Defence Science Journal, Vol. 59, No. 2, March 2009, pp. 166-174

REVIEW PAPAER

Image Pre-processing Algorithms for Detection of Small/Point Airborne Targets

Hari Babu Srivastava[1], Vinod Kumar[2], H.K. Verma[2], and S.S. Sundaram[1]

[1]Instruments Research & Development Establishment, Dehradun-248 008
[2]Indian Institute of Technology Roorkee, Roorkee-247 667

ABSTRACT

The problem of detecting small/point targets in infra-red imagery is an important research area for defence applications. The challenge is to achieve high sensitivity for detection of dim point like small targets with low false alarms and high detection probability. To detect the target in such scenario, pre-processing algorithms are used to predict the complex background and then to subtract predicted background from the original image. The difference image is passed to the detection algorithm to further distinguish between target and background and/or noise. The aim of the study is to fit the background as closely as possible in the original image without diminishing the target signal. A number of pre-processing algorithms (spatial, temporal and spatio-temporal) have been reported in the literature. In this paper a survey of different pre-processing algorithm is presented. An improved hybrid morphological filter, which provides high gain in signal-to-noise plus clutter ratio (SCNR), has been proposed for detection of small/point targets.

Keywords: Image pre-processing, algorithms, small/point airborne target, airborne target, SCNR, signal-to-noise plus clutter ratio, preprocessing filters

1. INTRODUCTION

The detection and processing of the small moving targets is an important subject in the area of signal/image processing, especially in the condition of complicated background and long ranges[1-13]. The difficulties for detection of small/point targets arise out of the facts that the target occupies single or few pixels on the image plane of the sensor, has no texture and shape information and has low signal-to-noise plus clutter ratio (SCNR). Target and background are both complex and dynamic. Pre-processing algorithms are used to enhance the SCNR to improve detection probability. The pre-processed image is passed to the detection algorithm to further distinguish between target and background/noise more accurately. Many pre-processing algorithms have been reported in the literature[14-35]. Some of them are spatial and others are either temporal or spatio-temporal in nature.

Median filter[14] is a popular filter for smoothing, enhancement and background prediction of image signals. It has been used very often to reduce "salt and pepper" noise in images. Median filtering is more effective than convolution when the goal is to simultaneously reduce noise and preserve edges. The generalisation of median filter is also called order-statistic (OS) filter. Morphology based filters[7] have been used as pre-processing filters. Other morphological filters like opening and closing filters have high importance in target detection application. Filters primarily used in 1-D signal processing like Gaussian[15], Weiner[16], etc. have been tried to judge their performance. The performance of mean[17], median[14], max-median[18], max-mean, selective median[19] and top-hat and bottom-hat filters[20] have been used in this simulation. The survey of the various pre-processing filters is presented in Section 2. A new pre-processing filter based on morphology called Improved Hybrid Morphological Filter, presented in the Section 3, is proposed in this paper.

2. PRE-PROCESSING FILTERS

The pre-processing algorithms are important in the small target detection. The usefulness of various spatial as well as temporal filters have been discussed. Irrespective of the method chosen, the pre-processing filter should perform the tasks of enhancing the isolated points (small-targets occupy single isolate pixel in the image plane), preserving the edge information and giving a weak response in the homogenous region. Some of the filters discussed in Section 2.1 have no direct application in small target detection, but they also have been studied in this survey.

2.1 Spatial Filters

A common method of target detection based on small size spatial filters works by predicting the background by image processing techniques and subtracting it from the original image[21]. Gaussian, statistical and morphological filters have been explored for small target detection applications. Recently, clutter suppression based on top-hat filter has been proposed by Jiancheng Yu[22], *et al*. Background inhibition network model and Renyi's entropy based pre-processing algorithms have been reported by Weidong[23]. Modified top-hat transform-based background suppression and target

Received 25 April 2008, revised 21 August 2008

detection have been presented by Xiangzhi Bai[24], *et al*. An integrated algorithm based on wavelet-transform and higher order is reported in statistic[25] for low SNR target detection.

2.1.1 Gaussian Filter

The Gaussian smoothing[15] operator is a 2-D convolution operator that is used to blur images and remove detail and noise. It uses a kernel that represents the shape of a Gaussian (bell-shaped) hump. In 2-D space, an isotropic (*i.e.*, circularly symmetric) Gaussian has the form:

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (1)$$

Gaussian smoothing uses this 2-D distribution as a point-spread function. This is achieved by convolution. Since the image is stored as a collection of discrete pixels, a discrete approximation to the Gaussian function is needed to perform the convolution. The kernel can be truncated at 3σ (σ: standard deviation) limits from the mean. Figures 1 and 2 show the difference between full Gaussian and truncated Gaussian kernels.

2.1.2 Statistical Filters

The statistical filters reported in literature for smoothing images are mean, median, max-median, max-mean and selective median.

