

# AD-A265 862



## DOCUMENTATION PAGE

Form Approved  
OMB No. 0704-0188

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1. AGENCY USE ONLY (Leave blank)		2. REPORT DATE April 1993		3. REPORT TYPE AND DATES COVERED Professional paper	
4. TITLE AND SUBTITLE DETECTION OF POINT OBJECTS IN SPATIALLY CORRELATED CLUTTER USING TWO DIMENSIONAL ADAPTIVE PREDICTION FILTERING				5. FUNDING NUMBERS PR: ZW51 PE: 0601152N WU: DN300155	
6. AUTHOR(S) T. Soni, J. R. Zeidler, W. H. Ku					
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Naval Command, Control and Ocean Surveillance Center (NCCOSC) RDT&E Division San Diego, CA 92152-5001				8. PERFORMING ORGANIZATION REPORT NUMBER	
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES) Office of Chief of Naval Research Independent Research Programs (IR) OCNR-10P Arlington, VA 22217-5000				10. SPONSORING/MONITORING AGENCY REPORT NUMBER	
11. SUPPLEMENTARY NOTES  <b>DLMS SELECTED SUB JUN 16 1993</b>					
12a. DISTRIBUTION/AVAILABILITY STATEMENT  Approved for public release; distribution is unlimited.				12b. DISTRIBUTION CODE	
13. ABSTRACT (Maximum 200 words)  This paper studies the performance of a two dimensional least mean square (TDLMS) adaptive filter as a prewhitening filter for the detection of small signals in infrared image data. The spatially broad clutter with long correlation length is seen to be narrowband in the two dimensional frequency domain. This narrowband clutter is predicted and subtracted from the input, leaving the spatially small signal in the residual output. The output energy in the residual and prediction channels of such a filter is seen to depend on the correlation length of the various components in the input signal, thus permitting the separation of short correlation targets from the longer correlation clutter. False alarm improvements and detection gains obtained by using this detection scheme on thermal infrared sensor data with known target points is presented.  Published in <i>Record of the 26th Asilomar Conference on Signals, Systems, &amp; Computers</i> , Vol 1 pp 846-851.					
14. SUBJECT TERMS image processing signal detection				15. NUMBER OF PAGES	
				16. PRICE CODE	
17. SECURITY CLASSIFICATION OF REPORT UNCLASSIFIED	18. SECURITY CLASSIFICATION OF THIS PAGE UNCLASSIFIED	19. SECURITY CLASSIFICATION OF ABSTRACT UNCLASSIFIED	20. LIMITATION OF ABSTRACT SAME AS REPORT		

21a. NAME OF RESPONSIBLE INDIVIDUAL J. R. Zeidler	21b. TELEPHONE (include Area Code) (619) 553-1581	21c. OFFICE SYMBOL Code 804

<b>Accession For</b>	
NTIS GRA&I	<input checked="" type="checkbox"/>
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Distribution/	
Availability Codes	
Dist	Avail and/or Special
A-120	

Conference Record of  
**The Twenty-Sixth  
Asilomar Conference on  
Signals, Systems & Computers**

Volume 2 of 2

October 26-28, 1992

Pacific Grove, California

*Edited by*

Avtar Singh

San Jose State University

*Sponsored by*

Naval Postgraduate School

Monterey, California

and

San Jose State University

San Jose, California

*In cooperation with*

IEEE Signal Processing Society

IEEE Computer Society



IEEE Computer Society Press

Los Alamitos, California

Washington • Brussels • Tokyo

93 6 15 18 2

93-13491



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# Detection of Point Objects in Spatially Correlated Clutter Using Two Dimensional Adaptive Prediction Filtering\*

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## Abstract

*This paper studies the performance of a two dimensional least mean square (TDLMS) adaptive filter as a prewhitening filter for the detection of small signals in infrared image data. The spatially broad clutter with long correlation length is seen to be narrowband in the two dimensional frequency domain. This narrowband clutter is predicted and subtracted from the input, leaving the spatially small signal in the residual output. The output energy in the residual and prediction channels of such a filter is seen to depend on the correlation length of the various components in the input signal, thus permitting the separation of short correlation targets from the longer correlation clutter. False alarm improvements and detection gains obtained by using this detection scheme on thermal infrared sensor data with known target points is presented.*

