# A NOVEL APPROACH TO THE NOISE REMOVAL AND DETECTION OF SMALL OBJECTS WITH LOW CONTRAST

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**ABSTRACT**

An effective approach for detection of small objects with low contrast is proposed. In our work, small moving objects are detected in an image sequence captured from a video camera. The detection system includes two modules, namely region of interest (ROI) locating and contour extraction. In the former module, image-differencing technique is employed on consecutive images to generate rough candidates of objects appearing in the images. Next, a novel neighboring encoding technique is devised to effectively remove noise that usually severely affect the performance of detection. The noise-removed candidates are then bounded by minimum enclosing rectangles to obtain ROI. However, the generated results provide insufficient information characterizing object contours. Traditional contour extraction methods cannot obtain satisfactory results under this circumstance. We adopt the watershed algorithm incorporating with region-matching technique to obtain accurate object contours. Experimental results demonstrate the feasibility and effectiveness of proposed approach.

## 1. INTRODUCTION

During the past decade, object detection plays an important role in the area of computer vision. There are some problems in small objects extracting which is important to some applications, such as vehicle tracking for transportation systems or target tracking for military purpose. Particularly, noise is a critical problem encountered in object detection, which might severely affect the detection results. The detection results are usually very poor when the detected objects are small and with low contrast by employing traditional image-differencing methods. To remedy the problem, an effective and efficient object detection method is proposed in this paper to detect small moving objects with low contrast in video sequences.

Palmer *et al* [1] proposed an algorithm to detect the small objects in FLIR (Forward Looking Infrared) image sequences. They used the wavelet-based filter to increase the robustness of their algorithm. Ffrench *et al* [2] proposed a 2-D adaptive lattice algorithm to improve the image quality by removing clutter noise. However, both of the algorithms are too computational expensive to be applied in real-time applications. Moreover, the detected objects are too small to find the complete contour information. Only the rough regions of targets (called region of interest, ROI) can be obtained by using the thresholding operation. Hence, it is necessary to further extract the more exact contour information from the ROI by using an efficient segmentation algorithm.

The watershed transformation is a powerful tool for image segmentation where the watershed lines divide individual catchment basins in a gradient image. It can generate a closed contour for each region in the original image [3]. Beucher [4] proposed a watershed segmentation scheme based on the markers to provide better segmentation results. However, over-segmentation and poor efficiency are two significant problems addressed in many literatures [4][5][6][7]. Many modified algorithms have been proposed to overcome these problems. Smet *et al* [5] proposed a rain-falling watershed algorithm to control the number of catchment basins by setting the drowning level criteria. Hernandez *et al* [6] proposed an efficient watershed segmentation algorithm using the properties of Local Intensity Minima (LIM) and Morphological Gradient Direction (MGD).

In this paper, a novel object detection method is proposed to detect small objects with low contrast. As we know, noise presented in small objects usually drastically affects the detection performance because it is sometimes difficult to distinguish noise from small objects. In our proposed approach, a novel noise removal technique is devised by encoding the pixel and its neighbors according to the noise distribution to effectively remove all possible non-object noise. Then, the more accurate ROI can be located by thresholding the noise-removed image. Last, a watershed segmentation algorithm is employed on the

ROI to extract accurate object contours. Experimental results demonstrate that the watershed segmentation algorithm is indeed superior to other segmentation algorithms in extracting contour of small objects. Moreover, the execution speed of the proposed approach is real-time, which is much faster than traditional algorithms.

The rest of the abstracted summary is organized as follows. The noise properties and the proposed noise removal algorithm are summarized in Section 2. In Section 3, the watershed segmentation algorithm is designed for the extraction of object contours. The examination of time complexity of the proposed object detection method is addressed in Section 4. Experimental results are illustrated in Section 5 to demonstrate the feasibility and validity of the proposed approach in detecting small objects. Finally, concluding remarks are given in Section 6.

## 2. NOISE REMOVAL AND ROI LOCATING

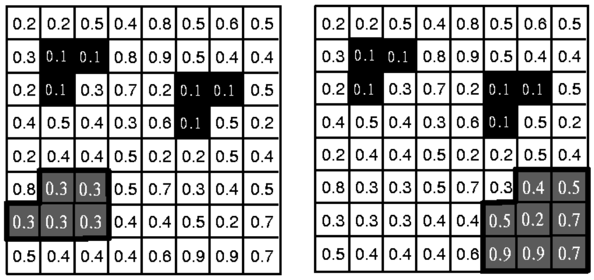
In our work, the detection of small objects in video sequences is implemented based on image-differencing technique. Under the processed environment, the number of noise pixels could be much more than the number of target pixels. Hence, the histogram-based technique adopted in traditional image-differencing method is inappropriate to resolve the problem. Median filter-based approach [8] is the commonly used method for noise removal in image processing. However, this approach will eliminate not only noise but also small targets. To remedy this problem, a novel noise removal algorithm is devised to remove the clutter noise by encoding each pixel and its neighbors according to the noise distribution.