Mean filter[14]: It is simple, intuitive and easy to implement. It reduces the amount of intensity variation between one pixel and the next. Each pixel value in an image is replaced with the mean of its neighbors, including itself. This eliminates pixels which are unrepresentative of their surroundings. Mean filtering is based around a kernel, which represents the shape and size of the neighborhood to be sampled when calculating the mean. Often a 3×3 square kernel is used, although larger kernel sizes or repetitive usage of small kernel may be used for better (but not identical) results.

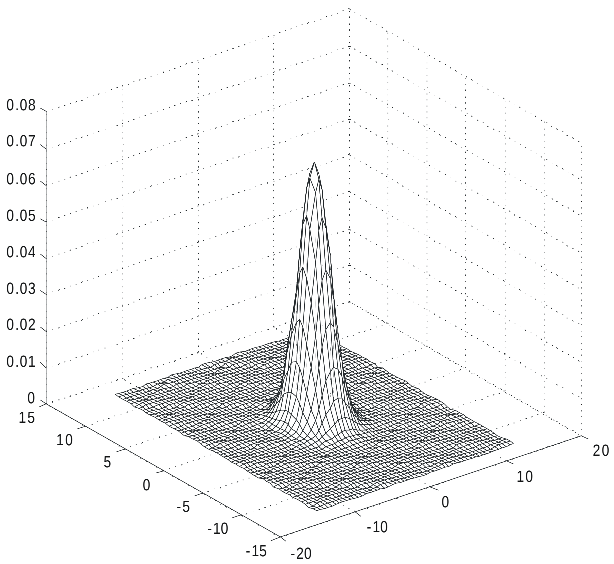

Figure 1. 2-D Gaussian distribution with mean (0, 0) and σ=1.5

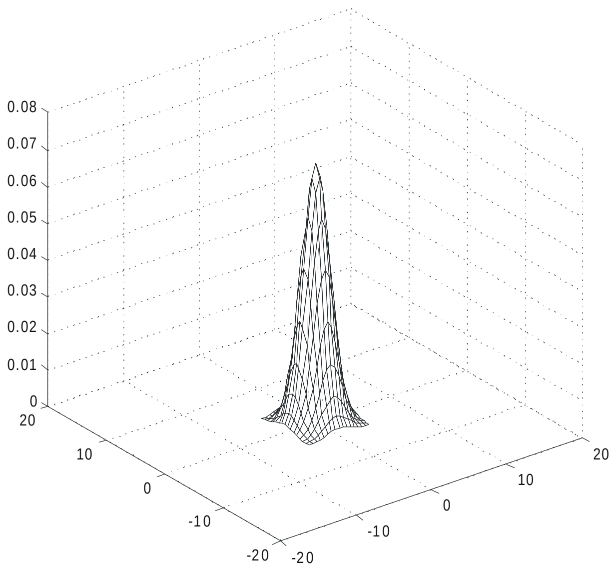

Figure 2. Truncated Gaussian kernel with mean (0, 0) and σ=1.5

Median filter[17]: It is used to reduce, like mean filter, noise in an image. However, it is better in preserving useful detail in the image than the mean filter. Like the mean filter, the median filter considers each pixel in the image and replaces it with the median of the neighbourhood pixel values. The median filter has two main advantages over the mean filter:

- It is a more robust estimation than the mean. A single unrepresentative pixel in a neighborhood will not affect the median significantly.
- It does not create new unrealistic pixel values, since the median must actually be the value of one of the pixels in the neighbourhood.

Max-median/Max-mean filters[18]: These remove the shortcomings of median/mean filters (loss of important features of interest). These filters effectively remove noise and preserve geometrical features of the signals and are called max-median filters. The max-median/mean of a pixel in its neighbourhood is calculated as:

$$y(m,n) = \max[z_1, z_2, z_3, z_4] \quad (2)$$

where $y(m, n)$ is the output of the $(2N+1)^{th}$ order max-median/mean filter and z_1, z_2, z_3 and z_4 are median/mean of the middle row, middle column, and the two diagonals of the convolution kernel centred around the pixel of interest, respectively. The larger the value of N, the more is the spike suppression. This property is used to detect small targets.

Selective median filter[19]: It is a special form of median filter. It replaces the central pixel with a local median of selected pixel intensities inside the window.

The background reconstruction is performed using a median filter of window size n×n given by the equation:

$$I(x, y, k) = median\left(f\left(x+2i, y+2j, t\right)\right)$$

$$\text{where } i, j \in \left[-\left\lfloor\frac{n-1}{4}\right\rfloor, \left\lfloor\frac{n+1}{4}\right\rfloor\right] \quad (3)$$

By considering alternate pixel position for the median filter, it is able to capture even dim targets with gradually decreasing intensity.

