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# Performance analysis of an improved target detection technique based on quadratic correlation filters for surveillance applications

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This article is dedicated to Prof Kehar Singh for his contributions to Optics & Photonics

An improved target detection method based on Quadratic Correlation Filters (QCF) is proposed for surveillance application to detect the target amid the clutter in visible imagery. The proposed improvement helps in reducing the false alarm rate thereby improving the performance. The performance evaluation of the proposed method is carried out on the frames of a video sequence by varying three parameters – target window size, variance check value, and positive filter threshold value. 

**Keywords**: Target detection, Recognition, Quadratic correlation filter, Variance, Target recognition performance analysis.

## 1 Introduction

The detection and recognition of multiple targets amid clutter in a scene is one of the important requirements for a surveillance system. Considerable work has been done for automatic detection of ground, naval and aerial targets in thermal as well as in visible imagery over a wide field of view. The problem of detecting the target amid the background clutter is a challenging task in pattern recognition [1-3]. Several methods have been investigated including statistical methods based on feature extraction and model based techniques. In general, the potential targets are segmented from the background and the internal feature extracted from processed target chip. Segmentation based techniques perform poorly when the target and background have relatively poor contrast or targets are close to or occluded by the clutter [4].

Linear correlation filters are broadly used in pattern recognition and image processing because of their inherent simplicity and well-known properties which gives satisfactory performance for various applications. Correlation filters [5-9] have the advantage of linear shift invariance with no separate steps needed for segmentation or feature extraction. However, the filter design requires the extraction of targets from the scene. The matched spatial filter (MSF) was one of the first linear correlation filters used to detect the target signal buried in additive Gaussian noise. However, MSF does not perform well for non-Gaussian signal statistics and multiplicative noise. To characterize the real-world situation, it is necessary to consider the nonlinearities. Among the non-linear filters used for various applications, quadratic correlation filters are the simplest and belong to the class of polynomial (Volterra) filter [10]. The quadratic correlation filters correspond to the first nonlinear term of the Volterra expansion. The two most interesting properties of the quadratic (Volterra) filters [11,12] are – (i) the output of filter depends linearly on the kernel elements and (ii) nonlinearity is expressed in terms of multidimensional operators functioning on products of input samples i.e. it can be interpreted as multidimensional convolution.

The paper proposes an improved target detection technique based on quadratic correlation filter (QCF) [13-16]. A variance check procedure is used to reduce the false alarm rate. The factors that affect the

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performance of the QCF filter such as target window size and the number of positive and negative filters have been studied.

## 2 Target detection using QCF

In a surveillance system, the input video is processed rapidly by a target detection algorithm to detect whether a target belonging to a predefined class is present in the scene under surveillance. The scene may contain one or more potential targets amid clutter. The clutter could be vegetation or other background objects. These targets are detected by the target detection algorithm that uses pre-trained detection filters. The output of the QCF is a single correlation plane that is a combination of the outputs of several linear filters in parallel [17-20]. The targets are then ranked by the strength of the correlation peak. A high rank would mean that the detected object belongs to the class of pre-defined targets with very high confidence level. The confidence provided by the detection algorithm is used as the confidence of finding a target at the specified location. The main steps in the target detection algorithm are as follows:

The main steps involved are

(i) Selection of target and clutter chips of a predefined window size from the training data set images,

(ii) Calculation of correlation matrix $R_1$ for target class and $R_2$ for clutter class from training data set images,

(iii) Calculation of the eigenvectors and eigenvalues of the matrix $(R_1 + R_2)^{-1} (R_1 - R_2)$, and

(iv) Choosing $N_1$ positive eigenvectors greater than a positive threshold value as positive correlation filters *f*.

(v) Choosing $N_2$ negative eigenvectors less than a negative threshold value as negative correlation filters *g*.

