of such a detector, the noise properties are also modeled by means of a set of parameters.

2. DATA MODEL

One of the problems when using infrared imaging to detect land mines is that the infrared signature is embedded in noise caused by fluctuations of the soil and the surface. Assume that we record an infrared image $i(x,y), x \in -N,...,N, y \in -M,...,M$. Provided that a mine is present, the infrared image can be modeled as

$$i(x,y) = s(x,y;\theta_s) + n(x,y;\theta_n) \tag{1}$$

where $s(x,y;\theta_s)$ is the associated signature of the buried mine and $n(x,y;\theta_n)$ represents the noise. The noise then includes all contributions from the background. The variations of the possible signatures are modeled by means of the parameter vector θ_s, while the characteristics of the noise are modeled by the parameter vector θ_n.

2.1. Infrared Signature Model

As mentioned, the signature can vary significantly due to external effects. For the same buried mine, the signature will have different amplitudes due to external parameters, such as moisture, burial depth, and solar radiation. For instance it should be noted that the signature can change sign due to rain. Further, the shape of the signature is also affected by the burial depth. This is schematically illustrated in Figure 1, which shows a cross-section of the soil, where the temperature is shown as intensities on the surface. To the left, a mine is buried at a shallow depth, causing the shape of the signature to look very much like the shape of the mine, and giving rise to a strong signature. On the other hand, if the mine is buried at a larger depth, as shown to the right in the image, the signature is much weaker, and the shape has been blurred due to the heat and moisture flow in the soil.

One way of obtaining an approximation of the thermal signature is to simulate the heat equation, by means of the Finite Element Method(FEM) [5]. In Figures 2a and 2b, the

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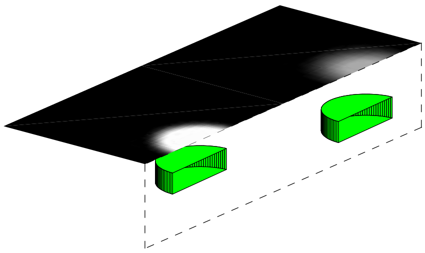

Figure 1: *A shallowly buried mine has a signature that is close to the top-view shape of the mine while a mine buried deeper show a weaker signature that has been smoothed by the thermal propagation in the soil.*

signature of two different scenarios are shown while using this approach[1]. The intentional use, as presented in [5], is mainly to understand which processes contribute to the signature in order to predict when a signature is detectable. Nevertheless, by using the surface nodes of such a model, the apparent temperature at the surface can be modeled yielding the infrared signature. One of the disadvantages in obtaining the signature this way is that we need separate models if the physical parameters, such as the burial depth, differ. Since we do not know for instance the burial depth a priori, this approach would require testing the infrared image to a set of different models.

An alternative approach is to model the set of possible mine signatures by means of a few parameters. This is attractive since we do not need to find all the parameters that govern the signature, but can model the whole set of possible signatures. Such a model would have to incorporate the possibility of different smooth signatures, as well as the possibility of having different scaling, possibly negative, of the signature. We propose to model the set of possible infrared signatures as a scaling with the parameter α of the convolution between the top-view shape of the buried object, $m(x, y)$ and a smoothing kernel depending on a smoothing parameter β:

$$s(x, y : \theta_s) = \alpha \cdot e^{-1/\beta(x^2+y^2)} * m(x, y) \qquad (2)$$

Here, $*$ denotes two-dimensional convolution. Also, the shape of the mine, $m(x, y)$, is assumed to be known, for instance circular shaped for a cylindrical mine. In Figures 2c and 2d, the deviation from the corresponding FEM model is shown when the parameters, α and β are fitted to the corresponding FEM model. As can be seen the differences is negligible compared to the overall signature.