2.1.3 Morphological Filters

Mathematical morphology which is based on shape[7] provides an approach to the processing of images. The morphological operations tend to simplify image data, preserving their essential shape characteristics and eliminating irrelevances. The fundamental operations of mathematical morphology are dilation and erosion. Their definition and rules are as follows:

The dilation of f by structuring element g is denoted by $f \bullet g$ and is defined by

$$(f \bullet g)(x) = \min_{u \in G}[f(u) + g(x-u)] \quad (4)$$

The erosion of f by structuring element g is denoted by $f \circ g$ and is defined by

$$(f \circ g)(x) = \min_{u \in G}[f(u) - g(x-u)] \quad (5)$$

The gray-scale opening of f by structuring element g is denoted by

$$O_g(f) = (f \circ g) \bullet g(x) \quad (6)$$

The gray-scale closing of f by structuring element g is denoted by

$$C_g(f) = (f \bullet g) \circ g(x) \quad (7)$$

Opening process (erosion of image by structuring element, followed by dilation of the result by the same structuring element) eliminates bridges (narrow edge like set of pixels) connecting two regions of the image. It rounds outwards pointing corners in the image while leaving the inwards pointing corners unaffected.

The closing process (dilation of image by structuring element, followed by erosion of the result by the same structuring element) rounds the inward-pointing corners in the image while leaving the outward corners unaffected. These properties are utilized for smoothing of image.

The problem with morphological filters is that the result is highly dependent on size and shape of structuring element. The adaptive selection of size and shape of structuring element is a challenging task.

Selective morphology filter: It is somewhat similar to selective median filter. The kernel of the filter will have zero values for alternate pixels in the window in either row or column or both, with reference to the pixel of interest.

2.1.4 Watershed Segmentation

Image segmentation is a time-tested technique to extract the contour information of objects in an image, and can hence be used to detect small targets in an image. Feng[26] *et al*. have proposed watershed segmentation technique to detect dim small targets. The noise removal technique[26] is described by encoding each pixel and its neighbours according to the noise distribution to effectively remove non-object noise. Accurate region of interest (ROI) is located by thresholding the noise-removed image.

2.1.5 Gradient Weighted Background Reconstruction (GWBR) Filter

The gradient-weighted background reconstruction (GWBR) filter[27] is proposed to suppress the strong undulant clouds. In k^{th} frame of the image sequence, the pixel correlation function $R(x, y, z)$ is given as

$$R(x,y,k) = \sum_{m=-p, m\neq 0}^{p} \sum_{n=-p, n\neq 0}^{p} mark_{x,y,k}(m,n) \quad (8)$$

where p is the order of GWBR filter and mark denotes binary mark information with mean 0 or 1:

$$mark_{x,y,k}(m,n) = \begin{cases} 1 & \left|f(x,y,k) - f(x+m, y+n, k)\right| \le th \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

for a given pixel, the inverse gradient in its neighbourhood is defined as

$$d_{x,y,k}(m,n) = \begin{cases} R(x,y,k) & \left|f(x,y,k) - f(x+m,y+n,k)\right| \le th \\ \dfrac{1}{\left|f(x,y,k) - f(x+m,y+n,k)\right|} & \text{otherwise} \end{cases} \quad (10)$$

The gradient-weighted two-dimensional filter is defined as

$$h_{x,y,k}(m,n) = \begin{cases} \dfrac{1}{R(x,y,k)} & m=0, n=0 \\ \left(1 - \dfrac{1}{R(x,y,k)}\right) \dfrac{d_{x,y,k}(m,n)}{\sum_{m=-p,m\neq 0}^{p} \sum_{n=-p,n\neq 0}^{p} d_{x,y,k}(m,n)} & \text{otherwise} \end{cases} \quad (11)$$

The output of the filter is denoted by $\hat{B}(x,y,k)$ which is given as

$$\hat{B}(x,y,k) = \sum_{m=-p}^{p} \sum_{n=-p}^{p} f(x+m, y+n, k)\, h_{x,y,k}(m,n) \quad (12)$$

$\hat{B}(x,y,k)$ is image after applying GWBR filter to original image.

2.1.6 Eigentarget-based Background Suppression

A detection method for infrared point targets based on eigen targets is presented in Ruiming[28], *et al*. The concept of eigentargets is proposed by making reference to eigenfaces in the field of face recognition. After creating the target training images using the Gaussian intensity function, the eigentargets are obtained. These eigentargets are then used to calculate the target map, defined by a target map function, at every location in the image where targets are to be detected. The large values in the target map image indicate the presence of targets. It has better performance with better receiver operating characteristics, and larger signal-to-noise ratio (SNR), and background suppression factor.

Consider a set of N training target images $\{x_1, x_2, x_3, ...x_N\}$ that are $m \times m$ in size. Convert these to column vectors $\{\Gamma_1, \Gamma_2, \Gamma_3, ...\Gamma_N\}$. The average target is defined by $\Psi = (1/N)\sum_{n=1}^{N}\Gamma_n$. Then the covariance matrix can be calculated by

$$C = \frac{1}{N}\sum_{n=1}^{N}(\Gamma_n - \psi)(\Gamma_n - \psi)^T \tag{13}$$

C is factorised into the form as given below.

$$C = \Phi\Delta\Phi^T \tag{14}$$

where Φ is a matrix with the eigenvectors of C, and Δ is a diagonal matrix with the corresponding eigenvalues as elements of its main diagonal. For all supervised learning methods, the selection of the training set is very important for their performance. There are two approaches to generate the target-training images. One is cropping from the real IR images to be detected. The other is using the synthetic images generated by the Gaussian intensity function.

