

# ENHANCED SUPPORT REGION FOR SCALE-SPACE BLOB DETECTION

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## ABSTRACT

This paper presents a new criterion for blob detection applied in the framework of scale-space based segmentation of objects from digital medical images. The proposed method is based on fitting the blob to a standard shape, such as the Gaussian, subject to constraints based on the blob support area or the total variation. The method has been verified and compared with the conventional procedures using a variety of synthetic images as well as the real images used in medical diagnostics. The examples include detection of abnormalities in digital retinal images and microscope cell imagery.

*Index Terms*—Scale space, Blob detection

## 1. INTRODUCTION

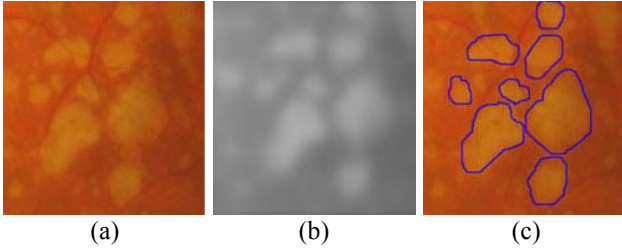
The scale-space theory offers a good solution to detecting variable size objects in digital images. The methods are based on the idea that objects appear for the observer in different ways depending on the scale of observation and only meaningful structures appear over certain ranges of scale. This is ideal for medical image understanding applications where abnormalities often appear with different sizes and shapes in the same image. An example of exudates with variable sizes in a digital fundus image is shown in Figure 1(a).

The mathematical foundations of the scale-space analysis were first proposed by Witkin [1] and Koenderink [2] to obtain a multi-scale representation of a measured signal by embedding it into a scale-parameter family of blurred signals. Later, Lindeberg [3]-[4] employed this concept to analyze details in digital images. The scale-space analysis employs blurring the input image so that the objects are smoothed and eventually turn into the so-called light blobs [4], as an example in Figure 1(b). Throughout the

blurring process, smaller blobs are merged into larger ones until the entire image contains only one light blob.

However, certain applications such as the detection of drusen or exudates (tiny yellow or white deposits on the retina or on the optic nerve), small objects of interest sitting close to each other tend to merge too fast when a conventional blob detection method is used. That is because the conventional detection usually does not take into account the shape of the peak of the object, but finds supporting regions using information from local maxima or minima only. In order to avoid fast merging, the scale-space theory suggests changing scale of blurring to finer steps to slow down the merging. However, it also slows down the entire process. Besides, the resulting blob obtained by the conventional algorithm tends to be much bigger than the expected object of interest. Therefore, instead of slowing down the blurring process, the blob detection methods should be analyzed and improved. There are many other blob detection methods available [5]-[9] but most of them require a priori information about an approximate size of the object embedded in the resulting blob or predetermined features of the blob. Many parameters such as template matching operator's window size need to be optimized using training sets. In the above mentioned case of exudates, the deposits in the retina appear as yellowish objects having different sizes and shapes and scatter around the same image. In such cases the template matching often fails to produce appropriate results.

This paper offers a new blob detection method applied in the framework of scale-space based segmentation of objects from digital medical images. The proposed method is based on fitting the blob to a standard shape, such as the Gaussian, subject to constraints based on the blob support area or the total variation. In spite of its simplicity, the method overperforms conventional blob detection as applied to a variety of synthetic images as well as to real medical images.



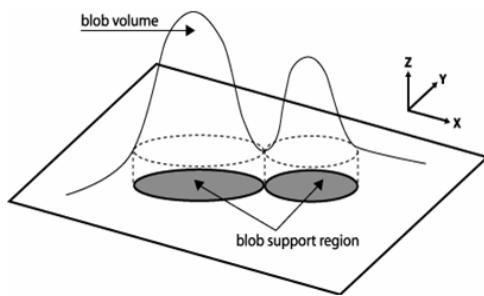
**Figure 1.** A part of retinal image which contains exudates. (a) Original image. (b) Smoothed result obtained by applying Gaussian filtering with  $\sigma=5$ . (c) Example of expected result.

