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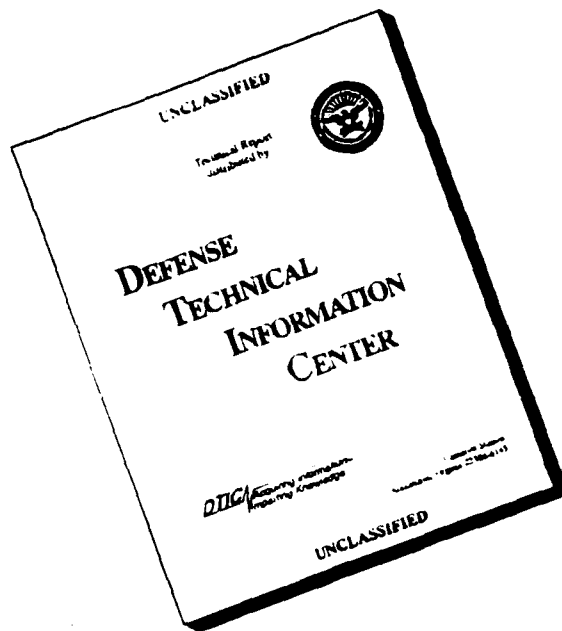
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ABSTRACT

In passive detection of small infrared targets in image data, we are faced with the difficult task of enhancing some characteristic of the target or signal while suppressing the clutter or background image noise. We reported that an effective means by which targets may be identified is to exploit characteristics which exist between scenes measured in different bands in the Long Wave Infrared (LWIR) region of the electromagnetic (EM) spectrum.¹ These methods are broadly termed multispectral techniques. In this paper we present a method by which a two-dimensional least-mean square (LMS) adaptive filter is used to distinguish between target and clutter using multispectral techniques.

1. INTRODUCTION

Passive detection of small targets embedded in infrared image data is a difficult task. In many cases, the target exhibits only a slight variation in temperature from the background clutter. Recently we showed that information from two bands from the thermal infrared region of the EM spectrum can be processed to cancel the ground clutter and improve the detectability of targets.¹

Image data has been modeled successfully as a Gaussian process with spatially varying mean and covariance.² In the optical and infrared wavelengths, small targets in image data carry information in the texture of the scene obtained by removing the local mean. Margalit, et al.³ demonstrates that when local mean removal is used on subimage sections, the image data begins to locally exhibit Gaussian characteristics. Using this fact, a likelihood ratio detection scheme is developed in which we may detect small optical (or infrared) targets by using two correlated data sets of the same scene.³ The detection statistic used reduces to the error in an LMS estimation of the data in one scene given the data in the other scene.

Multispectral algorithms, when used for target detection, exploit two facts.¹ First, the clutter from vegetation in image data from two bands in the long-wave infrared region of the EM spectrum are highly spatially correlated. Second, the infrared signature of manmade point targets embedded in clutter dominated scenes does not exhibit the same interband correlation properties. Manmade objects tend to be selective radiators, so their interband signature depends on view angle and wavelength. Using these two facts we introduce a two-dimensional LMS adaptive scheme which effectively locates small manmade targets in clutter dominated scenes by reducing the standard deviation of the clutter pixels while enhancing the strength of target pixels relative to the mean.

The idea is similar to that of the one-dimensional LMS adaptive event detectors described by Ahmed, et al.,⁴ and Clark and Rogers⁵ because small targets in image data represent transient events rather than signals which permeate the complete two-dimensional data field. Consequently, we will refer to the technique evaluated as an Multispectral Adaptive Event Detector (MAED). The algorithm is applied to multispectral infrared images of a wooded scene containing two army tanks. Comparison of the results to those obtained with the differencing algorithms developed in reference 1 is provided to illustrate the conditions for which the LMS adaptive procedures are advantageous.

Section 2 contains some preliminary discussion on the image model used and on the two-dimensional LMS algorithm. Section 3 gives a description of the two-channel MAED. Section 4 gives the details of the actual implementation and the results on the testing of the algorithm. Section 5 gives an analysis of the results and concluding remarks.