2.2 Temporal and Spatio-temporal Filters

As opposed to early spatial pre-processing algorithms which predict the clutter spatially in each image and then apply detection algorithm, recent approaches have used multiple frames to incorporate temporal as well as spatial information. These algorithms are often part of track-before-detect (TbD) algorithms[29]. Spatial clutter suppression algorithms employed only spatial correlation. Additional performance gain can be achieved by refining these to adapt locally to changing clutter. Spatial pre-processing algorithms are both simpler to develop and computationally less costly than the algorithms which exploit temporal correlation. However, spatial correlation of the background clutter is generally not as strong as the temporal correlation[30]. The drive to obtain the improved performance in clutter has, therefore, led to the consideration of algorithms which exploit the temporal behaviour of the clutter. Such types of filters are discussedw.

2.2.1 3-D Matched Filter

The three-dimensional matched filter[31] requires the processing of entire image sequence containing the target. To detect target with unknown velocity, a bank of filters are tuned to range of target velocities run concurrently. The complexity involved in 3-D match is enormous as banks of filters have to run concurrently. The operation performed by 3-D matched filter can be represented as three-dimensional convolution:

$$y_{i,j,k} = \sum_{l,m,n} h_{l,m,n} x_{i-l,j-m,k-n} \tag{15}$$

where $y_{i,j,k}$ the output of the processor, $x_{i,j,k}$ is the input, and $h_{i,j,k}$ is the filter kernel. The response of the system to a target is given by:

$$\gamma_{td} = \sum_{l,m,n} h_{l,m,n} s_{-l,-m,-n} \tag{16}$$

where $s_{i,j,k}$ is the sampled version of the target at the input to the processor. Figure 3 illustrates an interpretation as clutter cancellation operation followed by a matched filter on the residual. The signal lines, which have the notation (N+1), are paths where multiple frames of data are available simultaneously. The lower path averages over the frames in the observation interval and then passes this average through a spatial filter for estimating the constant component of the clutter in the presence of the temporally-independent component.

2.2.2 Triple Temporal Filter (TTF)

The triple temporal filter (TTF)[32] has outstanding signal to clutter gain in evolving clouds and still retain good signal-to-temporal noise sensitivity in blue sky or night data. The generic temporal filter is a damped sinusoid, implemented recursively. The TTF is based on six parameters, consists of two damped sinusoids followed by an exponential average filter, along with an edge suppression feature.

The damped sinusoid is recursively implemented by the following set of equations:

$$Z_{k+1} = Z_k \alpha e^{i\theta} + D_{k+1} e^{i\varphi} \tag{17}$$

where Z_k is the complex output of the k[th] iteration, α is the damping constant (memory persistence) given by,

$$\alpha = e^{\log(0.5)/L} \tag{18}$$

where L is the number of frames to reach 50 percent damping, θ is the angular shift per iteration of the sinusoid given by $\theta = 2\pi/P$, where P is the sinusoid period in number of frames, D_{k+1} is the next pixel data value and the phase ϕ is given by:

$$\tan\phi = (1 - \alpha\cos\theta)/(\alpha\sin\theta) \tag{19}$$

where ϕ is that phase shift of the sinusoid which ensures that the real part of Z_k has zero response to a constant-intensity signal.

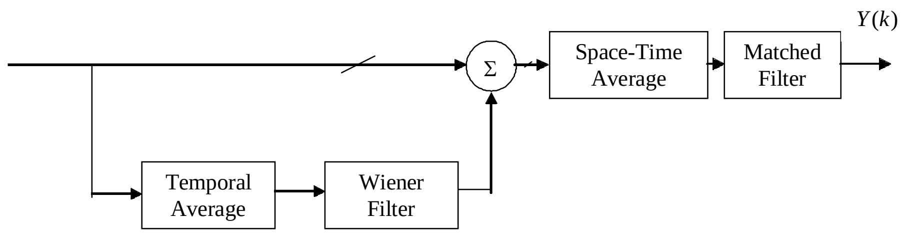

Figure 3. 3-Dimensional matched filter interpretation.

The limitation of using TTF is to select these parameters optimally for best results.

2.2.3 Adaptive Mean and Variance Filter

Lim[33], *et al*. proposed a temporal filter based on adaptive mean and variance. They have presented a modified temporal model for moving clutter. The characteristics of a scene are the combination of static object, target, and the cloud edge. For these, the models have been generated. Pixels seeing static or slow moving objects, such as inner portion of clouds and clear skies, have roughly constant intensities. The temporal profile of pixels seeing static objects is modelled as constant plus some random noise. In general, the target temporal profile of pixel seeing a target can be modelled as disturbance signal generated when target moves across the staring pixel plus the variance associate with random process noise. A first-order Morkov model suggested by Alexis[4] has been adopted to model temporal profile of pixels seen by cloud edges.