## 1 Introduction

This paper addresses the problem of detecting small objects of very small spatial extent masked by

\*This work was supported by the NSF I/UC Research Center on Ultra High Speed Integrated Circuits and Systems (ICAS) at the University of California, San Diego, The Office of Naval Research and the National Science Foundation under grant #ECD89-16669 and the U.S. Naval Command Control Ocean Surveillance Center, R.D.T.&E. Division's Independent Research Program.

large and correlated clutter in image data. Methods based on image models and prediction of clutter are often applied to such applications [1, 2]. In the absence of a well defined model for the image data, the relevant parameters of the image clutter have to be estimated. Further in the case of nonstationary clutter these parameters may have to be continuously updated, before cancellation can be done. One dimensional adaptive linear prediction filters have been applied to the detection of narrow band signals embedded in non-stationary noise as well as to the removal of narrow band interference from broad band data [3-5]. In the first case a narrow band signal of interest is extracted from the prediction channel of the adaptive filter. In the second case the broad band signal of interest is extracted from the residual error of the adaptive filter [3, 4].

Adaptive filters analogous to the LMS and lattice implementations in one dimension, have been recently extended to two dimensions with applications in image processing [6, 7]. These algorithms update the filter weights based on the spatial coherence between the signal and noise components of the data and minimize the variance of the prediction error (residual) without explicit assumptions about the noise statistics. In this paper the performance of two dimensional least mean square (TDLMS) adaptive filters in the line enhancer configuration [8, 9] for the detection of small targets is studied. The components of the input image data are seen to be separated based on their correlation lengths. Thus long correlation clutter is predicted and can be cancelled from the input with the residual containing the signal of interest.

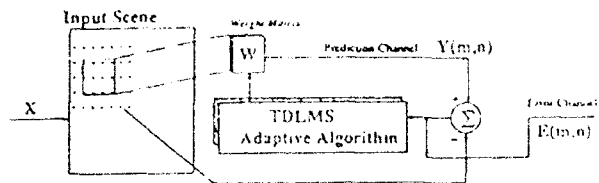


Figure 1: The Two Dimensional LMS Adaptive Filter.

A detector based on TDLMS prewhitening filters is applied to thermal multispectral infrared sensor data with an appreciable decrease in the number of false alarms.

Section 2 describes the TDLMS filter used briefly. Section 3 describes the separation of the input image energy into two channels, the prediction and the error channels based on the correlation lengths of the various components of the input image. Section 4 describes the gain obtained by such a filter and its dependence on the adaptive time constant of the filter. Section 5 describes the application of such preprocessing on a single band image from a multi-spectral data set and the improvement in the false alarm rate obtained.

## 2 The TDLMS Filter

The TDLMS adaptive filter [6] shown in Fig. 1 predicts an image pixel as a weighted average of a small window of pixels as

$$Y(m, n) = \sum_{l=0}^{N-1} \sum_{k=0}^{N-1} W_j(l, k) X(m-l, n-k) \quad (1)$$

where,  $X$  is the input image of size  $M \times M$ ,  $Y$  is the predicted image and  $W_j$  is the weight matrix at the  $j^{\text{th}}$  iteration. The window size (and hence the weight matrix) is  $N \times N$ . If the image is scanned lexicographically,  $j = mM + n$ . The predicted pixel value is compared with a reference image  $D(m, n)$ , which is a shifted version of the primary image in the line enhancer configuration. The error is then found as

$$E(m, n) = \epsilon_j = D(m, n) - Y(m, n). \quad (2)$$

In the absence of any knowledge of the statistics of the input, the LMS algorithm uses instantaneous estimates. Then, the steepest descent algorithm leads to the weight update equation