2.2 Two-dimensional adaptive LMS algorithm

The solution to many filtering, prediction, and interpolation problems is often formulated from a standpoint of optimizing some chosen performance criterion. If these data are assumed stationary, a physically realizable Wiener filter provides an approximation to an optimum solution in the sense of minimum-mean-square estimation error. A diagram of the two-dimensional Wiener filtering problem is shown in Fig. 2. As usual the process $w(m,n)$ is to minimize the variance of the difference between the desired signal, $s(m,n)$, and the estimate of the signal, $\hat{s}(m,n)$. The FIR filter that would produce the best linear estimate from the observed data would be the solution to an equation of the form

$$P(m,n) = \sum_p \sum_q w^0(p,q) R(m-p, n-q) \quad (4)$$

where w^0 is the desired filter-coefficient matrix, R is an approximation to the auto-covariance matrix of the input process, and P is an approximation to the cross-covariance matrix between the desired process and the input process. This process for obtaining the solution is unsatisfactory for image data for two main reasons. First, the inherent nonstationarities in image data render any approximations of the auto- and cross-covariance quantities somewhat useless. Second, even if the data for a given image are quasi-stationary, the computations involved are prohibitive.

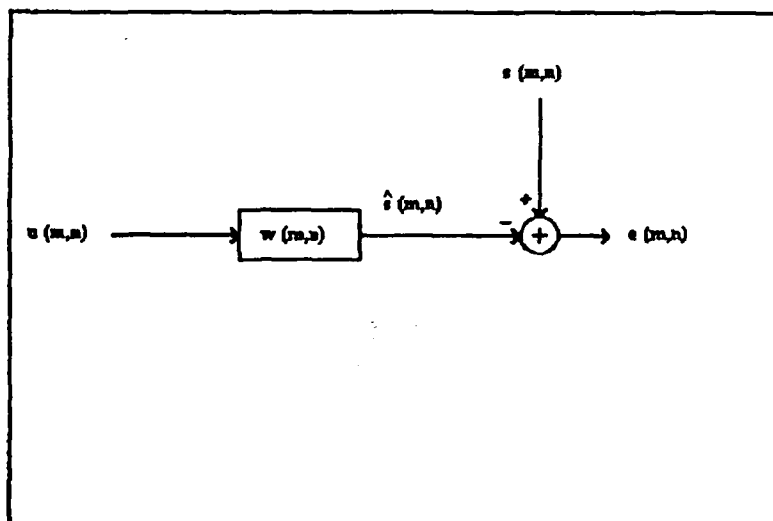


Fig. 2. Two-dimensional Wiener filter.

To circumvent these problems, one can approach the problem from another direction. The solution for the optimum filter was arrived at by taking the gradient of an estimate of the expected value of the squared error and solving for the zeros. The steepest descent algorithm uses a local approximation to the gradient to recursively solve for the minimum-mean-square error.^{7,8,9,10} Since the solution depends on the local character of the data and not on estimates of the second order statistics, stationarity is not such a problem. As long as the statistics of the data are not changing too rapidly, the filter can track the changes and maintain near-optimal performance. Fig. 3 shows a diagram of the LMS adaptive filter. The filter weights are updated at each pixel according to the recursion

$$w_i = w_{i-1} + \mu \hat{g} \quad (5)$$

where

$$j = Mm + n \quad (8)$$

or

$$j = m + Mn \quad (9)$$

depending on the scan. Here $w_j(\bullet, \bullet)$ are the steepest descent adaptive filter coefficients defined in section 2, $u_1(\bullet, \bullet)$ and $u_2(\bullet, \bullet)$ are the input channels, and $e(\bullet, \bullet)$ is the error signal whose variance is to be minimized by the adaptive filter. Fig. 4 shows a diagram of the complete system. We emphasize that the pertinent target information is contained in the texture (or high frequency) components of the signal. The high-pass filter at the processor input essentially removes irrelevant local mean (low frequency) information and returns the data to a near zero-mean Gaussian process with space varying second-order statistics. Although the two signals are decorrelated to an extent by the high-pass filters, a certain degree of spatial correlation exists at their outputs between neighboring pixels at short lags. These data at the output of the high-pass filters are also highly correlated between bands at the zeroth lag. Fig. 5 shows a section of image surrounding the treeline tank measured in two different bands after high-pass filtering. Fig. 6 shows the interdependence on close-neighboring pixels between bands is evident from the cross-correlation estimate of the data in the two segments. This short-term correlation can be used to effect an approximate Wiener minimum-mean-square-error filter.

