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# Confidence-driven infrared target detection

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The confidence of target detection can be used to evaluate the reliability and risk level of the detected targets and can effective help to exclude the false alarms, but very little investigation was involved in the past. In this letter, a confidence-driven infrared target detection method is proposed. We develop three confidence evaluating methods: (1) the median classification confidence of the cascade classifier; (2) the context confidence based on the number and the confidence of the merged detection rectangles around the detected target; and (3) the contrast confidence based on the difference between the detected target distribution and the around background distribution. The three confidences are combined to form the final confidence of the detected targets. We then use the confidence to refine the localization of the targets. The evaluation using real infrared images demonstrates the good performance of the proposed confidence-driven infrared detection algorithm on both undetected error and false alarm.



## 1. Introduction

As the development of infrared imaging technology, infrared target detection has received more and more attention and be widely applied in automatic target recognition (ATR), especially in military field due to the robust imaging to the weather situation, the change of climate and the good performance of all-day working [1,2]. The infrared target detection is always a challenging task because of the high variability of target signatures and highly unpredictable nature of thermal exchange with the environment [3].

Most of the traditional infrared target detection methods are based on the difference of the appearance features between the targets and background. For example, the contrast and the light feature are usually used to distinguish the targets from the background [4]. However, due to the serious clutter disturbances in sea, the significant cloud occlusion in sky or the complex and varied ground background the feature-based technologies often fail to extract the true targets or bring about too many false alarms. It is rather difficult to develop a general approach to detect all kinds of targets in the different backgrounds [5].

Another noteworthy thing is that the existing infrared target detection methods are lacking in the confidence evaluation to target detection. Confidence evaluation can be seen as a variable which has high correlation with the probability of correct target detection, and it can be used to measure the reliability of the detected targets. The extracted targets from images can be sorted by the order of confidence and more attention should be paid to the targets with high confidence, which is especially important in military application. The confidence of target detection can help to determine the risk level of the detected targets when multiple targets appear, then decide the defending order of the Early Warning System (EWS). The confidence can also help to exclude the false alarms. Therefore, target detection with confidence evaluation is extremely significant in ATR of military field.

To develop a general infrared target detection which can be adaptively applied to all kinds of military targets such as airplane, missile and warships, we resort to the machine learning technologies which are extensively used to object recognition and classification in natural scene [6]. We choose AdaBoost learning algorithm to build our target detection framework. The AdaBoost learning algorithm has been successful applied in face detection [7] where a simple and efficient classifier is built to select a small number of critical visual features from a very large set of potential features [8] to achieve high detection rates. Simultaneously, two strategies, the integral image representation and cascade combination of

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classifiers are used to make the algorithm capable of processing images extremely rapidly. The integral image representation allows the features to be computed very quickly and the cascade combination can discard background regions of the image quickly while spending more computation on promising object regions [7]. The algorithm in [7] is very suitable to infrared target detection of military applications due to high detection rates and good real time performance.

To build our infrared target detection framework, the simple harr-like features [8] is used to train the cascade classifier among which the sub-classifier in every level will output a confidence for test regions and those regions with low confidence will be rejected. Only those regions that can pass all the sub-classifiers in the cascade framework can be regarded as targets. Therefore, a large number of background regions are discarded in the first few level sub-classifiers in cascade framework. However, the algorithm in [7] does not provide the confidence evaluation to the detected targets. In this paper, we will focus on the confidence computation of the target detection and apply the confidence to drive more accurate target localization.

The first confidence evaluation is related to the output confidence of all the sub-classifiers in the cascade framework. We combine all the confidences by the cascade classifiers to construct the classifier confidence of the target detection. Besides the classifier confidence, the second confidence evaluation involves the context of the candidate targets. The cascade classifier will output many overlapped target rectangles in target area. These overlapped target rectangles will be merged to form one. The number of the overlapped rectangles related to one candidate target can be used to evaluate its confidence. The more the number of the overlapped rectangles is, the higher the confidence of the candidate target is. Thirdly, for infrared image, the targets are usually the bright parts in image. Therefore, the contrast between the target region and the around background can be used to measure the confidence of the candidate targets. We evaluate the confidence of the detected targets by computing the distance between the target distribution and the around background distribution. All the three confidences of the candidate target are combined to form the final confidence.