$$W_{j+1}(l, k) = W_j + \mu \epsilon_j X(m-l, n-k) \quad (3)$$

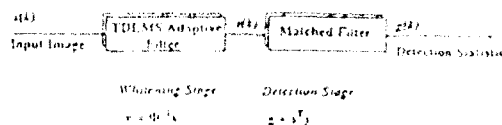


Figure 2: A two stage filtering and detection process

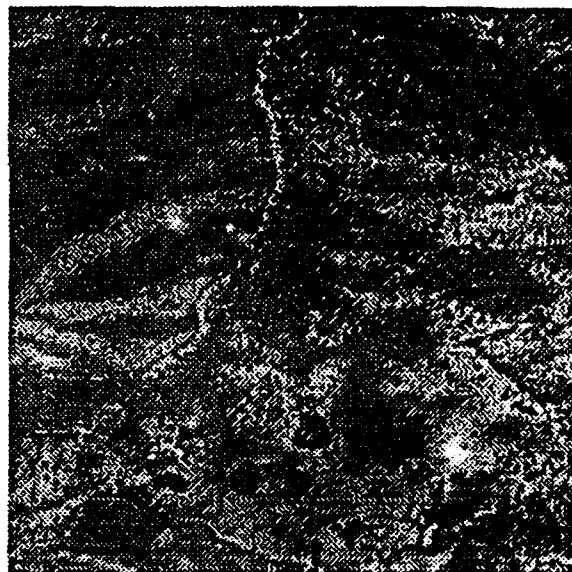


Figure 3: Signal with two components: object of interest at (100,100) with correlation spread of  $\sigma^2 = 2$  and spurious component at (200,200) with correlation spread of  $\sigma^2 = 98$ .

In our implementation a causal window with quarter plane support and a left to right lexicographic scan were used.

## 3 Separation by Differences in Correlation Lengths

In this section we present the results obtained by applying the two stage augmented detector shown in Fig. 2 to infrared image data. The adaptive filter used for prewhitening was the two dimensional adaptive LMS filter described in section 2. The image used was channel 4 of a 6 channel data set collected by the NASA Thermal Infrared Multispectral Scanner (TIMS) sensor and includes a rural background over the hills of Adelaide, Australia [10]. This section includes performance data from injected point

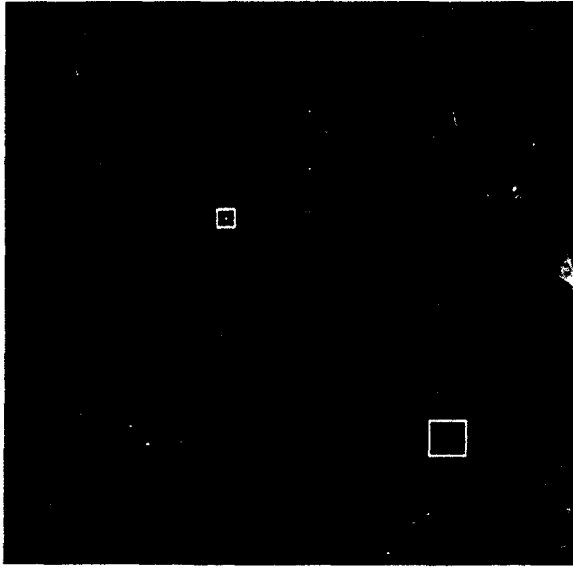


Figure 4: The residual channel output for Fig. 15. TDLMS was used with a 3x3 window and  $\mu = 1e - 7$ . LSBR at (100,100) = 16.024dB and LSBR at (200,200) = -16.75dB.

objects in TIMS sensor output data. The injected objects were utilized to illustrate the performance of the TDLMS filter for known object parameters.

To study the ability of the TDLMS prewhitener to separate signals based on spatial correlation, simulation studies were conducted with varying signal spread. The infrared signal model developed by Chan et. al. [11] was used for these simulations. This model leads to a Gaussian intensity function for the object, of the form

$$I(x, y) = \Gamma e^{-\left(\frac{(x-x_0)^2}{\sigma_x^2} + \frac{(y-y_0)^2}{\sigma_y^2}\right)} \quad (4)$$

where  $\Gamma$  is the maximum value of the object intensity function,  $(x_0, y_0)$  is the position of the center of the object, and  $(\sigma_x, \sigma_y)$  define the spatial spread of the object.

