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# Real Time Object Detection from Infrared Image Using Ring Filter

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## Summary

Object detection, recognition and tracking are very essential for video surveillance systems, and so a lot of research works have been done in this field. SVM is one of the most widely−used machine learning methods for its simplicity and accuracy. Furthermore, it is easy to deal with high−dimensional data by using SVM. Meanwhile, Gabor filter is popular for feature extraction to represent target objects. In this paper we propose a novel approach to detect multiple objects such as vessels or helicopters from an infrared image in real time. Once candidates have been chosen by means of ring filter, their Gabor filter feature vectors are classified through SVM with the use of Gaussian radial basis function kernel.

*Keywords*: Object detection; Gabor filter; SVM; Infrared image; Surveillance system

## 1. Introduction

There have been various approaches for object detection such as feature−based methods, template−based methods, classifier−based methods, motion−based methods, etc. [4, 8]. Motion−based object detection methods which employ background subtraction technique are widely used for video surveillance systems [3, 6, 7, 11]. Nowadays machine learning based object detection methods have attracted public attention. These methods extract feature vectors of a given object and classify them as a member of a predefined class using lots of training images [1]. Adaboost and SVM (Support Vector Machine) are the typical means for object classification [2, 9, 10]. Meanwhile, for machine learning, features from an input image should be extracted. For SVM training, various features can be used according to the specific properties of objects. Recently features extracted by Gabor filter parade exceptionally good performance in many modern problems and applications of computer vision [5].

In this paper, we propose a new method for detection of objects such as vessels or helicopters in real time and accurately from infrared images as shown in Fig. 1(a). There are several problems to detect such objects. Firstly, the background subtraction technique is inapplicable to detection of vessels or helicopters from such infrared images because it seems that they are not moving in many cases. Secondly, there are some background regions similar to target objects (for example, isles, clouds, etc.) and these regions affect object detection negatively. Lastly, there is no given fixed aspect ratio of a target object; rather it may vary within a wide range. For instance, when a vessel is captured from its front or rear, the aspect ratio of its image is nearly 1: 1. But if we get an image from one side of the ship whose aspect ratio can vary from 1: 2 to 1: 5, we can't use a fixed−size search window.

One solution to the first problem is to detect objects only by using spatial information from a single image; the second problem can be solved by a good classifier, and we use SVM classifier and Gabor filter for feature extraction; and the last problem by applying variable size search windows whose aspect ratio can vary from 1: 1 to 1: 5. However, it will be computationally expensive to apply SVM and Gabor filter over the whole image with variable size search windows. The proposed real−time object detection has two steps. Firstly, we scan the input image with ring filter to search candidate regions, and secondly, we verify the candidates with the use of Gabor filter features and SVM.

The rest of this paper is organized as follows. Section 2 describes a candidate selection method using ring filter. Section 3 explains object verification. Section 4 shows experimental results and conclusion is given in Section 5.

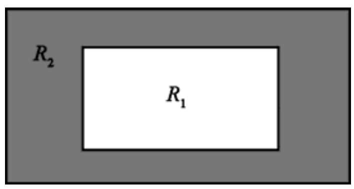
## 2. Candidate Selection by Ring Filter

As can be seen in Figre 1(a), the pixel values inside a target object in an infrared image are higher than those on the object's surroundings. To represent this feature, we define a ring filter as shown in Fig. 1(b). Region $R_1$ shaded in white in the Fig. 1(b) is a search window and the region $R_2$ filled with dark grey is an extension of $R_1$. The number of pixels in $R_1$ is the same as that in $R_2$. Response of the ring filter on the search window $R_1$ is defined as

$$h_{R_1} = \frac{1}{\sqrt{A_{R_1}}}\left(\sum_{i,j\in R_1} f(i,\ j) - \sum_{i,j\in R_2} f(i,\ j)\right) \tag{1}$$

where $A_{R_1}$ is the number of pixels inside of $R_1$.

a)




b)

**Figure 1.** (a) Infrared images. (b) Ring filter.

Thus the response of the filter is just the difference between the sum of values of $R_1$ pixels and the sum of values of $R_2$ pixels. It is divided by the square root of $A_{R_1}$ for normalization which varies nonlinearly according to the size of $R_1$.

If a response of a ring filter is greater than a predefined threshold, the corresponding region is selected as a candidate. In other words, the larger the response of the ring filter we get, the higher probability of being selected as a candidate the region has. Scanning the input image with a search window of a given size, we select the regions in which the response of ring filter is greater than the threshold, and mark them as candidates. Changing the size of the search window, we iterate scanning the image and selecting candidates. The results are shown in Fig. 2(a).

