Mixed segmentation–detection-based technique for point target detection in nonhomogeneous sky

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This paper deals with point target detection in infrared images of the sky for which there are local variations of the gray level mean value. We show that considering a simple image model with the gray level mean value varying as a linear or a quadratic function of the pixel coordinates can improve mixed segmentation–detection performance in comparison to homogeneous model-based approaches. © 2010 Optical Society of America

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1. Introduction

Nowadays, target detection is an important task in infrared surveillance applications [1–6], especially in naval environment for which point target detection [7–10] in the sky around the horizon and with low signal-to-noise ratio (SNR) is a difficult problem. Indeed, targets have to be detected with a high detection probability and a low probability of false alarm (Pfa), and without knowing the sky intensity mean value, its local second-order fluctuation characteristics, the target SNR, or the detector noise variance [11,12]. Furthermore, the technique has to be robust to the presence of coasts, clouds, and horizon. The intensity mean value and its variance thus must be estimated from the analyzed images, which is generally performed in a spatial neighborhood of the tested target location [13–16]. However, in order to obtain efficient detection with constant Pfa, this neighborhood needs to contain a large number of pixels and to correspond to a homogeneous statistical sample [17–19]. Detection techniques based on a preliminary segmentation of the image have thus been proposed [18,20–22], instead of using sliding windows to define the neighborhood of the tested target location. Indeed, segmentation-based techniques allow one to obtain homogeneous regions in the image and, thus, to improve target detection performance near discontinuities, such as horizon, coasts, or clouds with sharp edges. These segmentation techniques are generally based on an image model that corresponds to a patchwork of homogeneous uncorrelated random fields. However, a careful analysis of infrared images shows that there exist spatial variations of the mean value of the sky intensity, which can decrease target detection performance if not properly taken into account.

We propose to show that a simple mixed segmentation–detection technique that takes into account local variations of the intensity mean value can be efficiently implemented and can improve detection performance in comparison to techniques that segment the image into a patchwork of homogeneous uncorrelated random fields.

This paper is organized as follows. In the Section 2, we present the infrared images and the problematic considered in this paper. We then show that the mean
value of the image can be approximated with a linear or a quadratic function of the pixel coordinates with spatially quasi-un correlated residual fluctuations. In Section 3, we compare the performance of three different generalized likelihood ratio test (GLRT) detectors adapted to additive white Gaussian noise with unknown variance and unknown mean value that can be a constant, a linear, or a quadratic function of the pixel coordinates. In particular, the influence on the detection performance of the number of pixels in the target neighborhood considered for the GLRT detector is analyzed. In Section 4, it is shown that the segmentation technique developed in [23, 24] and generalized in [25] to a non-constant mean value background can be efficiently applied to segment infrared images of the sky. It is then shown that this allows one to obtain on the considered images sufficiently large regions to detect point targets without strong loss of detection probability due to the estimation of the image parameters. In Section 5, these results are illustrated on point target detection in infrared images. Section 6 is devoted to a conclusion and to the discussion of perspectives.

2. Model Analysis of Infrared Images

A. Presentation of the Considered Images

We show in Fig. 1 some extracts \([637 \times 233 \text{ pixels for Fig. 1(a), } 636 \times 244 \text{ pixels for Fig. 1(b), }\) and \(638 \times 244 \text{ pixels for Fig. 1(c)}\] of infrared images provided by Thales Optronics SA that correspond to a typical sky background considered in this paper. These images come from sequences acquired by an infrared sensor in the 3.5–5 \(\mu m\) spectral window with a 16 bit gray level resolution. The angular field of view of these extracts is approximately equal to 27° horizontally.

The main difficulty with such images, as considered in this paper, is to be able to detect point targets near the horizon, where there are important intensity variations.