Two objects with symmetric Gaussian intensity functions ( $\sigma_x = \sigma_y$ ) defined by Eq.4 were inserted in the infrared background. Fig.3 shows an image with the two components inserted in the background. One is the object of interest (at pixel location 100,100) which is a Gaussian shape with  $\sigma^2 = 2$  and the other is a component of the same shape but with  $\sigma^2 = 98$ . Fig.4 shows the output of the TDLMS whitener for this case, where the component of the input with

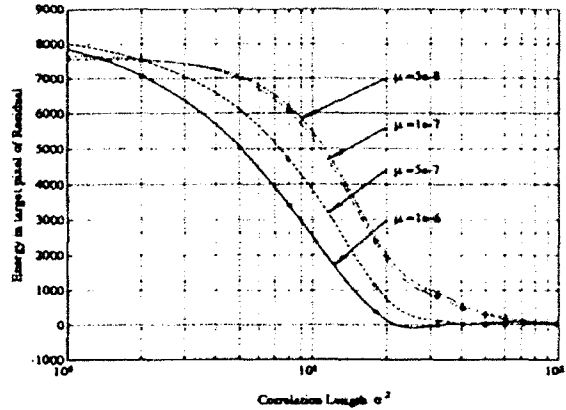


Figure 5: Energy at the pixel of interest in the output of the TDLMS as a function of the correlation length.

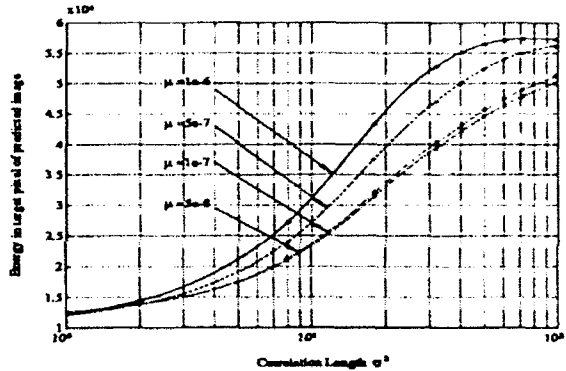


Figure 6: Energy at the pixel of interest in the prediction channel of the TDLMS as a function of the correlation length.

$\sigma^2 = 2$  is seen to be present, while the output for the  $\sigma^2 = 98$  case is absent.

Figure 5 shows the energy at the pixel of interest in the residual channel output of the TDLMS filter as a function of the signal correlation length ( $\sigma^2$ ). The pixel intensity at the output was observed for an object defined by Eq.4. It is seen that as the correlation length increases, the output energy at the pixel of interest decreases. Further, as shown in Fig.6, the energy in the prediction channel of the TDLMS filter correspondingly increases as the correlation length increases. It should be noted that the prediction channel output always contains the energy due to the non zero mean of the image which is seen in Fig.6 as a base level of  $1.3 \times 10^4$ .

In both these plots, depending on  $\mu$ , three regions

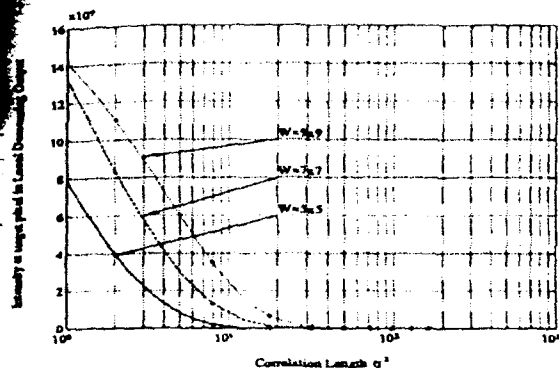


Figure 7: Energy at the pixel of interest in the output of the Local Demeaning filter as a function of the correlation length.

can be defined for this TDLMS adaptive filter:

- For objects with very small correlation length, the energy is contained almost totally in the output channel.
- For objects of long correlation length, the energy is absent from the output.
- For objects of intermediate correlation length, there is a partial decorrelation between the input and reference channels. In such cases the energy of the object is split between both channels.

A similar plot for the local demeaning filter is shown in Fig.7, and it is seen that the local demeaning filter is not able to provide a clear boundary between the two regions of differing correlation spread. Thus we see that the TDLMS is able to separate the object of interest from the clutter based on their correlation spread.