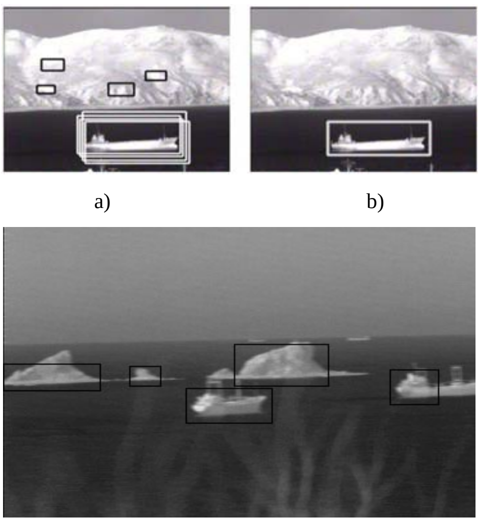
In Fig. 2(a) we can see that several candidate regions are overlapped each other on a real object. But there are a few candidate regions selected on a false object. This fact implies that we can suppress false candidates. Meanwhile, in the case of a real object on which there are many overlapped candidates, we select only a region where the response of ring filter is the greatest as shown in Fig. 2(b). The Fig. 2(c) shows result of candidate selection from another input image. As in Fig. 2(c), not only vessels but also isles can be selected. These uninterested candidate regions can be suppressed by the following object verification step.

## 3. Object Verification Using Gabor Features and SVM

Now we verify the selected candidates using SVM with their Gabor filter responses. The objective of this verification is to determine whether the selected candidates are real target objects or not. At first, we normalize the candidates so that all of them have identical resolution (for example, 24×24 pixels). Then the normalized candidates are used in the rest of processing.

### 3.1 Extracting Gabor Features

Though there are various useful features, Gabor feature is a preferable choice because of its ability to represent local pieces of information.



a) b) c)

**Figure 2.** Regions with higher response of ring filter a), a candidate with the greatest response b) and result from candidate selection step c)

We first divide a normalized candidate into small blocks (8×8pixels). Then we apply Gabor filter on the blocks to extract spatial local features of different 8 directions and 5 scales. If the size of a normalized candidate is 24×24pixels, then the dimension of Gabor feature vector is 9×8×5=360.

### 3.2 Classification by SVM

We employ the SVM classifier with the use of Gaussian radial basis function. So we need a training dataset for SVM learning. The candidates from training images can be automatically collected by a ring filter while verification of training data should be done manually. When testing takes place, a new input is classified by the trained SVM.

## 4. Experimental Result

We used 86 and 114 infrared images that contain vessels and helicopters, respectively. All of them were CIF (352×288) images. In candidate selection, we scanned each of the 86 input images that contain vessels iteratively changing aspect ratio of search window from 1: 1 to 1: 5. For the 114 helicopter images, we set the aspect ratio as 1: 1. On the other hand, we iterated the scan in both cases changing the height of the search window between the minimum and maximum object heights chosen in advance. Fig. 3 shows some examples of selected candidates. 187 candidate regions were selected from the 86 vessel images, 156 of them were true vessels while 31 of them were not. And 141 candidate regions were selected from the 114 helicopter images, 111 of them were true helicopters while 30 of them were not.

Then these all candidate regions were classified manually and normalized. The size of the normalized region was 24×24 pixels. SVM was trained on Gabor features extracted from the normalized candidates. In case of vessels, the penalty parameter was 29.0 and the RBF sigma parameter was 6580. For helicopters, the best penalty parameter and the RBF sigma parameter were 42.5 and 6 000, respectively.

We classified 355 new test images by using the trained SVM on a system with 2.2GHz Intel Pentium 4 CPU and 1GB RAM. 180 of them were vessel images and 175 of them were helicopter images. Table 1 shows the classification results.

From Table 1, we can verify that the proposed method exhibits sufficiently good performance of high classification accuracy and detects target objects very fast even on a low−cost system. The misclassified regions can be used to retrain SVM for improvement of its accuracy.

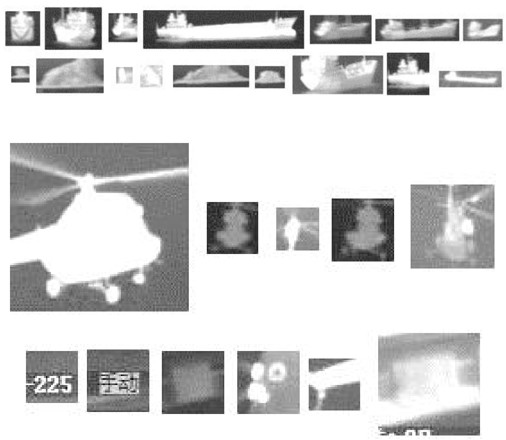



**Figure 3.** Example of selected candidates

**Table 1.** Performance of the proposed system

| Object Type | FRR, % | FAR, % | Computational Time, ms |
|---|---|---|---|
| Vessel | 4.44 | 3.89 | 29.4 |
| Helicopter | 4.0 | 3.43 | 21.2 |

## 5. Conclusion

A novel approach for real–time detection of vessels or helicopters from an infrared image has been proposed in this paper. The proposed method is composed of two steps: selection of candidates by ring filter and verification of the candidates by using Gabor feature and SVM. From the experimental result, we can verify effectiveness of the presented method for creating a real–time infrared camera surveillance system.

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