B. Comparison of Different Image Models

In this subsection, different possible image models that will be implemented for detection and segmentation are compared. More precisely, let \(x[i, j]\) be the gray level of the pixel of coordinates \((i, j)\) in a given region \(\Omega\), of the image (in general, \(\Omega\) can be of arbitrary shape but contains the pixel of coordinates \((i, j)\)). In the absence of target, the considered image model is \(x[i, j] = m[i, j] + n[i, j]\), where \(n[i, j]\) is a statistically independent Gaussian noise with zero mean and variance \(\sigma^2_n\) in the region \(\Omega\). Three different image models are considered for \(m[i, j]\) that correspond to the statistical mean value of \(x[i, j]\) in \(\Omega\):

- a constant model \((\mathcal{M}_C)\), for which

\[
m^{(C)}_{\Omega}[i, j] = \mu_{\Omega},
\]

- a linear model \((\mathcal{M}_L)\), for which

\[
m^{(L)}_{\Omega}[i, j] = a_0 i + b_0 j + \gamma_{\Omega},
\]

and

- a quadratic model \((\mathcal{M}_Q)\), for which

\[
m^{(Q)}_{\Omega}[i, j] = a_0 i^2 + b_0 j^2 + c_0 ij + d_0 i + e_0 j + f_{\Omega}.
\]

To compare these models and to check if the noise can be considered spatially statistically independent with a good approximation, we propose to analyze the power spectral density of the residual fluctuations between the infrared image and the mean value estimated in \(16 \times 16 = 256\) pixel square windows located on the sky. For that purpose, 64 of such 256 pixel square windows have been selected on the three images in Fig. 1, allowing one to average the spectral densities (i.e., the Fourier transform square modulus) obtained in each square window. The parameters of these image models inside each of the previous 64 windows have been estimated considering a constant mean value, a linear regression, or a quadratic regression that best fits the pixel gray
level values in the least-squares sense \([26,27]\). More precisely, the parameters (i.e., \(\mu_\Omega\) for the constant model; \(a_\Omega, b_\Omega, \) and \(\gamma_\Omega\) for the linear model; and \(a_\Omega, b_\Omega, c_\Omega, d_\Omega, e_\Omega,\) and \(f_\Omega\) for the quadratic model) have been estimated minimizing \(\sum_{(i,j)\in \Omega} (x[i,j] - m_\Omega^{(U)}[i,j])^2\). At pixel \((i,j)\), three estimations of the mean value \(\hat{m}_\Omega^{(U)}[i,j]\) have thus been obtained (with \(U = C, L, Q\)). The average spectral densities of the residual fluctuations \(r_\Omega^{(U)}[i,j] = x[i,j] - \hat{m}_\Omega^{(U)}[i,j]\) over the 64 windows are provided in Fig. 2 for the three models \(U = C, L, Q\). These results show that assuming a constant mean value with uncorrelated residual fluctuations is not appropriate, whereas linear or quadratic variations for the mean value lead to approximately uncorrelated fluctuations.

The histograms of the residual fluctuations \(r_\Omega^{(U)}[i,j]\) are reported in Fig. 3 for the three models. It can be observed that they exhibit a bell shape, notably for the linear and the quadratic models. The probability density function (PDF) of the residual fluctuations will thus be considered Gaussian in the following.

3. Performance Analysis of the Generalized Likelihood Ratio Test

A. Introduction

Point target detection can be performed using a GLRT technique \([28–30]\). For that purpose, a neighbor hood \(\Omega_{i_0,j_0}^{(U)}\) of the tested pixel of coordinates \((i_0,j_0)\), which can have in general an arbitrary shape, is defined so that \(\Omega_{i_0,j_0}^{(U)}\) does not include the tested pixel. Two possibilities are then considered:

- the pixel of coordinates \((i_0,j_0)\) and the pixels in \(\Omega_{i_0,j_0}^{(U)}\) are both distributed with a Gaussian PDF with the same variance but with different mean values.

