A COMPARISON OF CFAR STRATEGIES FOR BLOB DETECTION IN TEXTURED IMAGES

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ABSTRACT

Traditional *CFAR* (constant false alarm rate) approaches applied to the detection of objects in images have proved useful in locating small patches on non-stationary backgrounds. However, the topic of detecting arbitrarily large objects by means of these approaches has received less attention. In this paper we make a comparative analysis of the performance of several *CFAR* strategies applied to the detection and segmentation of *blobs* in textured images. The difference in the strategies lies in the way the references for the estimation of the parameters of the detector are considered. By treating four detection schemes through MonteCarlo simulation, we show that directional approaches to the target have better results than non-directional ones. The fourth approach, refered to as 'gradient-guided', is the most promising philosophy.

1 INTRODUCTION

Automatic detection of irregularly shaped objects ('blobs') is a problem that has received considerable attention in the image analysis literature. It appears in a myriad of applications, such as medical diagnosis, defect detection in manufacturing processes, air traffic control and others. Traditional thresholding approaches to this problem rely on the assumption that the background on which the blobs are superimposed remains stationary in the field of view, and thus the problem is stated as finding the proper threshold to detect the blobs, possibly adding a spatial constraint, such as relaxation [3] or local use of global information [4].

For non-stationary backgrounds, a spatially adaptive threshold selection technique is to be used so that the detector keeps its performance constant throughout the image; *CFAR* techniques have thus proved useful in detecting objects in changing backgrounds, since the thresholds are calculated according to the estimated statistics of the background around each pixel under test. However, most of the proposals in *CFAR* detection in images focus either on the problem of detecting very small objects [6][7], or they assume there is some prior knowledge of the object to be detected, so that a target template is used, from which the statistics of the object can be estimated[8].

In this contribution we extend our basic *CFAR* point detector in textured backgrounds to the case of spatially extensive unknown-shaped blobs. In [1] we consider a textured background as a realization of a two dimensional non-stationary stochastic process, whose intensity distribution can be approximated by means of the family of gamma distributions. The decisions are made by comparing the intensity of the pixel under test to a threshold, which is adaptively calculated so that the Pfa (probability of false alarm, that is, the probability to incorrectly label a background pixel as a target pixel) remains constant. The threshold is estimated from the data within a window (estimation reference or simply reference) next to the pixel under test.

Our purpose is to determine a rule to place the estimation reference with respect to the pixel under test, so that the probability of detection is maximized, regardless of the blob spatial extension. To that end we deal with a number of choices of references of estimation, and we carry out a comparative analysis of their performance, in terms of probability of detection, as a function of two variables, namely, the relative mean brightness of the blob with respect to the background mode, and the blob size.

This contribution is structured as follows: section 2 describes four configurations of the reference of estimation: 'isotropic', 'censored isotropic', 'integrator' and 'gradient guided'. Section 3 describes the experiment that has been realized for our comparative purpose and shows the results by means of curves of probability of detection. Finally section 4 summarizes the conclusions and proposes some guidelines for further research.

2 ESTIMATION REFERENCES

The references that will be considered in our analysis are the following:

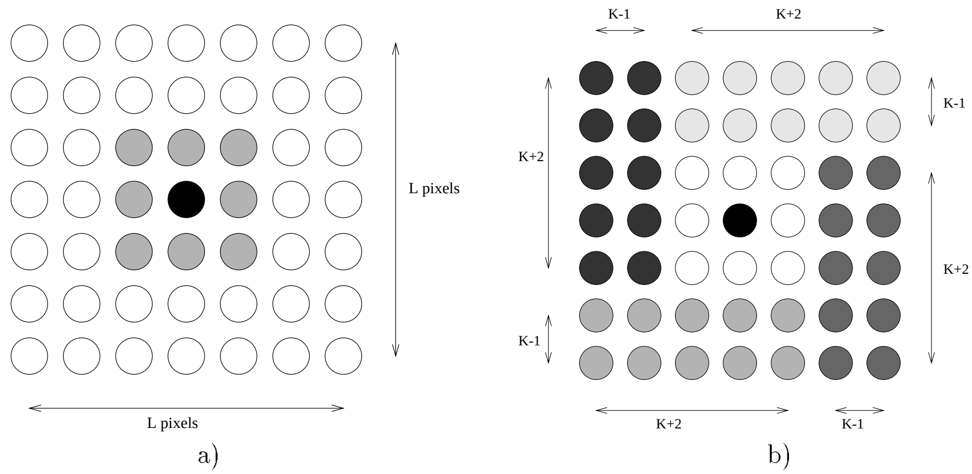

Figure 1: a) Isotropic reference. b) Four subreferences corresponding to the Integrator scheme.