2.2. Background Model

The noise will inherently be spatially correlated due to thermal propagation and surface structure. We model the colored noise by means of a quarter-plane causal Auto Regressive (AR) process [2]. The process can be described by

$$n(x, y) = -\sum_{\substack{k=0 \\ (k,l)\neq(0,0)}}^{K-1} \sum_{l=0}^{L-1} a_{k,l} \cdot n(x-k, y-l) + e(x, y), \qquad (3)$$

where $e(x, y)$ is white Gaussian noise. The process is then described by the parameters $\theta_n = [a_{0,1}, a_{0,2}, ..., a_{K-1,L-1}]^T$. Autoregressive models mainly have two advantages:

- The parameters can easily be estimated from data by means of the least-squares method.
- The whitening of an AR process can be obtained using an FIR filter.

Both these properties will be explored later when implementing the detector. For the AR model to be appropriate, the noise has to be stationary and zero-mean. If this is not satisfied for the disturbances in the infrared image, preprocessing is required. The noise models the infrared image for the no-mine scenario. For the purpose of modeling the image statistics, there are more accurate methods within the area of texture analysis [6]. The complexity of such models, though make them impractible to use for our purposes.

3. DETECTION

Let the hypothesis $\mathcal{H}_1$ define the scenario when a mine is present, and let $\mathcal{H}_0$ define the situation where no mine is present. The detector that, from the infrared image $i(x, y)$, decides whether a mine is present or not, can be formulated into the composite hypothesis test [3], deciding between the hypotheses

$$\begin{array}{ll} \mathcal{H}_0 : & i(x, y) = n(x, y; \theta_n) \\ \mathcal{H}_1 : & i(x, y,) = s(x, y; \theta_s) + n(x, y; \theta_n). \end{array} \qquad (4)$$

Here, $\theta_s = [\alpha\ \beta]^T$ represents the unknown parameters of the mine signature, and θ_n represents the unknown parameters

[1] The author would like to thank Stefan Sjökvist for providing these models.

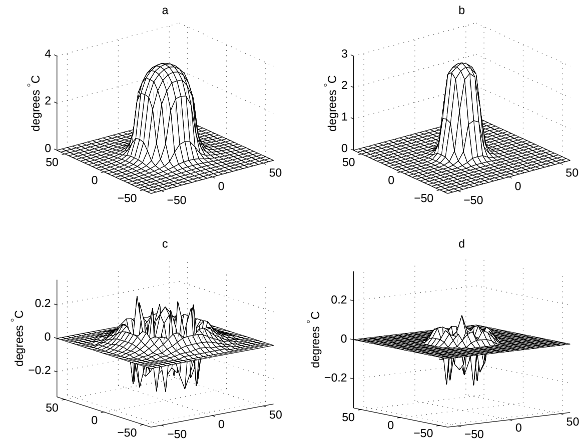

Figure 2: *From left to right and top to bottom: a)-d). a) The signature of a Anti-Tank (AT) mine buried at 5cm as given by FEM modeling. b) The signature of a shallowly buried (5mm) plastic Anti-Personnel (AP) mine as given by FEM. c) The error when fitting the parametric model to the FEM model for the AT mine given in a). d) The corresponding error when fitting the AP mine in b).*

of the autoregressive noise. For the case when both the signal and the noise have unknown parameters, it is difficult to obtain an analytical solution to the commonly used Generalized Likelihood Ratio Test (GLRT). Only for specific signals $s(\theta_s)$, such as DC levels and sinusoids, is it possible to obtain an analytical GLRT, see [4]. Further, for linear models, an alternative approach is to use the Rao test [3]. In our case this is not possible since, due to the non-linear parameterization in $s(\theta_s)$, the Fisher information matrix regarding the signal parameters becomes singular under $\mathcal{H}_0$.