The ratio of the likelihood of both hypotheses is then compared to a threshold. However, although the PDF of the pixel gray levels are assumed Gaussian, their parameters are unknown. The GLRT technique consists of estimating these parameters.
in the maximum likelihood sense, leading to the comparison to a threshold of the following statistics [31]:

\[
\rho_{i,j_0}^{(U)} = \frac{[x[i_0,j_0] - m_{\Omega_{i,j_0}}^{(U)}]_2}{\sigma_{\Omega_{i,j_0}}^{(U)}},
\]

(4)

where \(m_{\Omega_{i,j_0}}^{(U)}\) is estimated in \(\Omega_{i,j_0}\) minimizing

\[
\sum_{(i,j)\in \Omega_{i,j_0}} (x[i,j] - \hat{m}_{\Omega_{i,j_0}}^{(U)})^2,
\]

and where \(|\rho_{i,j_0}^{(U)}|^2 = \frac{1}{N_r} \sum_{(i,j)\in \Omega_{i,j_0}} (x[i,j] - \hat{m}_{\Omega_{i,j_0}}^{(U)})^2\), with \(N_r\) the number of pixels inside \(\Omega_{i,j_0}\). Three detectors can then be implemented, i.e., with a constant \((U = C)\), a linear \((U = L)\), or a quadratic \((U = Q)\) mean value model.

B. Comparison of the Performance of the Constant, Linear, and Quadratic Model-Based GLRT

The GLRT consists of the comparison of \(\rho_{i,j_0}^{(U)}\) to a threshold \(\eta_{i,j_0}^{(U)}\), so that a target is detected if

\[
\rho_{i,j_0}^{(U)} > \eta_{i,j_0}^{(U)},
\]

and no target is detected otherwise. This threshold \(\eta_{i,j_0}^{(U)}\) depends directly on the chosen Pfa, on \(N_r\), on the shape of \(\Omega_{i,j_0}\), and on the tested location \((i_0,j_0)\).

To compare the performance of the constant, linear, and quadratic models, the evolution of the detection probability as a function of the Pfa is plotted in Fig. 4 for a constant [Fig. 4(a)] and a linear [Figs. 4(b) and 4(c)] background (i.e., a background for which the mean value is a linear function of the pixel coordinates). In both cases, target detection has been performed using the \(M_C\) model (solid curves), the \(M_L\) model (dashed curves), and the \(M_Q\) model (dotted curves) inside \(11 \times 11\) pixel regions. The target SNR has been fixed to \(11\) dB (with a positive contrast, i.e., the target gray level is higher than the background gray levels at the target location), where the SNR in decibels is defined as

\[
\text{SNR} = 10\log_{10} \left( \frac{\left(x[i,j] - \mu_{\Omega_{i,j_0}}^{(U)}\right)^2}{\sigma_{\Omega_{i,j_0}}^{(U)}} \right).
\]

These results illustrate that considering a constant model when the background mean value is a linear function of the pixel coordinates can lead to a strong degradation of the detection performance compared to the use of the appropriate model [i.e., the \(M_L\) model in Figs. 4(b) and 4(c)]. Indeed, although no variation of the curve of the detection probability as a function of the Pfa would have been observed for a centered target, as soon as the target is shifted from the window center, the estimates of the background mean and variance using the \(M_C\) model on a linear background are