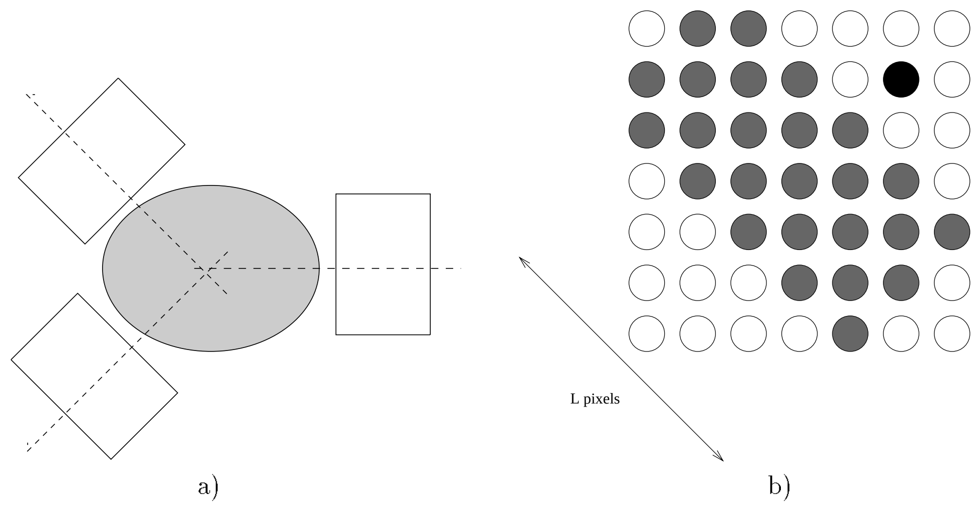

Figure 2: a) An example of gradient-guided references. b) Reference of estimation for phase gradient $\theta = \frac{\pi}{4}$.

2.1 Isotropic

This reference is basically that proposed in [7] for object detection in gaussian correlated clutter. A diagram of this reference is shown in figure 1a), where each pixel has been represented by a circle. As can be seen from the figure, the pixels that are used for calculating the decision threshold are compactly clusterized around the pixel under test (shown filled in black). A ring of eight pixels (filled in light gray) inscribing the pixel under test is also drawn: these pixels are not used for threshold calculation, in order to avoid that any power smearing from a potential target due to the imaging process might degrade the estimation of the background statistics. These pixels will be refered to as 'guards'.

As can be deduced from this figure, any target whose extension is bigger that a two pixel-sided square will be so that pixels from the target will be part of the estimation reference when it is used to determine the decision threshold at another point from the target. This will lead the threshold to increase (since the target is assumed to be brighter than the background) and thus to obscure that pixel to the detector.

Therefore, it is presumable (although it will be quantified in section 3) that this configuration will not be able to detect extensive targets. The following configurations will try to alleviate this -yet unjustified- problem.

2.2 Censored Isotropic

The censored isotropic scheme [2] employs the same reference as that depicted in figure 1a). However, data within the reference are processed differently. This processing scheme is a two stage detector: first, an initial decision is made about whether the cells within the reference are background pixels or target pixels. Only those cells designated as belonging to background are considered in a second stage, from which a better estimate of the parameters of the detector can be achieved. This way, the detector tries to avoid unnecessary high thresholds due to inhomogeneities in the reference. Since the detector is based on a first decision, the parameters in the second stage are estimated from a truncated gamma distribution; thus a correction of this effect is needed to guarantee the *CFAR* property in the detector.

2.3 Integrator

A different way to overcome the problem of the overlap between the reference of estimation and the pixels of the target is to divide the reference shown in figure 1a) into four independent subreferences, as shown in figure 1b), and to make a decision in each of them. The detection operation can be stated in terms of fusing the decisions obtained from every subreference. With this philosophy the sensible fusion rule is the OR logical function: the detector ignores its location with respect to the boundary of the blob (this is precisely what the process of detection is about); and thus there is no reason to weight the decision from a given subreference more than the ones from the other three; additionally, pixels located on the blob boundaries will typically trigger only one of the decisions; being so the case, the system will decide target present if at least one of the subreferences obtains a positive decision.