## 2. PROPOSED METHODS

This section describes the proposed method. Section 2.1 gives a general background on the multi-scale representation and conventional blob detection. In section 2.2, new criteria for finding the blob support region are proposed.

### 2.1. Multi-scale Representation

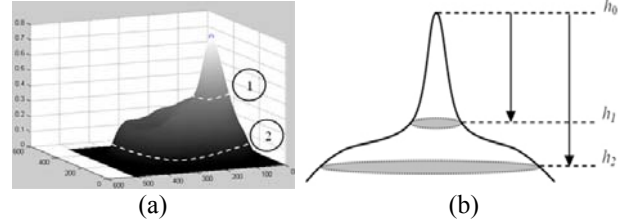
In scale-space theory, a multi-scale representation of a two-dimension image,  $f(x, y)$ , is defined by a convolution with the Gaussian kernel  $f(x, y, \sigma)$ . The successive smoothing process generates a set of output images in various scales,  $\sigma$ . At the finest scale the output is the original image itself. The increment of scale parameter results in suppressing the image structures and creating light blobs. Throughout the process, the Gaussian blurring simplifies the image without producing new spurious structures (Figure 2). Smaller light blobs that are close together merge into larger ones until the whole image eventually contains only one blob.



**Figure 2.** Blob structures.

To obtain a blob by a conventional algorithm, we have to find a base level of each blob based on the sequential grey-level blob detection algorithm [3]. Since the idea of the traditional blob detection algorithm is to let a blob seed expands until it meets other neighboring maximum or minimum, in many cases we may encounter problems of the

overestimated base level expanded because there is no neighboring maximum (Figure 3(a) and Figure 3(b)). From this example, the good result of blob detection should be as close to the object as possible. In other words, the resulting blob should be defined by the support area at level 1 (Figure 3(a)) rather than level 2.



**Figure 3.** (a) Example of a blob in 3D. (b) Blob height measurement.

### 2.2. Proposed Grey-level Blob Detection Methods

To overcome the above mentioned drawbacks of the conventional methods, a new simple procedure based on a constraint least square fit is proposed. The assumption is that after a certain number of the Gaussian blurring steps, the object of interest is transformed into a Gaussian shaped object. Therefore, the objective function combines the best Gaussian fit performed while increasing the height of the blob (see Figure 3(b)). The fitting is combined with conditions which indicate that at this height the blob boundary may have been reached. The boundary indicators are the blob support area and the total variation of the gray level of the surface. The procedure can be easily adapted to an arbitrary fitting function.

#### 2.2.1. Blob Detecting Criteria

Since the Gaussian filtering is used in the blurring process the blobs of interest will have a Gaussian-like shape after a certain numbers of iterations. The blob boundary should be also characterized by the sharp variation of the grey level (the edge). Therefore we introduce the following simple estimates.

1. The least square error  $\varepsilon(h)$  of the Gaussian fit given by

$$\varepsilon(h) = (V_{act}(h) - V_{Gaus}(h))^2, (1)$$

where  $h$  is height of the blob measured from peak,  $V_{act}(h)$  and  $V_{Gaus}(h)$  are the volumes of the actual blob and the ideal Gaussian blob at height  $h$ , respectively. A parameter

Gaussian fit  $he^{-\frac{(x^2+y^2)}{2\sigma^2}}$  is optimized with regard to for each  $h$ . Note that the method is not confined by the

Gaussian shape. As a matter of fact any fitting function can be used depending on the nature of the problem.