By assuming noise to be Gaussian-distributed, we deductively conclude that any pixel is not possible to be surrounded by four or more noise pixels. Hence, only the pixels surrounding by three or less than three non-zero neighbors need to be examined in a difference image. From this point of view, the method encodes every pixel and its neighbors and then builds a histogram to determine noise threshold in the difference image. With noise being removed, the regions of interest (ROI) can thus be accurately obtained for later contour extraction.

## 3. CONTOUR EXTRACTION USING THE WATERSHED TRANSFORMTAION

According to our implementation experience, the LIM-based approach mentioned in Section 1 is sensitive to the noise which will result in the over-segmentation problem. In this paper, we modify the MGD-based algorithm by replacing the LIM criterion with the drowning level.

The Sobel gradient magnitudes of all pixels are firstly calculated and then normalized to the range of [0, 1]. The watershed transformation is executed on the gradient images. If the gradient magnitude of a pixel is lower than a fixed drowning level, this pixel is marked as the pixel belonging to one initial region. After all pixels have been examined, all marked pixels which are 4-connected are grouped together and assigned with the same label. Then, defining the direction of an unlabeled pixel as the direction of pointing to the neighbor with the lowest gradient magnitude. All unlabeled pixels will reach an initial region by following their gradient direction downhill. Then, assign the identity of the reached initial region to these unlabeled pixels.




(a) (b)

Fig 1. (a) An example illustrating plateau problem. The region in the gray area is a plateau. (b) The region in the gray area is an unlabeled region. The pixels inside unlabeled region can not follow their gradient direction to reach a labeled pixel (the drowning level is 0.1).

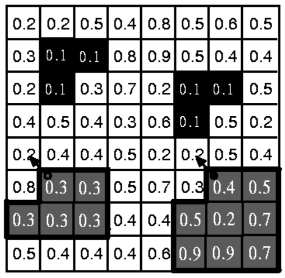



Fig 2. The treatment of plateau and unlabeled region as a “larger pixel”.

In performing the watershed algorithm, a problem frequently occurs resulting in unlabeled regions. An unlabeled region is formed by those unlabeled pixels which can not be directed to any existing labeled region. Fig 1 illustrates two examples of unlabeled regions. The appearing of unlabeled regions will usually affect the results of contour extraction, which is especially prominent for small objects. A simple method to solve this problem is to group these pixels into a “larger pixel” before performing the watershed segmentation. Unlabeled regions can be treated as a "larger pixel" and assigned the identity of the neighbor having the lowest gradient value as illustrated in Fig 2.

Since watershed-based segmentation algorithm performs directly on the gradient image, it might generate pseudo objects resulted from background clutters. To discriminate pseudo objects from real objects, we can examine the result generated by the watershed-based segmentation algorithm and the result in the difference image after noise removal. If the object is a real object, it must have certain degree of coincidence in these two results. Following the above property, all regions extracted by the proposed watershed-based segmentation algorithm are examined. The regions containing 50% or more non-zeros pixels in difference image are chosen as the real objects. This step is called "region matching".

## 4. TIME COMPLEXITY

In this section, the execution speed of the proposed algorithms is examined. In the noise removal step, only one pass has to be executed to count the numbers of non-zero neighbors of all pixels in the difference image. The next task in noise removal is the construction of non-zero neighbor histogram and the thresholding of noisy pixels. Both of these two processes are executed in constant time. Hence, the overall execution speed of the noise removal step is extremely fast in practice. Next, the efficiency of the watershed transformation lies mainly on the calculation of gradient magnitudes and the performing of the watershed segmentation. To calculate the gradient magnitudes, two gradient values, horizontal and vertical gradient, are computed by horizontal and vertical convolutions, respectively, which can be calculated by a series of addition instead of multiplication. Then, the square-sum-root of the two gradient values is calculated. Although the gradient calculation is a simple one-pass operation, it is still probably the most costly step in the watershed transformation because it involves the most additions.

The execution of the watershed segmentation is usually time-consuming for a large image. Fortunately, it only needs to be performed on the ROI in our work, which is relatively small comparing to the whole image. Hence, it can avoid the time-consuming problem which leads to be applicable in real-time.

## 5. EXPERIMENTAL RESULTS

In this section, experimental results are illustrated to demonstrate the feasibility and validity of the proposed approach in detecting small objects in video sequences. The objects that we deal with are aircrafts, and a video camera with 30 frames/second was operated to capture image sequences containing small aircrafts. Shown in Fig 3 is an example illustrating our object detection process.