The adaptive mean and variance filter is fast and efficient as all the calculations can be performed recursively. Furthermore, the parameters used in the algorithms can be tuned automatically. The algorithm operates in two stages. The first stage of the filter utilises the differences of temporal intensity variations. The disturbance signals induced by the targets deviate much more relative to the background noise. However, since cloud edge pixels can also obtain high deviation signals, hence, a second-stage filter is added to differentiate signals induced by the targets and cloud edge pixels.

2.2.4 Connecting Line of Stagnation Point-based Temporal Profile

Liu[34], *et al* analysed the statistical characteristics, particularly covariance of the three classes of temporal profiles, viz., static background, target, and cloud edges. The covariance enables discrimination of targets from the static background, and cloud clutter temporal profile. The adaptive covariance filter is suitable for static background. However, if the deviation of the pixels seeing cloud edges greater compared to that of static background, degradation of the detection performance will occur if the covariance of cloud edge and target is equivalent. The residual temporal profile is obtained by subtracting the baseline from the temporal profile. The distribution of the residual temporal profile can be modelled by Gaussian distribution and that the occurrences of the targets have intensity values that deviate significantly from the distribution of the residual temporal profile.

3. IMPROVED HYBRID MORPHOLOGICAL FILTER

As discussed mathematical morphological operations tend to simplify image data, preserving their essential shape characteristics and eliminating irrelevances. The language of mathematical morphology is that of set theory. Gray-scale mathematical morphological technique is developed from the application of mathematical morphology to image filtering. The fundamental operations of mathematical morphology are dilation and erosion.

In the estimation of the background of the imagery, it is required that the spikes (high-intensity pixels) be smoothened, while preserving the background. It may be recalled that the dilation process bridges the gaps, while the erosion process removes the irrelevant details from the imagery.

When opening operation is performed on the image, most of the noise in the image as well as target gets removed. However, gaps in the image (elimination of outward-pointing corners) may be created by this operation. To overcome this undesirable effect, dilation operation is performed. The effect of dilation operation, however, could be thickening of the inward corners, which can be remedied by erosion. The last two operations constitute the closing operation. Thus opening of image followed by closing by a suitably chosen structuring element results in a reasonably noise free image but with some discontinuities in the image. Similarly, closing of an image followed by opening operation will result in reasonably noise-free image but with some discontinuities in the image. Similarly, closing of an image followed by opening operation will result in reasonably noise-free image but with some regions joined together. The repetitive use of opening and closing operations, like repetitive use of other types of filters, will thus result in much improved SCNR but with the drawbacks mentioned above. The easiest way to overcome the above drawbacks is to take the average of the two processes. Various hybrid morphological filters have been suggested in literature.

The hybrid morphological CO_OC filter is defined as,

$$hyb_{co\_oc}(f) = (C_g(O_g(f)) + C_g(O_g(f)))/2 \tag{20}$$

The hybrid morphological COC_OCO filter, which repeats the operations of opening and closing one more time, is defined as,

$$hyb_{coc\_oco}(f) = (O_g(C_g(O_g(f))) + C_g(O_gC_g(f)))/2 \tag{21}$$

From the foregoing discussion, it can be seen that the hybrid morphological COC_OCO filter will give better results as compared to hybrid morphological CO_OC filter. It is also clear that the application of the erosion and dilation operations will further improve the performance of hybrid morphological COC_OCO filter. This filter, named as improved hybrid morphological filter and given in Eqn (21) is proposed for the intended application.

The improved hybrid morphological filter is defined as:

$$I_{hyb} = (f \circ g(O_g(C_g(O_g(f)))) + f \bullet g(C_g(O_gC_g(f))))/2 \tag{22}$$

The proposed filter is able to predict the background quite well and hence has relatively better SCNR improvement capability in difference image. The simulation result of the proposed spatial filter with comparison to other spatial filters is presented.

Table 1. Simulation results

Pre-processing filter	Output SCNR (dB)	
	Filtered image	Difference image
Morphology (C_O)	7.9251	7.8301
Hybrid Morphology1 (CoO_OoC)	-	9.7511
Hybrid Morphology2 (CoOoC_OoCoO)	-	9.7511
Improved Hybrid Morphology (EoCoOoC_DoOoCoO)	-	11.1460
Median	1.2016	10.2481
Max	7.3602	-
Min	-	6.1910
Min-Max	-1.9733	-
Mean-Median	-	10.7745
Bottom-Hat	2.8694	-
Adaptive Weinner	-6.5374	-
Laplacian of Gaussian (LoG)	5.1481	-
Selective Median	-	9.4486
Selective Morphology (CoO_OoC)	3.2390	9.2818
Hybrid Median	-2.0748	3.7086
Prewitt	-	2.6005
Sobel	-	3.4541
Total Variation Denoising (TVD)	-	2.4094
Relaxed Median	-5.5863	9.3543
Bilateral	-	4.0309

4. SIMULATION RESULTS

Spatial filters discussed in Section 2.1 have been simulated on sample infrared image frames. The small targets are embedded synthetically in the input image frame with known target characteristics (target position, shape, and SCNR) to calculate the SCNR improvement in difference image.