3.1. Proposed approach

The approach taken in this paper is to estimate the unknown parameters under the hypothesis $\mathcal{H}_1$, then use these as the true values when applied to the Likelihood Ratio Test (LRT). To simplify notation, let $\mathbf{i}$ be any vectorized version of $i(x,y)$ and let $\mathbf{s}$ and $\mathbf{n}$ be defined with the same indexes. Further, let $\mathbf{R} = E\{\mathbf{n}\mathbf{n}^T\}$. Given estimates, $\hat{\theta} = [\hat{\theta}_s\ \hat{\theta}_n]^T$, the conditional likelihood functions under the two hypotheses equals

$$\begin{aligned} f(\mathbf{i};\mathcal{H}_1,\hat{\theta}) &= c|\mathbf{R}(\hat{\theta}_\mathbf{n})|^{-1/2}\ \mathrm{e}^{-\frac{1}{2}(\mathbf{i}-\mathbf{s}(\hat{\theta}_s))^T\mathbf{R}^{-1}(\hat{\theta}_n)(\mathbf{i}-\mathbf{s}(\hat{\theta}_s))} \\ f(\mathbf{i};\mathcal{H}_0,\hat{\theta}) &= c|\mathbf{R}(\hat{\theta}_\mathbf{n})|^{-1/2}\ \mathrm{e}^{-\frac{1}{2}\mathbf{i}^T\mathbf{R}^{-1}(\hat{\theta}_n)\mathbf{i}}, \end{aligned} \tag{5}$$

where c is a constant. The LRT, given the estimated parameters, can then be formulated as

$$\frac{f(\mathbf{i};\mathcal{H}_1,\hat{\theta})}{f(\mathbf{i};\mathcal{H}_0,\hat{\theta})} \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \gamma \Leftrightarrow \left(\mathbf{R}(\hat{\theta}_n)^{-\frac{1}{2}}\mathbf{s}(\hat{\theta}_s)\right)^T\mathbf{R}(\hat{\theta}_n)^{-\frac{1}{2}}\mathbf{i} \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \gamma',$$

$$\Leftrightarrow \sum_{x,y}(\hat{a}_{x,y} * s_{x,y;\hat{\theta}_s})(\hat{a}_{x,y} * i_{x,y}) \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \gamma' \tag{6}$$

where $\hat{a}_{x,y} * s_{x,y;\hat{\theta}_s}$ denotes the convolution between $s_{x,y;\hat{\theta}_s}$ and the AR model parameters $\hat{a}_{k,l}$ in $\hat{\theta}_n$. The last step follows from the fact that $\mathbf{R}(\hat{\theta}_n)^{-\frac{1}{2}}\mathbf{x}$ represents the whitening of the signal $\mathbf{x}$ with respect to the color of $\mathbf{n}$. Since $n(x,y;\hat{\theta}_n)$ is modeled as an AR process , the whitening can be accomplished by convolving the signal $\mathbf{x}$ with the autoregressive parameters. This can be seen as a matched filter, where the whitened image, is correlated with the whitened version of the estimated signal. It should be noted that if no mine is present, β is unidentifiable. Nevertheless, in this case $\hat{\alpha}$ will be small and lead to a very weak signature. The output of the matched filter will therefore be small in this case. We remark that obtaining a threshold γ' that guarantees a fixed probability of detection/probability of false alarm is not straightforward.

3.2. Estimator for the unknown parameters

To implement the detector given by (6) we need to estimate $\theta = [\theta_s\ \theta_n]^T$ under $\mathcal{H}_1$. Under $\mathcal{H}_1$, $i(x,y)$ is given by (1), the signature is modeled by (2) and the AR noise is given by (3). By combining equations (1) and (3), $i(x,y)$ is:

$$\begin{aligned} i(x,y) = &-\sum_{\substack{k=0\\(k,l)\neq(0,0)}}^{K-1}\sum_{l=0}^{L-1} a_{k,l}\left[i(x-k,y-k)-s(x-k,y-l;\theta_s)\right] \\ &+ \quad s(x,y;\theta_s)+e(x,y). \end{aligned} \tag{7}$$

Since the driving noise, $e(x,y)$ is white, the least-squares estimator for θ becomes

$$\begin{aligned} \hat{\theta} \;=\; &\arg\min_{\theta}\sum_{x,y}\Bigg(i(x,y)-s(x,y;\theta_s) \\ &+\sum_{\substack{k=0\\(k,l)\neq(0,0)}}^{K}\sum_{l=0}^{L} a_{k,l}[i(x-k,y-k)-s(x-k,y-l;\theta_s)]\Bigg)^2 \end{aligned} \tag{8}$$

Further, since the driving noise is assumed to be Gaussian distributed, this also produces the Maximum Likelihood estimate. An analytical solution to (8) can be found only for specific signals $s(x,y;\theta_s)$, see [4]. Otherwise a non-linear minimization can be used, but since θ_n may involve many parameters this is undesirable.

