DETECTING AIRCRAFT WITH A LOW RESOLUTION INFRARED SENSOR

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ABSTRACT

We propose a new method, based on level sets, to detect aircraft on low resolution infrared images. Aircraft correspond to hot temperatures at the sensor level. Hence it is natural to rely on a test that considers the hottest pixels in the sensed image. If these pixels are close, they are likely to come from a target (*i.e.*, an aircraft); otherwise they belong to the clutter. Instead of manually testing the neighborhood of each hot pixel, we use level sets; this is the first contribution of the paper (corresponding to eq. 2). The other contribution is the calibration of the resulting test. The method is implemented and tested over a database containing $45\,604$ simulated aircraft images and provides 98.5% of correct detections.

***Index Terms*—** infrared surveillance, aircraft detection, image processing, image resolution.

1. INTRODUCTION

Detecting objects using only a single low-resolution image is usually a difficult task. Preferably, one circumvents the difficulty by using a bunch of such images and recover the details lacking in each image taken separately. In the context of aircraft detection, such methods are known as "Track Before Detect" (TBD) [1, 2]. Here we are going to deal with a specific problem, where the clutter did not completely destroy the image geometry. So we were able, using appropriate tools, to work with a single image and yet obtain good detection results. To the best of our knowledge, there are few work in this direction dealing with aircraft detection. Let us mention [3] that designed an algorithm that can adapt to various clutters and targets but first needs a learning step.

French Aerospace Lab ONERA designed an infrared sensor simulator along with an aircraft infrared signature simulator named CRIRA. This sensor's aim is to detect aircraft flying low. In order to be useful the sensor should be able to detect aircraft far ahead. Unfortunately, there are some physical obstacles that make the sensing quite intricate. First, the device has to be manheld, so its resolution has to be coarse (64×64 pixels), otherwise it would be too cumbersome. Then, at such distances, atmospheric absorption has an important impact on the sensed image. And finally, the sensed image depends on several unkown parameters such as the flight parameters of the aircraft, the presence of clouds, etc. Fig. 1 gives a hint of the kind of images we are going to cope with. In Fig. 1 (a), one can see a bright area in the middle, the aircraft is easy to spot. The corresponding histogram is shown in Fig. 1 (b): most of the pixels are cold (low values, less than .1) and few are hot (the max is about 1.0). On such images, looking at the hottest pixel provides a strong support for detection. However, some images are more challenging, like the one pictured in Fig. 1 (c): it is essentially white noise plus a couple of barely hot pixels (approx. .2).

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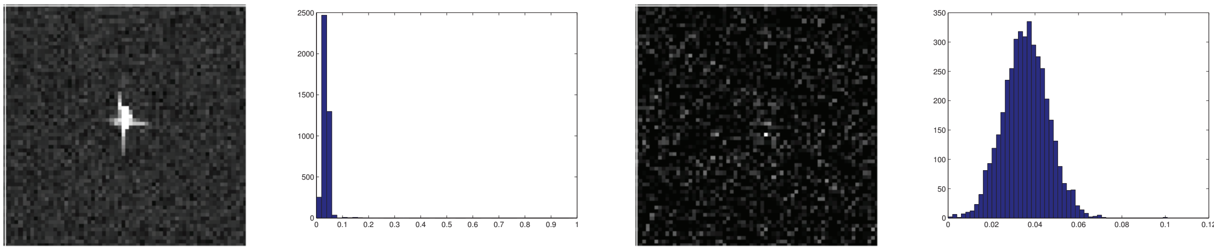

(a) (b) (c) (d)

Fig. 1. (a): Easy image, the aircraft yields a hot spot in the middle of the image. (b): Histogram of image a. Nearly all pixels are at the noise level, a few ones are clearly above. (c): Challenging image, the aircraft is barely visible, two pixels out of 4096 are hotter than noise. (d): Histogram of image c.