It is well known that the minimal bounding box of the expected target is preferred for the sake of highly accurate target localization. In most cases however, the detected target rectangle contains a lot of background, which degrades the accuracy of target localization. We propose to use the confidence of the detected targets to drive the more accurate target localization. Based on the cascade classifier target detection framework, the proposed confidence-driven infrared target detection is illustrated in Fig. 1. Firstly, the input image is processed by the cascade classifier and the candidate targets are extracted. Then the classifier confidence, context confidence and contrast confidence are computed and combined to get the final confidence of each detected candidate target. The targets with low confidence are excluded as false alarms. For each retained target rectangle we shrink the retained target rectangle to get new target rectangle and send it to the cascade classifier to evaluate its confidences. If the confidence of the new target rectangle increases compare with the previous target rectangle we further shrink the target rectangle to repeat the circle. Otherwise, the previous target rectangle and its confidence is output and the detection ends.

## 2. Confidence-driven target detection

### 2.1. Classifier confidence

The first confidence is the *classifier confidence*. Assume the cascade classifier is divided into $n$ stages and each stage has a sub-classifier. For each sub-classifier there is an independent classification threshold which is obtained by training a number of samples and the threshold of each stage can be adjusted so that detection error is reduced to minimum. Each sub-classifier will classify the input image region in the current sliding window and compute the classification confidence. The window whose confidence is less than the threshold will be labeled negative. Only those windows that pass through all the stages in the cascade classifier are labeled positive, or pruned as negative. This scheme results in high computational efficiency because a negative result can be pruned at any stage so that only a small number of sub-windows face a more difficult task than the others. However, few attentions are paid to the confidence analysis of the cascade classifier. In this letter, we give the formal definition of the confidence of the detected target by the cascade classifier.

Let $t_j (j = 1, \ldots, n)$ be the threshold of the stage $j$ of the cascade classifier, where $n$ is the number of the stages. For a given window $w_i$ in the input image $I$, the confidence by stage $j$ of the cascade classifier is defined as $C_{ij}$. If $C_{ij} > t_j$ for $j = 1, \ldots, n$ the window $w_i$ will be labeled positive, or negative. We define the normalized $C_{ij}$ as $NC_{ij}$.

$$NC_{ij} = e^{\frac{-\alpha t_j}{C_{ij} - t_j}} \tag{1}$$

where $\alpha$ is a constant that is used to control the confidence value of each stage in the cascade classifier. For a window $w_i$ labeled positive, the classifier confidence $C_i(\mathit{classifier})$ is defined as the median of $NC_{ij} (j = 1, \ldots, m)$.

$$C_i(\mathit{classifier}) = Median(NC_{ij} | j = 1, \ldots, n). \tag{2}$$

The computation of the confidence $C_i(\mathit{classifier})$ of the window $w_i$ is illustrated in Fig. 2.

### 2.2. Context confidence

The second confidence is the *context confidence*. The sliding window target detection method will classify every window with multiple different scales in image. Thus, there are many bounding boxes around the same detected target. Each bounding box corresponds to a labeled positive target with a confidence value by the cascade classifier. Then these bounding boxes are merged to form one target rectangle. One example is shown in Fig. 3, where two targets (two red rectangles) are extracted in Fig. 3(a). The green rectangles around the detected targets are merged into red target rectangles (Fig. 3(b)) among which one is false alarm. Fig. 3(c) shows the response map where each green window has a positive response given by its confidence. From the results in Fig. 3 we can see that the true positive red target rectangle is merged by a large number of green rectangles while the false positive is merged by a small number of green rectangles. Moreover, the response of the true positive is higher than the false positive. Based on the observation, we can construct the context confidence of the detected target according to the number of the bounding boxes around the target and their confidences. The more the number of the combined bounding boxes is and the higher their confidences are, the more reliable the detected target is. The context confidence is defined as:

$$C_i(\mathit{context}) = e^{\frac{-\beta}{\sum_{k=1}^{K} C_{ik}}} \tag{3}$$

where $\beta$ is a constant that is used to control the value of context confidence and $K$ is the number of the combined bounding boxes around the detected target. $C_{ik}$ denotes the classifier confidence of the $k$th bounding box around the detected target window $w_i$. The computation of the confidence $C_i(\mathit{context})$ of the window $w_i$ is illustrated in Fig. 4.