![Fig. 4. Evolution of the detection probability as a function of the Pfa for (a) a constant background with \(\rho_0 = -2.110^4\) and \(\sigma_b = 90\) and, for (b) and (c), a linear background with \(\alpha_\Omega = 19\), \(\beta_\Omega = -4.4\), \(\tau_\Omega = 2.010^4\), and \(\tau_b = 18\), whose parameters correspond to typical parameter values estimated on the \(16 \times 16\) pixel square windows in Fig. 1(a). The region \(\Omega_{i,j_0}\) is a \(11 \times 11\) pixel window and the target (with a \(11\) dB SNR and a positive contrast) is not centered on the window but is located either \(d\) pixels upward (black curves) or \(d\) pixels downward (gray curves) from the window center. In (a) and (b), \(d = 1\) pixel and in (c), \(d = 2\) pixels. The target detection has been performed using either the \(M_C\) model (continuous curves), the \(M_L\) model (dashed curves) or the \(M_Q\) model (dotted curves). The crossed curves in (b) and (c) are the average between the two curves obtained with the \(M_C\) model. The plots have been obtained by averaging \(10^2\) samples.](image-url)
biased. This may slightly increase the performance in some cases, as, for example, in Figs. 4(b) and 4(c), when the target is shifted from 1 or 2 pixels downward from the window center (continuous gray curve), but it can also lead to very degraded results in the other considered case, i.e., when the target is shifted from one or two pixels upward (continuous black curve). However, these two continuous black and gray curves obtained with the $M_C$ model would have been reversed for a negative background parameter $\sigma_{\Omega_0}$, or for a target with a negative contrast (i.e., a target whose gray level is lower than the gray level mean value of the background). In practical situations, since the contrast of the target and the sign of the background parameter are known (which corresponds to a nonrealistic situation), the performance with the $M_C$, $M_L$, or $M_Q$ model will thus correspond, in average, to the mean value between the two curves obtained with the target located either upward or downward [see crossed curves in Figs. 4(b) and 4(c)]. Degraded performance is thus obtained in average in comparison to the $M_L$ and $M_Q$ models, and this decrease of performance is higher when the target is far from the window center. Thus, if the mean value is suspected to vary as a linear function of the pixel coordinates, it is preferable to use an appropriate model, such as the $M_L$ model.

Furthermore, it can also be observed that considering the $M_L$ or $M_Q$ model on background with constant mean value [see Fig. 4(a)] does not lead to a significant decrease of performance for $11 \times 11$ pixel windows. It is worthy of note that a different conclusion would have been obtained for smaller windows. This point will be illustrated in Subsection 3.C, where the analysis is performed as a function of the region size $N_r = |\Omega_r|$ (where $|\Omega_r|$ is the cardinal of the set $\Omega_r$).

C. Performance Analysis as a Function of the Region Size

The GLRT of Eq. (5) leads to a constant Pfa with an appropriate choice of $\eta_{\Omega_0,j_0}^{(U)}$ [31]. This threshold $\eta_{\Omega_0,j_0}^{(U)}$ is a function of $N_r$ and, as shown in Fig. 5 for the three models $M_C$, $M_L$, and $M_Q$, and for three different fixed Pfa ($10^{-3}$, $10^{-4}$, $10^{-5}$) this pixel number $N_r$ can have a strong influence on the detection probability. Indeed, estimating $\rho_{\Omega_0,j_0}^{(U)}$ and $\sigma_{\Omega_0,j_0}^{(U)}$ increases the fluctuations of $\rho_{\Omega_0,j_0}^{(U)}$ and, thus, decreases the detection probability for a fixed Pfa in comparison to the ideal detector, whose parameters are known (which corresponds to a nonrealistic situation but represents the best achievable performance). This effect increases when the region size decreases. This can clearly be seen in Fig. 5, where the detection probability decreases significantly when $N_r$ is smaller than 150 pixels. Moreover, when $N_r > 150$ pixels, similar detection probabilities are obtained with the three models.

It can also be checked on Fig. 6 that, for the considered Pfa ($10^{-3}$, $10^{-4}$, $10^{-5}$), this evolution of the detection probability as a function of the region size is not very sensitive to the shape of the rectangular region. It thus appears important that the implemented segmentation technique allows one to obtain as few as possible regions $\Omega$, with less than 150 pixels, for efficient target detection with the $M_C$, $M_L$, or $M_Q$ image model.