2. STATISTICAL FRAMEWORK

2.1. Model and Notations

An infrared image is an $n \times n$ matrix $\varphi : [1, n]^2 \to \mathbb{R}$ where n is the resolution of the sensor ($n = 64$ in our case).

It has already been seen that aircraft infrared images can vary widely. This is why modelling the infrared signature of an aircraft is a complicated problem. We circumvent the difficulty by modelling the absence of aircraft instead. Under clear sky assumption, white gaussian noise is a natural candidate. This is the null hypothesis, denoted by H_0 in the sequel. Under H_0,

$$\varphi \sim \mathcal{N}(0, \sigma^2 I_{n^2}) \tag{1}$$

after having stacked all the n^2 entries of φ in a single vector. The sensor is calibrated meaning that σ is *known* ($\sigma = .01$ in our case) but the following will not use this information in order to adapt to uncalibrated sensors. The alternative hypothesis H_1 is simply everything but H_0.

Of course, as H_1 is left unspecified, we cannot apply standard likelihood ratio tests. We have to design the test statistics $T(\varphi)$ so that it reflects our knowledge of the target. For instance, if the only thing we knew was the target to be hotter than the background, a straightforward idea would be to put $T(\varphi) = \max(\varphi)$. Then, we could calibrate the threshold on $T(\varphi)$ using the test distribution under H_0 and the probability of false alarm.

This kind of test gives good results on easy images as Fig. 1 (a), but would fail on difficult images such as the one represented in Fig. 1 (c). Fortunately, we also know that hot pixels coming from an aircraft infrared signature should also be *spatially* close.

2.2. Level Sets

Level sets have long proved their usefulness in image processing [4, 5, 6]. Here they provide a handy tool for testing spatial proximity of hot pixels. Let us recall some basic definitions (refer, for instance, to [7] for details). Let φ be a discrete image and $\tilde{\varphi}$ its bilinear interpolation (many other interpolation schemes could also be used as well). An upper level set for φ is a connected component (cc) of $S_\lambda = \{(x, y) : \tilde{\varphi}(x, y) \geq \lambda\}$. Since we will not deal with lower level sets, we omit the qualifier "upper". Fig. 2 compares two level sets with the same level λ extracted from Fig 1 (a) and (c).

Finally, the test statistics is the maximum area of all level sets with level λ:

$$T_\lambda(\varphi) = \max_{s \in \mathrm{cc}(S_\lambda)} |s| , \tag{2}$$

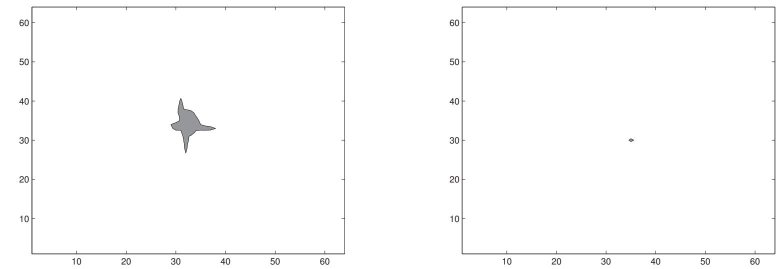

Fig. 2. Level sets corresponding to level $\lambda = .38$ for images Fig. 1 (a) and (c).

where $|s|$ denotes the area of set s. The idea underpinning this statistics family is the following. If there is no aircraft, gaussian white noise should yield level sets with small area when $\lambda \gg \sigma$ (this is the principle used by the morphological *grain* filter [8]). If there is indeed an aircraft, either atmospheric absorption has been small and has not eroded the aircraft geometric structure: in this case there is a large hot zone somewhere in the image, hence a level set with large area. Or the atmospheric absorption has left none but a very few pixels slightly above the noise level: in this case, these pixels should be close enough for a small level set to remain.