Instead we solve (8) using an alternating approach. First, we derive an estimator for θ_n assuming that θ_s is known, and then an estimator for θ_s assuming that θ_n is known. We can iterate between the two and use the estimate from the previous step as values for the assumed known parameters. First, to solve for θ_n given an estimate, $\hat{\theta}_s$, define $v(x,y) = i(x,y) - s(x,y;\hat{\theta}_s)$ and $\varphi(x,y) = [-v(x,y-1),...,-v(x-K+1,y-L+1)]^T$. Now, we can write (8) as the linear regression

$$\hat{\theta}_n = \arg\min_{\theta_n}\sum_{x,y}\left(v(x,y)-\varphi^T(x,y)\theta_n\right)^2 \tag{9}$$

which has the solution [2]

$$\begin{aligned} \hat{\theta}_n &= \mathbf{R}_{\varphi\varphi}^{-1}\mathbf{r}_{\varphi v} \\ \mathbf{R}_{\varphi\varphi} &= \sum_{x,y}\varphi(x,y)\varphi^T(x,y) \\ \mathbf{r}_{\varphi v} &= \sum_{x,y}\varphi(x,y)v(x,y). \end{aligned} \tag{10}$$

Secondly, to estimate $\theta_s = [\alpha\ \beta]^T$ given the estimate $\hat{\theta}_n$ we write (8) as

$$\hat{\theta}_s = \arg\min_{\theta_s}\sum_{x,y}\left(\hat{a}_{x,y}*i_{x,y}-\hat{a}_{x,y}*s_{x,y;\theta_s}\right)^2, \tag{11}$$

where the convolution $\sum_{k=0}^{K-1}\sum_{l=0}^{L-1}\hat{a}_{k,l}i(x-k,y-l)$ is denoted by $\hat{a}_{x,y}*i_{x,y}$, and $\hat{a}_{x,y}*s_{x,y;\theta_s}$ is defined accordingly. Note that this corresponds to a whitening with the color of the autoregressive process. By incorporating the model for the mine signature given by (2), we get

$$\hat{\theta}_s = \arg\min_{\theta_s}\sum_{x,y}\left(a_{x,y}*i_{x,y}-\alpha e^{\frac{-(x^2+y^2)}{\beta}}*a_{x,y}*m_{x,y}\right)^2 \tag{12}$$

Since the expression is linear in α, it can be shown that the value of α that minimizes (12) can be expressed in β as

$$\hat{\alpha}(\beta) = \frac{f(\beta)}{g(\beta)} \tag{13}$$

where

$$\begin{aligned} f(\beta) &= \sum_{x,y}(a_{x,y}*i_{x,y})\cdot\left(e^{\frac{-(x^2+y^2)}{\beta}}*a_{x,y}*m_{x,y}\right) \\ g(\beta) &= \sum_{x,y}\left(e^{\frac{-(x^2+y^2)}{\beta}}*a_{x,y}*m_{x,y}\right)^2. \end{aligned} \tag{14}$$

By straightforward calculations the solution for the parameter β can be found by a one-dimensional maximization

$$\hat{\beta} = \arg\max_{\beta} \frac{(f(\beta))^2}{g(\beta)}. \tag{15}$$

To initiate the iterations, one can either start by estimating θ_s assuming $\{a_{k,l}\} = 0$, or start by estimating θ_n, assuming $\alpha = 0$. The first approach is preferable for high Signal-to-Noise Ratio(SNR), while the second is better for low SNRs.