In order to guarantee an overall Pfa, the decision in every subreference has to be carried out with a different Pfa, namely Pfa_{sr}, which is obtained by solving the well-known binomial expression for this fusion rule

$$Pfa = \sum_{k=1}^{4} \binom{4}{k} Pfa_{sr}^{k} (1 - Pfa_{sr})^{(4-k)} \quad (1)$$

$$= 1 - (1 - Pfa_{sr})^{4} \quad (2)$$

which results in

$$Pfa_{sr} = 1 - (1 - Pfa)^{\frac{1}{4}} \quad (3)$$

2.4 Gradient Guided

The reference proposed in subsection 2.3 is directed at avoiding the effect of the overlap between the estimation reference and the target. However, this is done at the expense of reducing the extension of the references of estimation. This leads to a decrease in the statistical stability of the detector because the estimators that are used in its operation have a larger variance.

Other procedures can be conceived to reduce the overlap without incurring in this cause of degradation; the gradient guided is one of them. This procedure is based on the fact that the local gradient comprises the information of both the magnitude of the change in intensity values in the blob/background interface (modulus of the gradient operator), and of the direction in which this intensity change is ocurring (phase of this operator). Therefore, if the reference of estimation is placed in a normal direction with respect to the phase of the gradient, it will minimize the overlap between its pixels and those from the target (See the sketch of a hypothetical target in figure 2a) for three estimated phases. The estimation references are the white rectangles). Notice that the gradient points at the positive change in intensity. Thus, a reference guided by the information in the gradient phase will lie in the darker area, as it is necessary for our bright point detector.

We have used one of the well-known gradient estimators, namely, the Sobel operator[5]. Its phase has been quantized to eight directions (horizontal (left and right), vertical (up and down) and the four main diagonals). One example of the reference of estimation, specifically that corresponding to $\theta = \frac{\pi}{4}$, is shown in figure 2b). The pixels in the estimation reference (light gray filled circles) are separated from the pixel under test (filled with black) by a diagonal line of guards, in a similar way as 1a) and 1b).

3 PERFORMANCE EVALUATION

We have studied the detection performance of the four detection schemes as a function of two variables: difference in brightness between background and target, and area of the target. We have assumed a fluctuating target modelled by a uniform distribution, with constant width, and its mean is increased with respect to the mode of the background in uniform steps. A Pfa of 10^{-3} is considered. In every case the parameter L in figures 1 and 2b) has been set to 15. Correspondingly the parameter K in figure 1b) is 7 ($L = 2K + 1$). The experiment is directed at finding the blobs boundaries in every case. Therefore the probability of detection is calculated as the ratio between the number of detected pixels on the boudaries and the total number of pixels on them.

Figure 3a) shows the probability of detection of the four schemes for a target with area 3x3 pixels (small target). From this figure it is clear that the performances of the last three techniques are comparable. However, the isotropic approach has a lower probability of detection as we had predicted in subsection 2.1. For larger targets the results of both isotropic strategies (direct or censored) worsen rapidly. Censored isotropic is still capable of detecting a 4x4 pixel (not shown in the figures) but from there on results shrink fast. Figure 3b) shows the probability of detection corresponding to the integrator (solid line) and the gradient guided (dashed line) schemes for target areas 1x1 and 8x8 pixels. This figure highlights the fact that the gradient guided scheme is superior at avoiding the presence of target pixels in the estimation reference. Its performance is completely independent of the target size. However, the integrator scheme detects equally well a point target (its curve coincides with those from the gradient guided), but a larger target has to be brighter to approach the gradient guided detection performance. The reason for this fact can be deduced from expression (3). The integrator is only detecting in one of the subreferences, for which a lower Pfa has been set. Therefore, the lower the Pfa, the