#### 4 Dependence on the Adaptive Time Constant

Fig.8 shows the behavior of the TDLMS filter as a function of  $\mu$  for a one pixel signal at two different signal intensities. There is an optimum value of  $\mu$  at which the maximum gain is obtained. If  $\mu$  is less than this optimum value, the filter is not able to converge to the statistics of the clutter. Hence the residual channel contains some component of the correlated clutter leading to a reduced gain. If the value of  $\mu$  is higher than the optimum, the adaptive filter is very

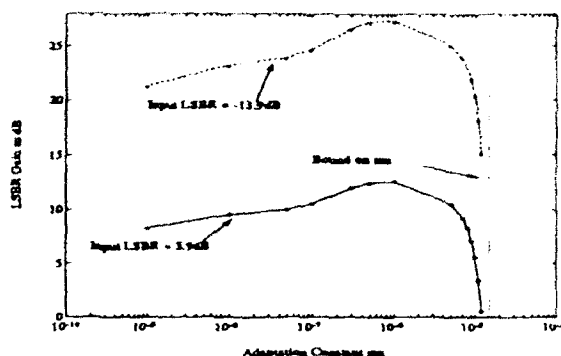


Figure 8: Gain vs.  $\mu$  for the Adelaide background with one pixel signal at (100,100).

sensitive to changes in the input, and some of the energy from the signal of interest is also predicted and cancelled. The misadjustment noise in the adaptive filter weights increases with  $\mu$  and is another factor contributing to the drop in gain as  $\mu$  increases.

#### 5 Reduction in False Alarm

In [10] Hoff et. al. identified 14 pixels which contained small objects in the TIMS sensor data described above. The 14 pixels were identified on the basis of multispectral data in the 6 separate bands. The locations designated in [10] are illustrated in by boxes in Fig.9. The pixel intensities at the output of the TDLMS filter (residual channel) is shown in Fig.10.

Fig.11 shows a high resolution intensity plot around the pixel (199,92). As seen in the figure, this pixel has a very high Local Signal to Background Ratio (LSBR) and this causes the object to be predicted. Fig.12 shows the corresponding output for this pixel. It is seen that there are a number of pixels in the local region with comparable intensity.

Fig.13 is a similar high resolution plot around the pixel (188,25). In this case, due to the low LSBR, the output (shown in Fig.14) is seen to contain energy due to the object pixel and there is a vast improvement in the detectability.

Though there is a loss in LSBR at some pixels it is seen that the detection performance of the filter improves considerably when the input image is processed by the TDLMS adaptive filter. For a threshold set to detect all 14 of the signals defined in [10], the number of false alarms in the image is significantly

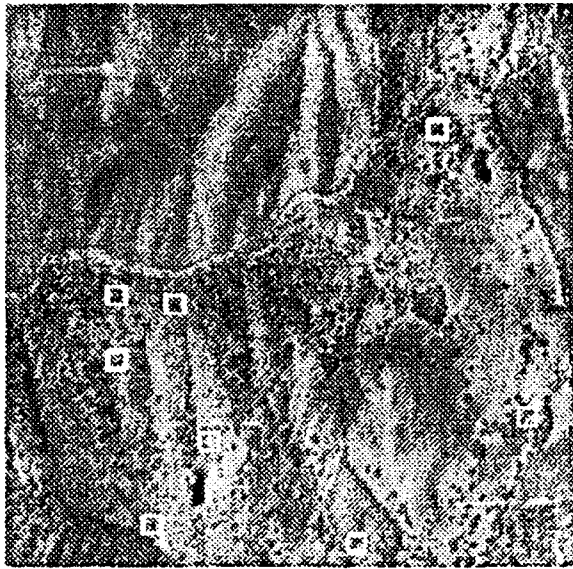


Figure 9: The infrared image data with the 14 pixels of interest. Note that some objects are clustered close to each other their enclosing boxes overlap.