4. PERFORMANCE SIMULATIONS

In the first example, low-frequency noise was generated using (3) with $\theta_n = [a_{0,1},\ a_{1,0},\ a_{1,1}]^T = [-0.3,\ -0.3,\ -0.4]^T$ and the variance of the driving noise $e(x, y)$ was set to one. Further, the size of the background image was set to (95×95), or $M = N = 47$, and when estimating the noise parameters it is assumed that $K = L = 3$, i.e., we estimate eight noise parameter. The scenario was set up to resemble the case where the mine is deeply buried, i.e, characterized by a weak signature (small α) which is blurred (large β). In the example $\alpha = 0.009$ and $\beta = 40$. The mine shape, $m(x, y)$ was chosen as a filled circle of radius 10 pixels, emulating a cylindrical shaped mine. Here the signal to noise-variance is low and both the signal and the noise have low-frequency characteristics. Hence, estimating the involved parameters is hard. The more similar the spectra are to each other, the more difficult it will be to estimate the parameters. Figure 3a shows the Receiver-Operating Characteristics(ROC) of three different detectors for the above described scenario. The ideal detector, implements the optimal LRT, using the true values for θ_s and θ_n. The squared matched filter is the detector that correlates the received image $i(x, y)$, with the known mine shape $m(x, y)$ and then threshold the square of the correlation. Note that the standard matched filter can not be used, because the sign of the amplitude is not known and can be negative. This detector actually equals the GLRT, assuming $s(x, y) = \alpha m(x, y)$ with unknown amplitude α, under white noise assumption[3]. The third detector is the proposed detector, as given by (6). Two iterations was used when estimating the unknown parameters, and the iterations where initiated by estimating the noise parameters. It can be seen that the proposed detector, for these parameters outperforms the squared matched filter, while it can not approach the performance of the ideal detector employing perfect parameter knowledge.

The performance of the proposed detector even as compared to the squared matched filter, varies with the underlying parameters. One can not claim that the proposed detector always outperforms the squared matched filter. This can be seen by simulating the same scenario as above but using $N = M = 1$, i.e., white noise, and a very small value of β. In this case, the squared matched filter is the GLRT. The simulations in Figure 3b show the scenario where a signature with parameters $\alpha = 0.07$ and $\beta = 10^{-6}$ was embedded in white noise of variance one. In this case the performance of the proposed detector actually equals that of the squared matched filter implementing the GLRT. This indicates that we do not loose significantly by estimating additional parameters and that the detector seems to be robust against different parameter values.

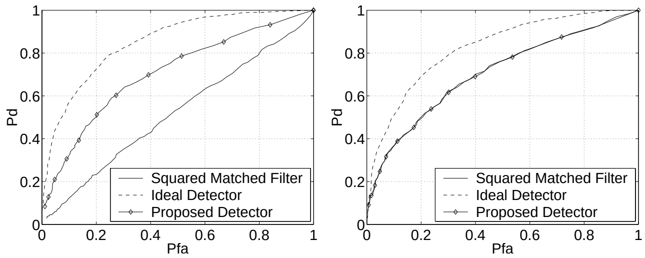

Figure 3: *From left to right: a)-b). a) Receiver-Operating-Characteristics(ROC) for the case modeling a deeply buried mine, in colored noise. b) ROC for the case of a shallowly buried mine in white noise*

5. CONCLUSIONS

Depending on physical parameters such as weather, soil type, burial depth, and time of burial, the infrared signature of buried land mines varies drastically. We proposed to use a parametric model where the signature is modeled by means of two parameters, one modeling the scaling, and one modeling the smoothing of the mine shape mainly due to burial depth. Based on the mine model and the assumption that the mine is embedded in autoregressive noise, a detector was derived. The performance of the detector was compared mainly that of the squared matched filter and indicates that for colored noise, the proposed detector outperforms the squared matched filter, while for white noise the performance of the two are the same. This indicates robustness as the the squared matched filter for white noise implements the GLRT. One problem of the proposed detector as to compared to the squared matched filter is that it is difficult to calculate the threshold given a certain probability of false alarm/probability of detection.

6. REFERENCES

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