D. Conclusion on the GLRT Performance Analysis

The above results show the importance of determining regions $\Omega_r$ whose gray level mean value is corrected by a linear or a quadratic function of the pixel coordinates and with a sufficient number of pixels.
PDF. This technique can be generalized to the \( \mathcal{M}_L \) and \( \mathcal{M}_Q \) models following the approach developed in [25,32,33] for image partitioning when the pixel mean values vary as linear or quadratic functions of the pixel coordinates. The considered segmentation techniques are based on the minimization of the stochastic complexity [34], which is equal to the sum of the negative of the generalized likelihood with the number of bits needed to code the partition and the PDF parameters in each region. For Gaussian PDF, the generalized likelihood is simply equal to \(-\sum \log \sigma_\Omega + C\), where the sum is performed over the different regions \( \Omega \), whose shapes and number are estimated, minimizing the stochastic complexity (which corresponds to a criterion without unknown parameter), where \( \sigma_\Omega \) denotes the estimation of the standard deviation of the residual fluctuations with respect to the estimated mean \( \hat{m}_\Omega \) in region \( \Omega \), see [23-25] for details) and where \( C \) is a constant term.

Since maximum likelihood estimation over a region \( \Omega \), of \( \hat{a}_\Omega \), \( \hat{b}_\Omega \), \( \hat{c}_\Omega \), and of \( \hat{a}_\Omega \), \( \hat{b}_\Omega \), \( \hat{c}_\Omega \), \( \hat{d}_\Omega \), \( \hat{e}_\Omega \), \( \hat{f}_\Omega \), for respectively, the \( \mathcal{M}_L \) and \( \mathcal{M}_Q \) models can be unstable in small regions, regions smaller than 10 pixels have been merged with the neighbor region that leads to the highest decrease of the stochastic complexity.

### B. Analysis of Segmentation Results

The segmentation results on the images in Figs. 1(a) and 1(b) obtained with the \( \mathcal{M}_C \), \( \mathcal{M}_L \), and \( \mathcal{M}_Q \) models are shown in Fig. 7, and similar results have been obtained on the image in Fig. 1(c). For example, with the image in Fig. 1(c), using the \( \mathcal{M}_C \) model, leads to 608 regions, their mean size is equal to 255 pixels, and 245 regions have fewer than 150 pixels. Using the \( \mathcal{M}_L \) model (respectively, the \( \mathcal{M}_Q \) model) leads to 143 regions (respectively, 110) whose mean size is equal to 1082 pixels (respectively, 1407) and only 19 regions (respectively, 26) have fewer than 150 pixels (typically regions should contain more than 150 pixels). We propose to show in Section 4 that such a goal can be reached with a simple segmentation technique.

### 4. Performance Analysis of Different Model-Based Segmentation Techniques

#### A. Introduction to the Considered Segmentation Techniques

Segmenting the image with the \( \mathcal{M}_C \) model can be performed with the technique developed in [23] for radar images and extended in [24] to Gaussian
pixels. Moreover, for the three images in Fig. 1, many small segmented regions obtained with the $M_C$ model are near the horizon, where targets are the most probably located. In the considered examples, the computational time for segmentation with the $M_L$ and $M_Q$ models are, respectively, multiplied approximately by a factor of 1.5 and 5.0, in comparison to segmentation with the $M_C$ model. We show in Fig. 8 the number of segmented regions containing fewer than $N$ pixels, as a function of $N$, when segmenting the images in Fig. 1 with the different considered segmentation algorithms. Since similar curves have been obtained for the three images in Fig. 1, only the average of the results obtained on the three images is presented in Fig. 8. These results show that segmentation of the sky images with the $M_L$ and $M_Q$ models leads to a smaller number of regions containing fewer than 150 pixels than with the $M_C$ model, although there exist regions for which their size is not significantly increased.