(*A*) *Estimation of correlation plane*

(i) The test image **x** is correlated with each of the $N_1$ positive correlation filters **f**. The intensity of each of the complex valued correlation output is added to obtain an intensity correlation plane $\mathbf{w_1}$

$$w_1(\cdot,*) = \sum_{i=1}^{N_1} |\mathbf{x}(\cdot,*) \otimes g_i(\cdot,*)|^2$$

(ii) The test image **x** is correlated with each of the $N_2$ negative correlation filters **g**. The intensity of each of the complex valued correlation output is added to obtain an intensity correlation plane $\mathbf{w_2}$

$$w_2(\cdot,*) = \sum_{i=1}^{N_2} |\mathbf{x}(\cdot,*) \otimes g_i(\cdot,*)|^2$$

$w_2$ is normalized so that the maximum value is 1.

(iii) The final correlation plane $w$ is estimated as follows

$$w(\cdot,*) = w_1(\cdot,*) - w_2(\cdot,*)$$

(iv) The correlation plane is normalized by dividing by the maximum absolute value so that the values are between +1 and –1.

(*B*) *Target detection*

(i) The peak value of the correlation plane and the location of the peak are estimated.

(ii) If the peak value is greater than a predetermined threshold, then a region of the input plane of size equal to the target chip is estimated as the target.

(iii) To reduce the false alarm rate, a variance check is done on the detected target chip as described in the following section.

(*C*) *Variance check to reduce false alarm rate*

Let $I$ be the detected target chip normalized with a value 255.

Step 1: $I$ is convolved with a rotationally symmetric Gaussian Low Pass filter $h$

$$I_l(\cdot,*) = I(\cdot,*) \otimes h(\cdot,*)$$

Step 2: $I^2$ is convolved with a rotationally symmetric Gaussian Low Pass filter $h$

$$II_l(\cdot,*) = I^2(\cdot,*) \otimes h(\cdot,*)$$

Step 3: σ is estimated as follows

$$\sigma(\cdot,*) = \sqrt{|II_l(\cdot,*) - I_l^2(\cdot,*)|}$$

Step 4: The matrix σ is converted to a vector $\sigma_v$ by lexicographically scanning column wise.

Step 5: The variance $\sigma_v$ is calculated

Step 6: If the variance is greater than a predetermined threshold value $\sigma_{th}$ called variance threshold value, the detected target chip is accepted as a valid target, otherwise it is rejected as a false target.

## 4 Performance evaluation

The proposed QCF based target detection algorithm has been extensively tested [21-26] for detecting targets amid clutter in visible imagery data from a video sequence. The video sequence recorded was that of a vehicle (target) moving on a road up in the mountain covered with green vegetation at a range of approximately 700m-1000m. The vehicle was clearly visible in some of the frames and is partially obscured or occluded behind the greenery in other frames. The target size in the recorded frames changes between 90 × 50 and 10 × 10 pixels. A frame recorded using the DALSACMOS sensor DS-21-001M0150 is shown in Fig 1. To generate the QCF, the target chips were extracted from 750 video frames that contained targets of sizes ranging from 10×10 to 70×50 pixels. The target chips were fitted to a window of predetermined size $W$. The default value for window size was chosen as 50×30 pixels. If the target chips were larger than the window size, they were suitably cropped. If they were smaller than the window size, they were suitably zero padded. Target chips were selected from 250 frames out of the total 750 frames. These images were used to generate the 1500×1500 target class correlation matrix $R_1$. A few target training images are shown in Fig 2.

Fig 1. Visible frame used in performance evaluation of target detection.

A 100 clutter chips were randomly selected per video frame from data set (the clutter chips can also be selected manually). These clutter chips were used to generate the clutter correlation matrix $R_2$. The dominant eigen vectors of the matrix $(R_1 + R_2)^{-1}(R_1 - R_2)$ were used to compute positive and negative correlation filters. They were reshaped to a size of 50 × 30 pixels. The positive and negative correlation filters of the filter bank were correlated with the test frames from a test video sequence different from that used to generate the correlation filters. The decision as to whether target is present or absent in the frame is made based on the strength of the correlation peak in the correlation plane. A typical correlation plane obtained is as shown in Fig 3. To further reduce the false alarm, a variance check was performed on the detected target chip as described in the previous section. The variance check was performed by convolving the detected target chip I and $I^2$ with a Gaussian Low Pass filter $h$ of size 7 × 7 pixels and standard deviation 7/6. If the variance is greater than the variance threshold $\sigma_{th}$, the detected target chip is accepted as a valid target, otherwise it is rejected as a false target.