3. THE PROPOSED ALGORITHM

In order to use the statistics T_λ (eq. 2) one needs to calibrate the test under H_0 (eq. 1) that is, determine its distribution under H_0 hypothesis. For $T(\varphi) = \max(\varphi)$ it can be carried over analytically using extreme value theory [9]:

$$\sqrt{2\log(n^2)}\frac{\max(\varphi)}{\sigma} - 2\log(n^2) - \frac{1}{2}(\log(4\pi) + \log\log(n^2)) \rightarrow \xi\,,$$

where ξ has a Gumbel distribution function $\exp(-\exp(-x))$ and the convergence takes place in distribution. But for T_λ such asymptotic results are difficult to obtain. This is why we resorted to Monte-Carlo simulation to calibrate T_λ. Fig. 3 illustrates the various pdf found for various values of λ.

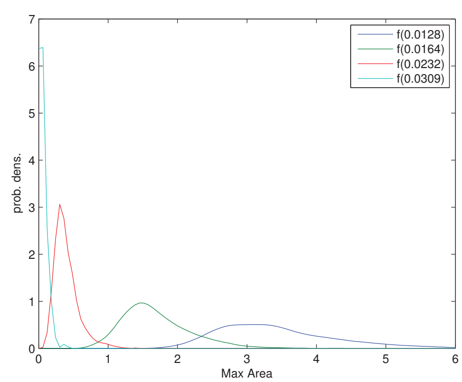

Fig. 3. Monte-Carlo estimation of pdf corresponding to $T_\lambda(\varphi)$ under H_0 for various values of λ. We used $\lambda_1 = q_{.95}$, $\lambda_2 = q_{.95}$, $\lambda_3 = q_{.99}$, $\lambda_4 = q_{.999}$, where q_α is the α^{th} quantile of a centered gaussian distribution with variance σ^2.

Once the level λ chosen, the desired probability of false alarm ε fixed, the previous Monte-Carlo simulation gives the corresponding threshold t_ε. The detection method is straightforward: if $T_\lambda(\varphi)$ is greater than t_ε, then reject H_0 and output the corresponding level set; otherwise accept H_0.

In all experiments we chose $\varepsilon = 10^{-3}$. We then estimate the noise standard deviation $\widehat{\sigma}$ using a robust estimator: discard 10% of extremes pixels, and use the standard estimate on the remaining pixels. Then we chose $\lambda = 2\widehat{\sigma}$ according to several tests made on our database. It is a reasonable values since, according to Fig. 3, level sets having area above 1 pixels are very unlikely under H_0 hypothesis.

We ran this algorithm on our infrared signatures database made of $45\,604$ aircraft images simulated under a wide range of parameters value (aircraft angular parameters, time of the day, weather, etc.). This database is mainly composed of "easy" images such as Fig. 1 (a). but a small proportion of images is very challenging as the one of Fig. 1 (c), and some are even impossible to detect, being completely black up to the thermal noise. We obtained 98.5% of correct detections, while ensuring that, when ran on pure white noise images the probability of false alarm was below 0.1%. Fig. 2 actually shows our detection result on the corresponding images.

4. CONCLUSION

We proposed a new method, based on level sets, to detect aircraft on low resolution infrared images, implemented it, and tested it over a database of $45\,604$ simulated aircraft images (while enforcing the probability of false alarm below a fixed level, 10E-3 in our experiments). This method gave good results on the database: 98.5% of correct detections; among the 1.5% of miss detection, some images (0.9%) being completely black (up to the thermal noise) due to massive atmospheric absorption. For easy detection the method gives an interesting output, namely the region of interest with accurate contour around the aircraft. This puts the user in good position to further processing: classification, parameter estimation, etc.

A weakness of the method is to rely on white noise assumption for the background model. Ongoing work, that will be the subject of a forthcoming paper, should allow us to relax this restrictive hypothesis and approximate the level sets area distribution for any Gaussian Field provided it is regular enough.

5. REFERENCES

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