It thus appears that using the $M_L$ image model for segmentation is a good trade-off because it can decrease the number of regions containing fewer than 150 pixels (for which detection performance is severely degraded) and because no significant improvement has been observed with the $M_Q$ model, although it leads to a nonnegligible increase of the computational time.

C. Conclusion on the Segmentation Technique Analysis

The analysis of segmentation results clearly show that considering the background mean value varying either as a linear or a quadratic function of the pixel coordinates is, for our purposes, preferable to considering a constant mean value in the sky of the considered infrared images. Analysis of computational times may lead to prefering the linear model and no significant performance loss has been observed on the analyzed images with the quadratic model instead of the linear one and vice versa.

5. Results of the Proposed Detection Mixed Approach

In this section, we propose comparing, on infrared images of the sky, the performance of point target detection obtained when combining segmentation and GLRT detection with the same $M_C$, $M_L$, or $M_Q$ model used for both segmentation and detection. For that purpose, the detection and false alarm probabilities have been estimated on the real image in Fig. 1(a). Since a large dataset is required to estimate these probabilities, 64 images extracted from the infrared video sequence in Fig. 1(a) have been used so that two consecutive images are separated by 1 s. These 64 images have been segmented with the $M_C$, $M_L$, and $M_Q$ models, and the different target detection algorithms considered in Section 3 have been applied, using the regions determined by the segmentation algorithms to estimate the background parameters without considering the value of the tested pixel, as explained in Section 3. The detections have then been counted inside the $431 \times 46$ pixel sky portion near the horizon shown in Fig. 1(a) (dashed gray rectangle).

Since these images are not supposed to contain any target, this number of detections allows one to estimate the Pfa over $431 \times 46 = 1.310^6$ samples. To estimate the detection probability, 30 target locations uniformly distributed inside the dashed gray rectangle shown in Fig. 1(a) have been chosen. Once a synthetic target has been inserted at one of these possible target locations, changing the pixel value according to the fixed SNR at the target location, segmentation and detection algorithms have been applied to the image. This process has then been repeated for each of the 30 target locations and for each of the 64 extracted images, allowing us to estimate the detection probability over $30 \times 64 = 1920$ samples.

In Fig. 9, the detection probability versus the Pfa has been plotted for a synthetic target with SNR equal to 11 dB (and a positive contrast) when the $M_C$, $M_L$, and $M_Q$ models are used for both segmentation and detection on the image sequence defined above. It appears that the techniques based on the $M_L$ and $M_Q$ models for both segmentation and detection have the same detection performance on this sequence, whereas the algorithm that relies on the $M_C$ model for both segmentation and detection leads to degraded detection performance. This performance loss can be caused by two phenomena. On the one hand, as previously shown, using the $M_C$ model for detection in the case of a background with linear or quadratic variations can lead to a strong decrease of the detection performance. Indeed, with a mixed segmentation–detection approach, the target, and thus the tested pixel, is not in general centered in the segmented region. On the other hand, since using the $M_C$ model for segmentation produces more regions containing fewer than 150 pixels than using the $M_L$ or the $M_Q$ model, the detection performance may be degraded with the $M_C$ model in comparison to the $M_L$ and $M_Q$ models. To analyze the influence of the model used for segmentation and of the model used for detection, the detection probability of the algorithm that relies on the $M_C$ model for segmenta-
tion and the $M_L$ model for detection versus its Pfa has also been plotted in Fig. 9. This graph shows that the detection performance of this algorithm is improved in comparison to the one that relies on the $M_C$ model for both segmentation and detection, but is still degraded in comparison to using the $M_L$ or the $M_Q$ model for both segmentation and detection.

In Fig. 10, an example of target detection is presented with the results of the different considered segmentations. For that purpose, a target whose SNR is equal to 13 dB and with a positive contrast has been inserted at the pixel marked with a cross in Fig. 1(b). We show in Fig. 10(a) an extract of Fig. 9. Evolution of the detection probability as a function of the Pfa for four mixed segmentation–detection techniques applied to 64 infrared images extracted from the same sequence as the image in Fig. 1(a). The SNR of the targets is set to 11 dB (with a positive contrast). The false alarm and detection probabilities have been estimated in the $431 \times 46$ pixel portion of the sky shown in Fig. 1(a) (dashed gray rectangle).