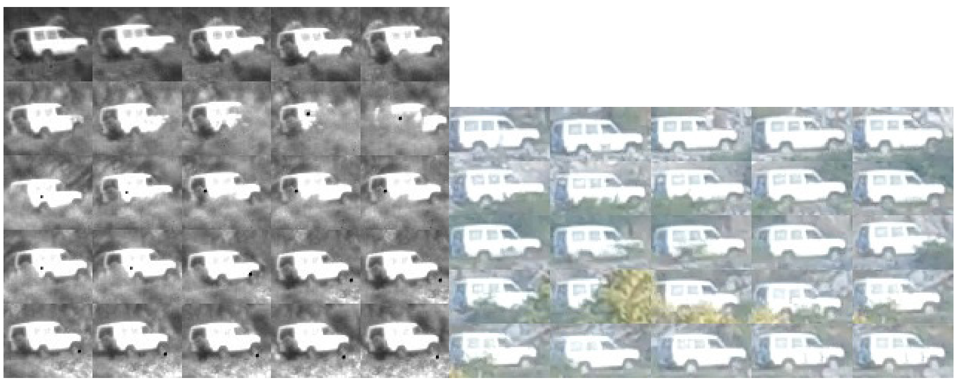


Fig 2. Training images of target chip used for filter generation.

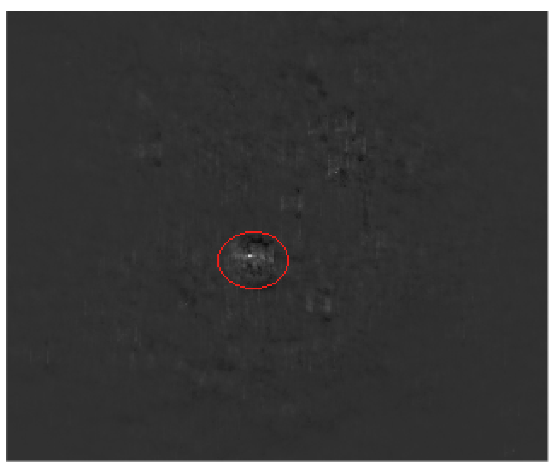


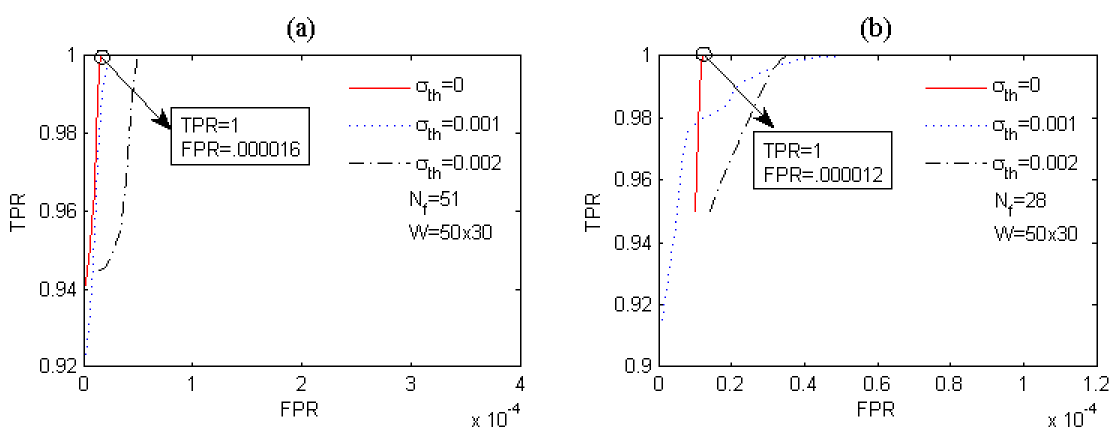
Fig 3. A typical correlation plane obtained by correlating a frame from test video sequence with filter bank of positive and negative filters. The correlation peak is marked by a circle.