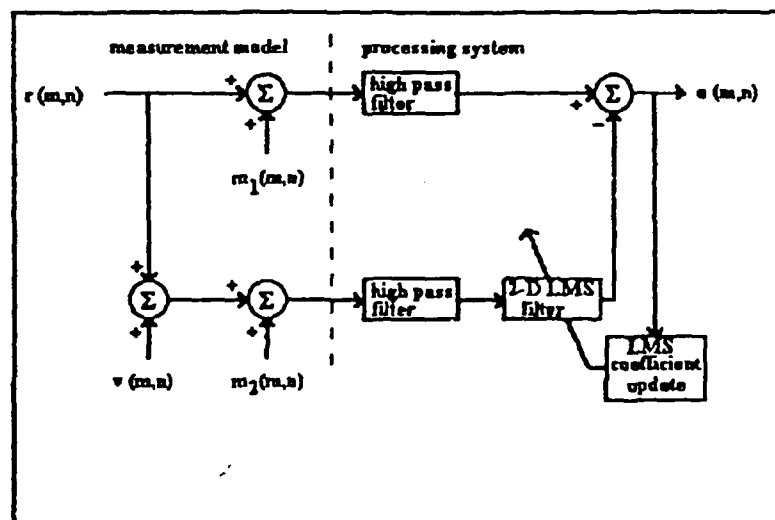


Fig. 4. Complete system.

We assume the nonstationarities (excluding the target) in the data after high-pass filtering are slowly varying over the extent of the signal. If the adaptive filter coefficients have converged on the local Wiener filter weights, the correlated part of the data will cancel at the output summing junction and the error channel will only contain the

minimum variance estimate of the residual error (containing the target) from the measurement model in Fig. 4. The idea is somewhat similar to that presented for one-dimensional correlated noise cancellation in references 8 and 9. In terms of multispectral-image processing, the technique is similar to the multilinear regression error model introduced in reference 11.

4. IMPLEMENTATION

As in most two-dimensional space domain filtering applications we have flexibility in selection of filter-mask geometry (i.e. causal, semicausal, or noncausal) and scan direction. The MAED relies on the spatial statistics of the data between bands to reduce the clutter contribution at the output. Abrupt changes in the data cause large errors and therefore the possibility of erroneous target detection. To increase the continuity of the data going to the filter, the filter scans the data back and forth across the image in the manner in Fig. 7(a). We have chosen a nonsymmetric half-plane (NSHP) geometry in Fig. 7(b) as our LMS filter mask.

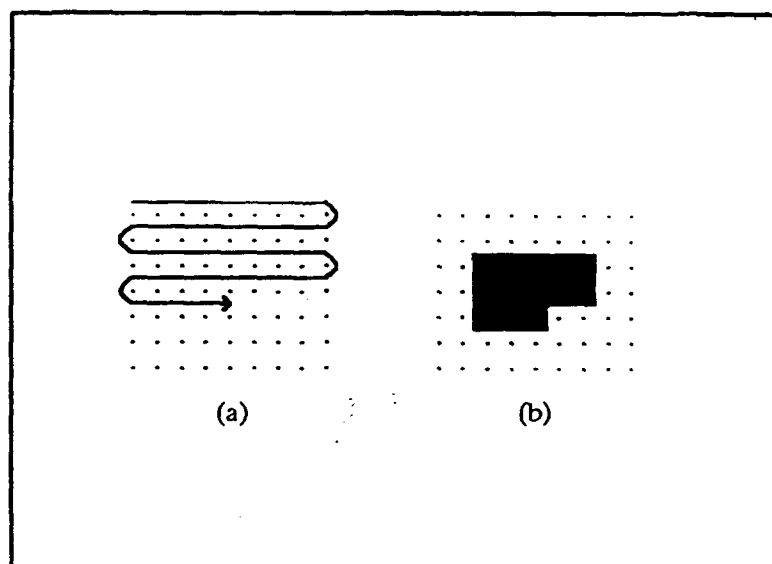


Fig. 7. Filter scan and mask.