Fig. 10. Insertion of a 13 dB target (with a positive contrast) in the sky of the infrared image in Fig. 1(b). (a) Zoom around the target location. Zoom of the segmentation results obtained on this image using (b) the $M_C$ model, (c) the $M_L$ model, and (d) the $M_Q$ model.

Fig. 11. GLRT values $\rho^{(U)}_{i,j}$ obtained in Fig. 10(a). A target is detected if $\rho^{(U)}_{i,j} > \eta^{(U)}_{i,j}$, where $\eta^{(U)}_{i,j}$ is shown by the dashed line so that the Pfa = $10^{-4}$. These values have been plotted for the line that contains the target, using (a) the $M_C$ model, (b) the $M_L$ model, and (c) the $M_Q$ model for both segmentation and detection and (d) using the $M_C$ model for segmentation and the $M_L$ model for detection. The target is located at column number 131.
the image in Fig. 1(b) around this target. The GLRT values $\rho_{\text{GLRT}}^{(U)}$ obtained on this image have been plotted in Fig. 11 for the line that contains the target, using the $\mathcal{M}_U$ models with $U = C, L, Q$ for both segmentation and detection, and using the $\mathcal{M}_C$ model for segmentation and the $\mathcal{M}_L$ model for detection. In this experiment, the threshold values $\eta_{\text{th}}^{(U)}$ also shown in Fig. 11, have been chosen in order to impose a Pfa of $10^{-4}$. Since a target is detected if $\rho_{\text{GLRT}}^{(U)}$ is greater than $\eta_{\text{th}}^{(U)}$, it can be seen that only the two algorithms using either the $\mathcal{M}_L$ or the $\mathcal{M}_Q$ model for both segmentation and detection are able to detect this target. On the contrary, the algorithm using the $\mathcal{M}_C$ model for segmentation does not allow one to detect the target, even when the $\mathcal{M}_L$ model is used for detection. Indeed, when looking at the segmentation obtained with the $\mathcal{M}_C$, $\mathcal{M}_L$, and $\mathcal{M}_Q$ models shown, respectively, in Figs. 10(b)–10(d), the target is located in a region that contains 1506 pixels with the $\mathcal{M}_L$ model, 7409 pixels with the $\mathcal{M}_Q$ model, but only 238 pixels with the $\mathcal{M}_C$ model, which is not sufficient to allow one to detect the target in that situation.

6. Conclusion and Perspectives

Using a polynomial model that consists of an approximation of the gray level mean values with a linear or a quadratic function of the pixel coordinates for both segmentation and detection seems to be an interesting approach to increasing detection performance in infrared images of the sky for point target detection. It leads to a simple technique that acts in two steps. In the first step, the image is segmented assuming a polynomial model of the pixel coordinates for the mean value, and without a tuning parameter in the optimized criterion. In the second step, detection is performed using a polynomial model, whose parameters are estimated in each region obtained in the first segmentation step but without considering the pixel under detection test. It also appears, on the considered infrared images, that a linear polynomial model seems to be a good trade-off between performance and computational time.

In further works, it will be interesting to analyze more carefully the robustness of the method, notably when another target or a defective pixel is present in the target region. Indeed, in the presence of an impulse signal in the target region, the background parameters can be misestimated and the detection performance can be degraded. It will be interesting to analyze precisely if the regions obtained with the proposed approach are sufficiently large to increase the robustness to the presence of such an impulse signal in the target region, or if nonlinear filters, such as a median filter [35] generalized to backgrounds with linear or quadratic variations of the gray level mean value, should be employed to estimate the background parameters.

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