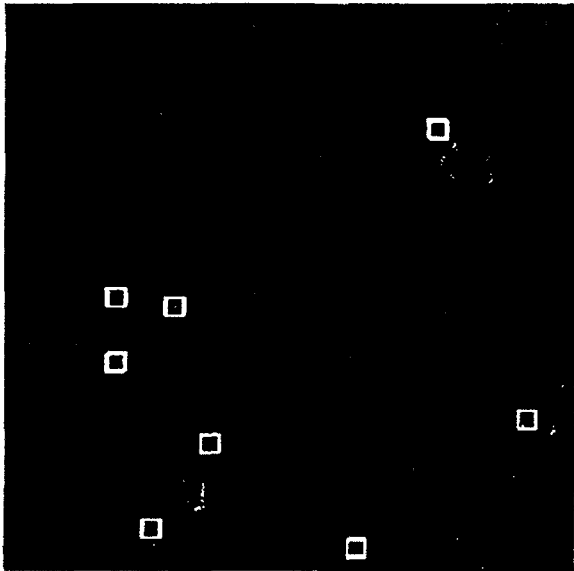


Figure 10: The infrared image data output from TDLMS adaptive filter for Fig.20.

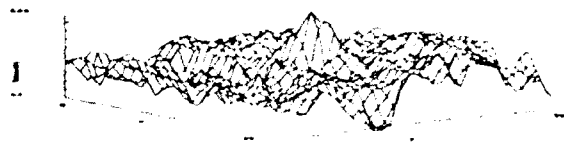


Figure 11: High resolution intensity plot of a 33x33 window around the pixel (199,92) before processing.



Figure 12: High resolution intensity plot of a 33x33 window around the pixel (199,92) after processing.

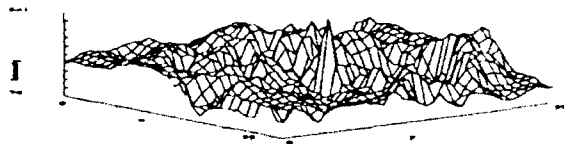


Figure 13: High resolution intensity plot of a 33x33 window around the pixel (188,235) before processing.



Figure 14: High resolution intensity plot of a 33x33 window around the pixel (188,235) after processing.



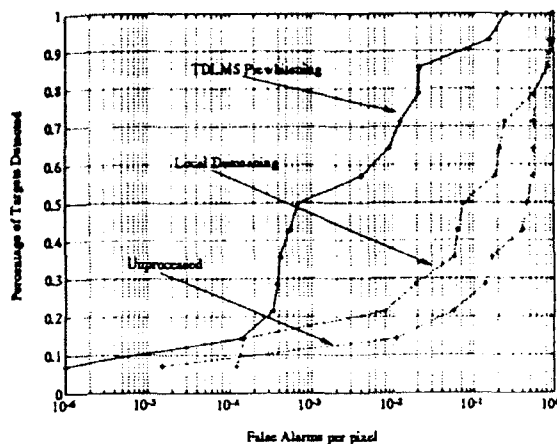


Figure 15: False alarms in the Adelaide image for known objects as the percentage of objects detected is lowered. TDLMS was used with  $\mu = 1e - 7$ .

reduced. If the detection criterion is changed to reduce the number of detected objects the number of false alarms in the image are further reduced. A plot of the percentage of objects detected as a function of the number of false alarms per pixel is shown in Fig.15. A similar plot for the local demeaning filter is also shown in this figure and it is seen that for a fixed number of false alarms per pixel the percentage of objects detected is much higher when the data is processed with the TDLMS based adaptive filter than with the local demeaning filter.

## 6 Conclusions

The line enhancer using a TDLMS adaptive prediction filter was applied to the problem of detecting a small object in infrared backgrounds. It is seen that for correlated background clutter, the adaptive filter predicts the background. The filter residual then contains the signal of interest, without the cluttering background.

The prediction characteristics of the TDLMS filter were seen to depend on  $\mu$  and permit the separation of components in the input of differing correlation lengths. This allows the detection system to distinguish between a signal of interest and a background cluttering phenomenon. It is seen that this cancellation of background clutter leads to a reduction in the number of false alarms obtained for any given threshold of the detector. For real data, it is seen that,

though the background clutter is not stationary, the TDLMS filter is able to predict parts of the clutter and cancel it, leading to an appreciable improvement in the detection performance.

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