The SCNR[36] is defined below as

$$SCNR(dB) = 10\log\left(\frac{(S_{max} - \mu)^2}{\sigma^2}\right) \tag{23}$$

where S_{max} is the signal peak value, μ is the mean, and σ is the standard deviation of the background.

In the simulation the target of size 3×3 pixels with input SCNR of 7.1298 dB, is embedded in the different sample image frames. Each frame is of size 320×244 pixels, each pixel intensity being represented in 8-bit gray scale. The simulation was carried out on an image sequence of 25 frames for each algorithm. The difference image was obtained by subtracting the filtered image from the original input image. Then the SCNR in the difference image frame was calculated. The results of the simulation are given in Table 1.

The sample simulation results of improved hybrid Morphological filter, median filter and selective-morphological filter are given in Figs 4, 5, and 6, respectively.

Simulation for analysis of various pre-processing filters has been carried out. It has been found that variants of morphological filters, median filter, mean-median filter, selective median filter, selective morphological filter (combination of CoO and OoC) and relaxed median filters are suitable for clutter prediction and provide enhancement in SCNR in difference image. From the simulation, it was also found that *Avg (EoCoOoC, DoOoCoO)* is outperforming the other pre-processing filters.

5. CONCLUSIONS

Pre-processing filters are very important for detection of small targets. Spatial pre-processing filters have less computation complexity but fair ability to predict dense and varying background. Morphological filters have better background-prediction capability but their performance mostly depend on the size and shape of the structuring element used. Selective median and morphological filters are able to reduce the computations, at the same time,

Figure 4. Sample simulation results using Avg (EoCoOoC, DoOoCoO) filter.

Figure 5. Sample simulation results using median filter.

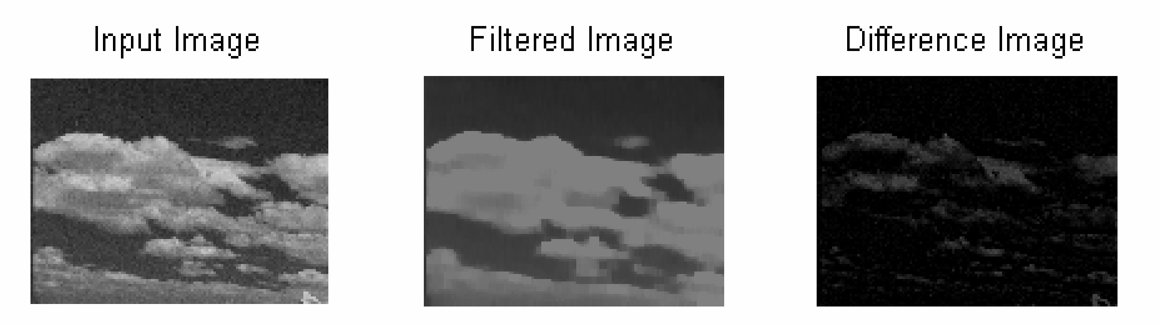

Figure 6. Sample simulation results using selective-morphological filter.

maintaining the background-prediction capability. Spatio-temporal filter is the solution to pre-processing algorithm for the detection of small targets, but obviously with additional cost, both in terms of computation time as well as memory.

ACKNOWLEDGEMENT

Authors acknowledge the contribution of Shri Ram Saran of Instruments Research & Development Establishment (IRDE), Dehradun, in the preparation of this manuscript.