ROC curves [27] were plotted for evaluating the performance of the target detection algorithm for various parameters - Variance check threshold $\sigma_{th}$, number of positive filters $N_1$ and window size W(c × r). For each set of plots, one of these parameters was varied at a time keeping the other two parameters fixed. The optimum (True positive rate) TPR and (False positive rate) FPR values for each set of plots are given in the Table 1 below.

Table 1. showing optimum TPR and FPR vales for various ROC plots in Fig 4

| No. of positive filers ($N_f$) | Window size (W) | Variance threshold ($\sigma_{th}$) | Optimum operating point (TPR,FPR) |
|---|---|---|---|
| 51 | 50 × 30 | 0.001 | $(1, 1.6 \times 10^{-5})$ |
| 51 | 50 × 30 | 0.002 | $(1, 2.5 \times 10^{-5})$ |
| 51 | 50 × 30 | 0 | $(1, 5 \times 10^{-5})$ |
| **28** | **50 ×30** | **0.001** | $\mathbf{(1, 1.2 \times 10^{-5})}$ |
| 28 | 50 × 30 | 0.002 | $(1, 3.6 \times 10^{-5})$ |
| 28 | 50 × 30 | 0 | $(1, 4.8 \times 10^{-5})$ |
| 17 | 50 × 30 | 0.001 | $(1, 1.6 \times 10^{-5})$ |
| 17 | 50 ×30 | 0.002 | $(1, 3.9 \times 10^{-5})$ |
| 17 | 50 × 30 | 0 | $(1, 3.3 \times 10^{-5})$ |
| 51 | 55 × 35 | 0.001 | $(0.96, 1.6 \times 10^{-5})$ |
| 51 | 40 × 30 | 0.001 | $(0.92, 1.1 \times 10^{-5})$ |
| 28 | 40 × 30 | 0.001 | $(0.965, 2.4 \times 10^{-5})$ |
| 28 | 55 × 35 | 0.001 | $(0.92, 5 \times 10^{-6})$ |
| 17 | 40 × 30 | 0.001 | $(0.95, 1.2 \times 10^{-5})$ |
| 17 | 55 × 35 | 0.001 | $(1, 1.7 \times 10^{-5})$ |

Figures 4(a) –(c) in the first row plots the ROC curves for three different cases of the number of positive filters- 51, 28, 17. The window size is 50 × 30 for all the three cases. For each case, ROC curves are plotted for the variance threshold value $\sigma_{th}$ as 0, 0.001 and 0.002. It is seen that for all the three cases $\sigma_{th}$ = 0.001 gives the best performance in terms of achieving the minimum FPR and maximum TPR. Figures 4(d)-(f) in the second row plots the ROC curves for three different cases of the number of positive filters- 51, 28 and 17. The variance threshold value $\sigma_{th}$ is 0.001 for all the three cases. For each case, ROC curves are plotted for three different cases of the window size- 50 × 30, 40 × 30, 55 × 35. For all the three cases when the number of positive filters is 51, 28 and 17, the maximum TPR and minimum FPR is achieved when the window size is 50 × 30. The value of maximum TPR and minimum FPR achieved for Figs 4 (a) – (f) is given in Table 1. It is seen that the maximum performance is achieved when variance [28] threshold value $\sigma_{th}$is 0.001, window size is 50 × 30 and number of positive filters is 28.