Fig. 4 indicates both bands were de-meant with a 5 by 5 high-pass filter prior to the application of the adaptive filter to remove the information deficient large-scale variations in the scene and leave the information bearing texture surfaces. The adaptive-filter mask was started with all taps equal to zero. The algorithm was applied to the images with a relatively large adaptation constant ($\mu = 1\text{E-}5$) so that the filter could "learn" the interband characteristics of the signals. The final minimum variance error output was obtained by applying the algorithm to the images again with the mask obtained with the first pass and an adaptation constant one tenth the magnitude of the original one.

The raw image data used to test the algorithm was measured with Thermal Infrared Multispectral Scanner (TIMS).¹² The TIMS sensor measures EM radiation in six bands of the 8- to 12- μm infrared region. Measurements in two of the bands, band 1 (8.2 to 8.6 μm) and band 4 (9.4 to 10.2 μm) are shown in Fig. 8a and b. The scene

is composed of two predominant areas of distinctly different natural vegetation. The western portion of the scene is dominated by a dark wooded area and the eastern portion of the scene is dominated by a lighter grassy field. Although the scene contains several manmade objects, we are interested in enhancing the detectability of two tanks. One is located in the middle of the grassy field and the other is located along the treeline (see Fig. 9). The treeline target is located at pixel 160,114 and the field target is located at pixel 104,182. All coordinates are referenced to 0,0 at the top left hand corner of the scene.

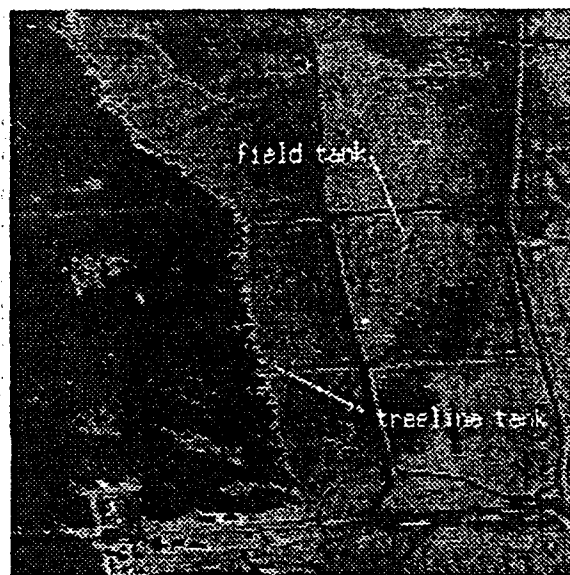
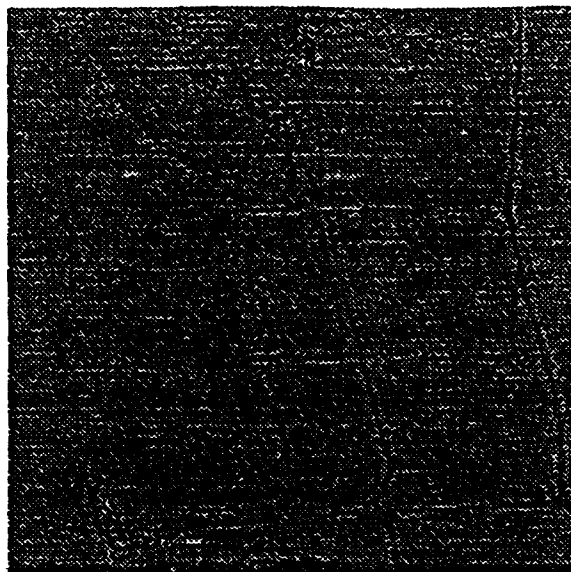