REFERENCES

1. Caefer, Charlene E.; Silverman, Jerry; Mooney, Jonathan M.; Tzannes, Alexis P. & Vickers,Virgil E. Signal processing algorithm for point target detection in consecutive frame staring imagery, *In* Infrared Technology. XIX, *In* SPIE, 1993, **2020**, pp. 93-103.
2. Caefer, Charlene E.; Silverman, Jerry. & Mooney, Jonathan M. Optimisation of point target tracking filters. *IEEE Trans. Aerosp. Electron. Syst.*,2000, **36**(1),15-25.
3. New, W.L.; Er, M.H. & Ronda,V. New method for detection of dim point targets in infrared images. *In* SPIE,1999, **3809**, pp. 141-50.
4. Tzannes, Alexis P. & Brooks, Dana H. Temporal filters for point target detection in IR images, *In* SPIE, 1997, **3061**, pp. 508-20.
5. Hewer, Gary.; Kuo,Wei.; Kenney, Charles.; Hanson, Grant & Bobinchak, Jim. Detection of small IR objects using wavelets, matched sub-space detectors, and registration. *S*ignal and Data Process. of Small Targets, *In Proceedings of SPIE*, 2002, **4728**, pp. 12-23.
6. Hsieh, Feng-Yang; Han, Chin Chauan; Wu, Nai-Shen, & Fan, Kuo-Chin. A novel approach to noise removal and detection of small objects with low contrast, www.fox1.csie.ncu.edu.tw/~Syncanph/paper/detection_wiamis04.pdf
7. Dong, Nengli; Jin, Gang; Qi, Bo & Jiaguang, Ma. New approach to detect dim moving point targets based on motion analysis. Signal and Data Process. of Small Targets, *In* Proceedings of SPIE, 2001, **4473**, pp. 34-42,
8. Silverman, Jerry.; Caefer, Charlene E.; DiSalvo, Steven. & Vickers,Virgil E. Temporal filtering for point target detection in staring IR imagery: II recursive variance filter. *In* Part of the *SPIE Conference* on *Signal and Data Processing of Small Targets*, Orlando, Florida, SPIE,1998, **3373**, 44-53, .
9. Gregoris, D.J.; Yu, S.K.W. & Tritchew, S. Wavelet transform-based filtering for the enhancement of dim targets in FLIR images, Eavelet Applications. *In SPIE*, 1994, **2242**. pp. 573-83.
10. Wang, Gang.; Inigo, Rafel M.& McVey, Eugene S. A pipeline algorithm for detection and tracking of pixel sized target trajectories, *In* Signal and Data Processing of Small Targets, SPIE, 1990, **1305**, 167-77,
11. Zaveri, Mukesh A.; Malewar, Anant ; Merchant, S.N. & Desai, Uday B.Wavelet-based detection and modified pipeline algorithm for multiple point targets in infra-red image sequences. *In ICVGIP,* 2002.
12. Srivastava, Hari Babu.; Ram Saran & Kumar, Ashok. Modified motion-based algorithm for detection of point targets in infra-red image sequences. *In* Optical Sensing II, SPIE, 2006, **6189**, 61-72.
13. Srivastava, Hari Babu.; Limbu,Y.B.; Saran, Ram. & Kumar, Ashok. Airborne infra-red search and track system. *Def. Sci. J.*, 2007, **57**(5), 739-531.
14. Boyle, R. & Thomas, R. Computer vision: A first course, *In* Blackwell Scientific Publications,1988, pp. 42-44.
15. Gonzalez,R. & Woods, R. Digital image processing,

Addison-Wesley Publishing Company, 1992. pp. 191.
16. Helstrom, C. Probability and Stochastic process for engineers. Macmillan, New York, 1991.
17. Boyle, R.&Thomas, R. Computer Vision: A First Course, Blackwell Scientific Publications,1988. pp. 32-34.
18. Deshpande, Suyog D.; Er, M. H. ; Ronda,V. &Chan, Phillip. Max-mean and max-median filters for detection of small-targets. *In* Signal and Data Processing of Small Targets, SPIE, 1999, **3809**, pp. 74-83.
19. Desai,Uday B. & Merchant, S. N. Development of signal processing/image processing techniques and IR scene simulator for infra-red search and track (IRST) systems- Phase II, *In* Final completion report to IRDE, Dehradun, 2006, pp. 23-24.
20. Bovik, Al. *In* Handbook of image and video processing, Academic Press, 2002. pp. 23-24.
21. Warren, R C. The performance of small support spatial and temporal filters for dim point target detection in IR image sequences. *In* DSTO Public Release, DRSTO-TR-1282, February 2002.
22. Jiancheng Yu,; Shengli Sun & Guilin Chen, Automatic target detection in dual band infrared imagery. *In* Infrared Materials, Devices, and Applications, SPIE, 2008, **6835**.
23. Weidong Yang,; Tianxu Zhang & Yunsheng Liu. Ship detection in low-resolution SAR images based on background suppression. *In* MIPPR 2007: Automatic Target Recognition and Image Analysis, SPIE, 2007, **6786**.
24. Xiangzhi Bai,; Fugen Zhou & Ting Jin. Infrared small target detection and tracking under the conditions of dim target intensity and clutter background, *In* MIPPR 2007: Automatic Target Recognition and Image Analysis; and Multispectral Image Acquisition, SPIE, 2007, **6786**.
25. Wang, Shu-man; Han, Jian-hui &Wang, Wei. Wavelet de-noising based on higher order statistics for infrared target detection. *In* MIPPR 2007: Remote Sensing and GIS Data Processing and Applications; and Innovative Multispectral Technology and Applications, SPIE, 2007, **6790**.
26. Feng-Yang Hsieh; Chin Chauan Han; Nai-Shen Wu, & Kuo-Chin Fan. A novel approach to noise removal and detection of small objects with low contrast. *In* WIAMIS, 2004.
27. Z. Li,; N. Dong & G. Jin. Dim small target detection in strong undulant clutter background based an adaptive filter, *In* Int. Conf. on Commun., Circuits and Syst., 2004, **2**. pp. 783-87.
28. Ruiming Liu,; Erqi Liu,; Jie Wang,; Tianhao Zhang &Yuan Cao. Point target detection of infrared images with eigentargets, *In* Opt. Eng. Lett., SPIE, 2007, **46** (11), 110502.1-110502.3.
29. Skirmantas Kligys,; Boris Rozovsky & Alexander Tartakovsky. Detection algorithms and track before detect architecture based on nonlinear filtering for infrared search and track systems, Centre for Applied Mathematical Science, Los Angeles, CA, Sep 1998. Technical Report CAMS-98.9.1.
30. Mac Hartless & Hong Wang. Adaptive model-based 3D target detection. *In Signal and Data Processing of Small Targets, SPIE,* 1992, **1698**, 77-87.
31. Fries, Robert W. Three dimensional matched filtering, in Infrared Systems and Components III, SPIE, 1989, **1050**, 19-27.
32. Silverman, Jerry.; Mooney, Jonathan M. & Caefer, Charlene E. Tracking point targets in cloud clutter, *In* Optical Engineering in Israel, SPIE, 1997, **3110**, 89-100.
33. Lim, Eng Thiam; Louis Shue & Ronda Venkarteswarlu. Adaptive mean and variance filter for detection of dim point-like targets. *In* Signal and data processing of small targets, SPIE, **4728**, 492-503.
34. Delian Liu,; Jianqi Zhang & Weike Dong. Temporal profile based small moving target detection algorithm in Infrared image sequences. *Int. J. Infrared Mill Waves*, 2007, **28**, 373-81.
35. Bin Wu & Hong-Bing Ji. Improved power-law-detector-based moving small dim target detection in infrared images. *In* Opt. Eng. Lett., SPIE, 2008, **47**(1), pp. 010503.1-010503.3.
36. Diani, M.; Baldacci, A. & Corcini, G. Novel background removal algorithm for navy infrared search and track systems, *Optical Engineering*, 2001, **40**(8),1729-734.