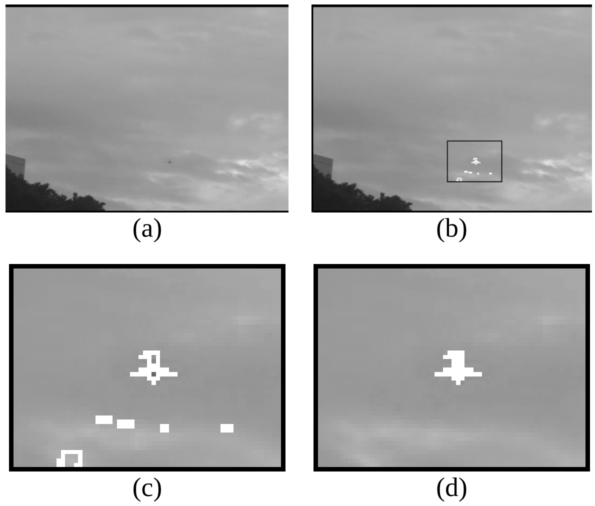



Fig 3. (a) One of two consecutive flying aircraft images. (b) The detected result. (c) Enlarged detected result. (d) The extracted object contour.


Fig 4. (a) An aircraft in cloudy sky. (b) The object region and object contour of (a).


Fig 5. (a) An aircraft in the environment of weaving trees in the bottom. (b) The detected object region and object contour of (a).

Fig 3(a) is one of two consecutive images containing a small flying aircraft. Fig 3(b) is the detected result. In the detected region, there are still some small blobs locating in the vicinity of the detected aircraft as can be perceived in the enlarged image of Fig 3(c). We can eliminate these small non-object blobs by overlapping the detected region with the same region in the difference image and the result is shown in Fig 3(d). Fig 4 and Fig 5 are another

| image sequence | no. of images | correct detection | incorrect detection | detection accuracy |
|---|---|---|---|---|
| 1 | 251 | 245 | 6 | 97.61 % |
| 2 | 71 | 70 | 1 | 98.59 % |
| 3 | 179 | 170 | 9 | 94.97 % |
| 4 | 305 | 288 | 17 | 94.43 % |
| 5 | 144 | 142 | 2 | 98.61 % |
| 6 | 125 | 123 | 2 | 98.40 % |
| 7 | 179 | 171 | 8 | 95.53 % |
| 8 | 377 | 365 | 12 | 96.82 % |
| 9 | 233 | 214 | 19 | 91.85 % |
| 10 | 287 | 266 | 21 | 92.68 % |
| 11 | 215 | 209 | 6 | 97.21 % |
| 12 | 99 | 99 | 0 | 100.0 % |
| 13 | 144 | 140 | 4 | 97.22 % |
| 14 | 179 | 174 | 5 | 97.21 % |
| 15 | 144 | 138 | 6 | 95.83 % |
| 16 | 179 | 165 | 14 | 92.18 % |
| total | 3111 | 2979 | 132 | 95.76 % |

Table 1. The accuracy rates of 16 video sequences.

two example images containing aircrafts in different environments. Shown in Fig 4(a) is an image with an aircraft in cloudy sky and the detected result is illustrated in Fig 4(b). Shown in Fig 5(a) is an image with weaving trees beneath the aircraft and the detected result is illustrated in Fig 5(b). It reveals that our proposed approach can still successfully detect aircrafts in various environments.

In our experiment, 16 video sequences with 3,111 images containing aircrafts were tested. Table 1 shows that an overall accuracy rate of 95.76% can be achieved. Experimental results demonstrate that the contours of the aircrafts can be accurately detected, where the objects are very small with low contrast. Meanwhile, it costs 0.90 second in average to processed thirty frames on a personal computer with AMD Athlon 1GHz processor. It demonstrates that the execution speed of the proposed approach is much faster than traditional object detection algorithms.

## 5. CONCLUSIONS

In this paper, a novel approach for the detection of small objects with low contrast in video sequences is presented which is admitted as a difficult problem because noise will dominate and dramatically affect the detection result. In our proposed approach, an efficient noise removal technique is first devised, which is operated on the difference image, to effectively remove noise. With bothering noise being removed, more accurate ROI can then be located. Last, a watershed-based segmentation algorithm is employed on the ROI to extract the object contours. By incorporating region-matching technique, accurate object contours can be detected. Experimental results reveal that our proposed approach is feasible and efficient in detecting the contours of small moving objects.

Sometimes, contrast of the objects is too low so that contours cannot be fully extracted. Performing of the watershed transformation with some lower drowning level may help to solve this problem. In the future, the development of an adaptive method in finding more suitable drowning level, which depends on the object contrast, is a subject to be pursued.

## 6. REFERENCES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