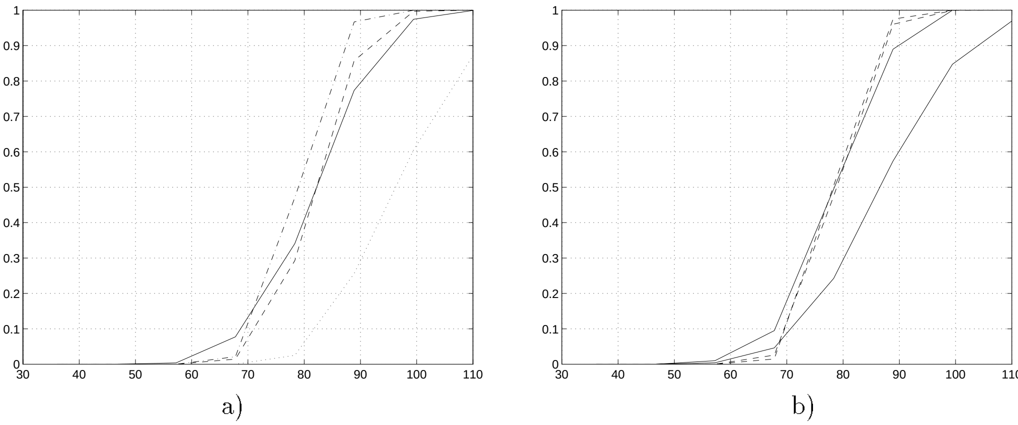

Figure 3: Results of the experiments of probability of detection (L= 15 pixels). a) isotropic is shown dotted, censored isotropic dashed, integrator solid and gradient guided dashdotted. b) Integrator and gradient guided (solid and dashed resp.) for two target areas. The isolated curve in the figure corresponds to a 8x8 pixels target. Both in a) and b) the magnitude in abscisae is the difference between the target mean intensity and the background mode.

lower the probability of detection for a given difference in brightness.

4 CONCLUSIONS

We have presented a comparative analysis of the detection performance of four strategies of definition of the reference of estimation. Results show that for moderated sizes of the target, the schemes termed as 'censored isotropic', 'integrator' and 'gradient guided' have comparable results . If targets of that extension are expected, the censored isotropic seems more appropriate, since it is more robust when applied to a non-stationary background because the estimation reference extends from the target less than in the gradient guided scheme, and a larger efective reference than that in the integrator scheme is used. For more extensive targets, the integrator and the gradient guided schemes should be used. We have shown that gradient guided scheme leads in the probability of detection in a way that suffers no degradation with an increasing target size. An isotropic scheme, as proposed in [7], shows many losses due to unnecessary high thresholds for non-point targets.

Further research should consider techniques to incorporate spatial information in the detection framework. Notice that we are making decisions at a pixel level, and thus, we make no use of the results of previous detections. However, previous detections show a sketch of the boundaries of the blob, which might be quite useful to guide following detection steps. Therefore, our contribution in this paper would be an 'entry-point' in the detection process, when other information is not available yet.

References

[1] C. Alberola, J. R. Casar, G. de Miguel, *CFAR* Real-Time Detection in Textured Images, *Proc. of the International Conference of Signal Processing, Applications and Technology*, ICSPAT-95, Vol. I, October 1995 pp. 1102-1106.

[2] C. Alberola, J. R. Casar, J. Ruiz, 2-Threshold 2-Parameter *CFAR* Detector Applied to the Detection and Segmentation of *Blobs* in Textured Images, *Proc. of the International Conference on Signal and Image Processing*, SIP-IASTED-95, Vol. I, November 1995, pp. 117-120.

[3] A.J. Danker, A. Rosenfeld, Blob Detection by Relaxation, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. PAMI-3, No. 1, January 1981, pp. 79-92.

[4] R. A. Narayanan, A. Rosenfeld, Image Smoothing by Local Use of Global Information, *IEEE Trans. on Systems, Man and Cybernetics*, Vol. SMC-11, No. 12, December 1981, pp. 826-831.

[5] W. K. Pratt, Digital Image Processing, *John Wiley and Sons Inc.*, 1991, pp. 503.

[6] T. Soni, J. Z. Zeidler, W. H. Ku, Performance Evaluation of 2-D Adaptive Prediction Filters for Detection of Small Objects in Textured Backgrounds, *IEEE Trans. on Image Processing*, Vol. 2, No. 3, July 1993, pp. 327-339.

[7] C. W. Therrien, T. F. Quatieri, D. E. Dudgeon, Statistical Model-Based Algorithms for Image Analysis, *Proceedings of the IEEE*, Vol. 74, No. 4, April 1986, pp. 532-551.

[8] X. Yu, I. S. Reed, A. D. Stocker, Comparative Performance Analysis of Adaptive Multispectral Detectors, *IEEE Trans. on Signal Processing*, Vol. 41, No. 8, August 1993, pp. 2639-2656.