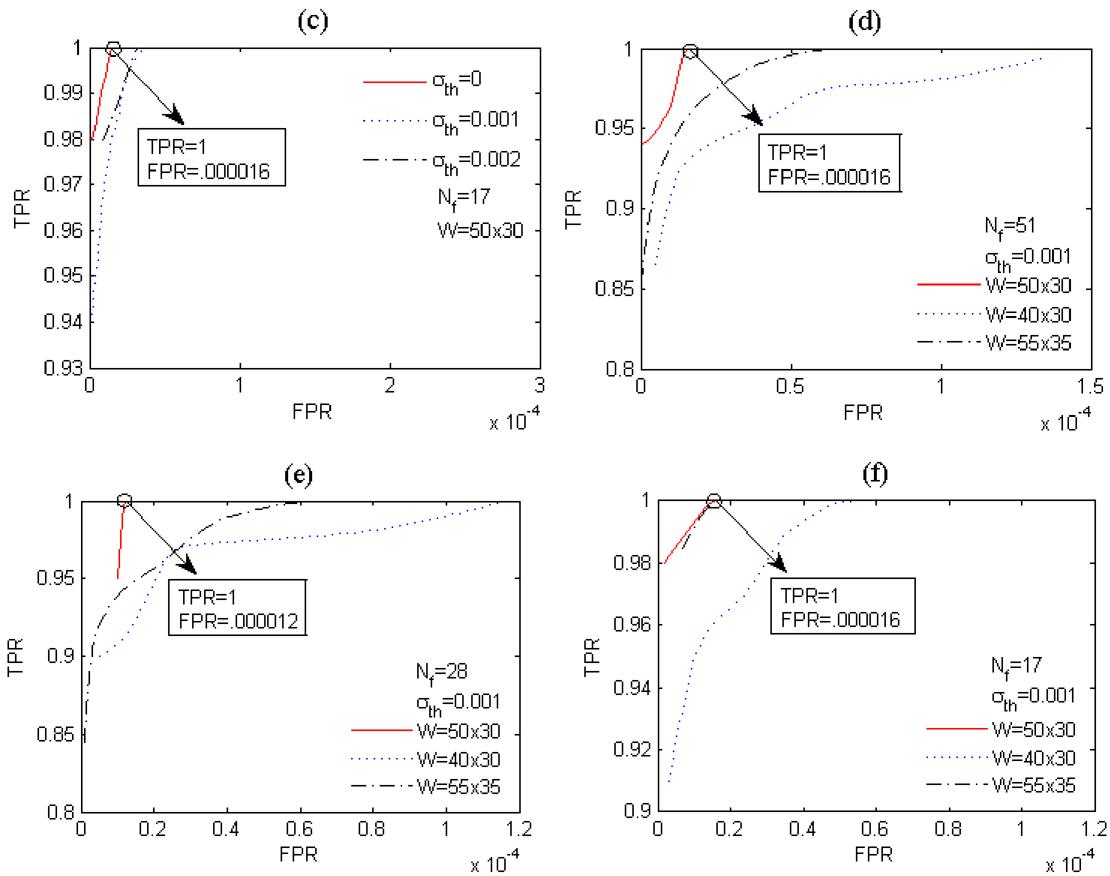



Fig 4. (a) – (c) ROC plots for $\sigma_{th}$= 0, 0.001, 0.002 when $N_f$= 51, 28 and 17, $W$ = 50 × 30 (d) – (f) ROC plots for $W$ = 50 × 30, 40 × 30,55 × 35 when $N_f$= 51, 28 and 17, $\sigma_{th}$ = 0.001.

## 5 Conclusion

In this paper, an improved target detection method is proposed based on Quadratic Correlation Filters (QCF) for surveillance application. The proposed method reduces the False Positive Rate by doing a variance check on the detected target chip. If the variance is above a certain threshold, the detected target chip passes the variance check and is accepted as a true target. The proposed method was evaluated on video sequences of a vehicle moving on a road in a mountain covered with green vegetation at a range of approximately 700m-1000m. The ROC curves were studied by varying three parameters- variance threshold, window size of the target and the number of positive filters used. In all the cases, it was found that the variance check helped in reducing False Positive Rate with optimum performance obtained for variance threshold value of 0.001. An IR surveillance system is also being developed based on the proposed technique and the results will be reported in a future communication.

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