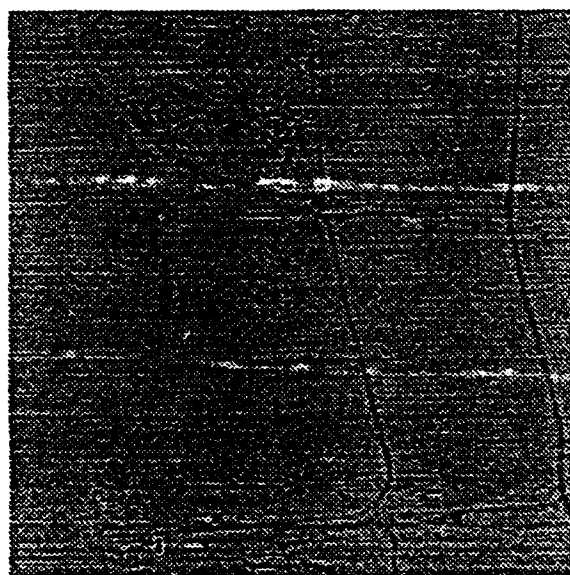
Fig. 9. Target locations.

Table 1 lists the pixel-color ratios between bands for the pixels in the neighborhood of the targets. We used a 32 by 32 subsection of the image surrounding the targets to compute the PSNR's. As mentioned before, a pixel-color ratio that deviates significantly from unity is desirable since it indicates dissimilarity in the target-pixel intensity between bands. We have chosen bands 1 and 4 for demonstration since they exhibit relatively low pixel-color ratios for both targets. We expect the result of the application of the algorithm to be better for the treeline tank since it shows a lower pixel-color ratio.

Table 2 compares the results of applying the two-dimensional LMS algorithm and the min-noise differencing algorithm to the data in bands 1 and 4.¹ For the LMS algorithm, band 1 was the reference channel and band 4 was the filtered channel. For the min-noise differencing algorithm, band 4 was subtracted from band 1. We show the output image data of the two algorithms in Figs. 10, 11, and 12.

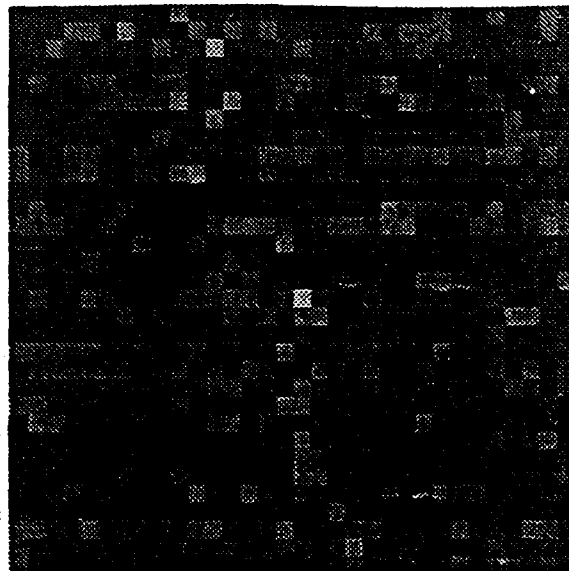


(a) LMS algorithm.

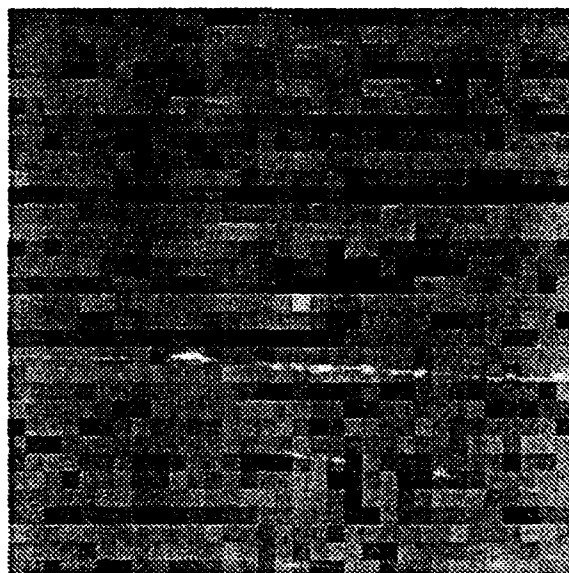


(b) Min-noise algorithm.

Fig. 10. Output image.



(a) LMS algorithm.



(b) Min-noise algorithm.

Fig. 12. Output image - treeline tank area.

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