Contributors

Mr Hari Babu Srivastava Scientist 'G' at IRDE, Dehra Dun and is currently heading the Fire Control System Design Center. He obtained his BE in Electrical Engg. from University of Roorkee in 1983. He completed his MTech in Electrical Engg. from Indian Institute of Technology, Kanpur in 1989. He is life member of Instrument Society of India & Optical Society of India and member of Computer Society of India and IEEE, USA. He has presented 20 research papers in various national/international conferences and published six research papers in refereed international/national journals.

Prof Vinod Kumar is Head of the Department of Electrical Engineering and Continuing Education Centre and the Coordinator of the Quality Improvement Centre at IIT Roorkee. He did his BSc. (Engg) from Punjab Engg. College, Chandigarh in 1973; M Tech. and Ph D in Electrical Engg. from University of Roorkee in 1975 and 1984, respectively. His research interests include ECG signal processing and analysis, digital signal processing and transducer instrumentation. He is the Life Fellow of the Institution of Engineers (I), Institution of Electronics & Telecommunication Engineers and Systems Society of India, Life Member of Indian Society for Continuing Engineering Education, Ultrasonic Society of India, Indian Society for Technical Education, Instrument

Society of India, Biomedical Engineering Society of India, IEE UK and Senior Member of IEEE, USA.

Prof H.K. Verma is at present the Deputy Director and Member of the Board of Governors of IIT, Roorkee. He has been the Head of the Department of Electrical Engineering, Dean of Research and Industry Liaison, Sponsored Research and Industrial Consultancy and Faculty Affairs at IIT, Roorkee. His research interests include measurement and instrumentation, digital protective relays, microprocessor and computer applications in instrumentation, power system protection, monitoring and control, medical instrumentation, telemedicine and medical-informatics, telemetry and remote / supervisory control, automated test Equipment and Systems. He is a member of National Working Group on Philosophy and Application of Backup Protection for Transmission Lines, Reactors and Busbars and CIGRE National Study Committee on "Information System and Telecommunication for Power Systems" with Head Office at Central Board of Irrigation and Power, New Delhi.

Mr S.S. Sundaram is presently the Director of IRDE, Dehra Dun. He is engaged in the development of optical instrumentation, night vision instrumen-tation and laser instrumentation for the services in addition to realisation of Fire Control Systems for tanks and ships. He has contributed considerably for the consortium of DRDO Labs, production partners in public and private sector in India and abroad and academia in fielding various sophisticated systems. He has vast experience in the field of communication electronic warfare and radar electronic warfare and has fielded integrated systems of high complexity, operating on wide area network, as leader of major programme/ projects. As chief designer, he has led technology teams in the development of communication electronic counter measure systems including the design of fast settling frequency synthesisers, surveillance and monitor receivers and jammer exciters in DLRL, Hyderabad. He is a fellow of IETE, Optical Society of India and Instrument Society of India.