2. The second criteria is the supporting area of the blob at height  $h$ ,  $A(h)$ , defined by a set of all pixel which has higher intensity value than the value of the peak minus the height (see Figure 3(b)). For a smooth Gaussian blob, the supporting area should be slowly increasing with approximately the same rate of change. A sudden surge of the size of the supporting area means that the base of the blob has been reached. **The sudden surge can be detected by calculating the first derivative of the graph of the relation between blob height and supporting area. The point that shows the maximum rate of change can be selected as a proper cutting level, or supporting region, of the blob.**

3. Finally, the third criteria also used to detect the boundary of the blob is the total variation given by

$$T = \iint_A \left( \frac{\partial f}{\partial x} \right)^2 + \left( \frac{\partial f}{\partial y} \right)^2 dx dy \quad (2)$$

The total variation of a smooth surface should be increased gradually from top to bottom of the blob. At the shoulder of the blob, the total variation should be suddenly changed and it could imply that it is at the maximum height of the blob.

### 2.2.2. The Constraint Minimization Problem

We seek

$$\arg \min_h \varepsilon(h), \quad (3)$$

subject to  $|T''| \leq \Delta_1$  or  $|A''| \leq \Delta_2$  where  $\Delta_1$  and  $\Delta_2$  are prescribed small numbers.

The zero crossing of the second derivative of either the total variation or the support area indicates a rough location of the blob boundary. In other words, we seek the best Gaussian fit subject to the condition that we are close to the edge of the blob. Note that if we have multiple zero crossings, it means that we have multiple blobs with different sizes sitting on each other. If the application is designed to segment outer blobs, the second or higher zero crossing can be chosen.

## 3. NUMERICAL EXPERIMENTS

We show the result of the experiment in this section. Section 3.1 gives both quantitative and qualitative results. Section 3.2 explains how these results are verified.

### 3.1. Results

In conventional scale-space analysis, the blobs in each scale are detected and then linked with blobs on the adjacent upper and lower scales. The significance of each scale-space blob is then calculated from both the volume and the lifetime of that blob. The top most-significant scale-space blobs indicate the most appropriate support regions for object segmentation. That part of the algorithm is done and assumed that we now know the scale and location of the peak from that step. For specific application that seeks a single object with unknown size, a binary search can be performed to find the minimum scale that the original image will be blurred to become just one single light blob.

To evaluate the efficiency of blob detection, we apply our method to two hundred synthesis images. A typical image is shown in Figure 4 Row 3. Two hundred images of a single object are synthesized by adding one random-shape, random-size lighter blob on another darker and bigger blob with also random shape and location. Salt-and-pepper noise is added before the whole image is blurred so that they do not have sharp edges. The conventional blob and the proposed methods are compared in Table 1. Examples of detection of in medical images are shown in Figure 4 Row 1 and 2.

Method	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)
Conventional blob detection	77.3	100.0	75.9	19.9
Proposed method	97.0	96.8	98.9	78.8

**Table 1.** Conventional blob detection vs. the proposed method.

## 4. CONCLUSIONS AND DISCUSSION

In this paper, we propose a simple edge based Gaussian fit as the blob detection mechanism of the scale-space theory. Our preliminary results show that in many cases the proposed criteria overperforms the conventional method. Specific applications with a single object detection can benefit from this new approach the most. The optic disc detection, where the size of the optic disc is not known or a variable size nucleus detection are among those examples. Since we seek to segment a single object, we go straight to the smallest scale that contains only a single light blob in the scale-space and apply the proposed blob detection algorithm. This is not the case for the conventional blob detection algorithm because at this scale the image is usually over-blurred. A multiple blob detection with the use of the proposed algorithm is also achievable, such as abnormalities in retinal images in Figure 1. Finally, an attractive feature of the new approach is that if there are multiple zero crossings of the second derivative of the support area or the total variation, it means that the first

smaller blob is sitting on a bigger one. If the application requires detecting the outer blob as shown in Figure 4 Row 3, the second zero crossing can be used instead.

### 5. ACKNOWLEDGEMENTS

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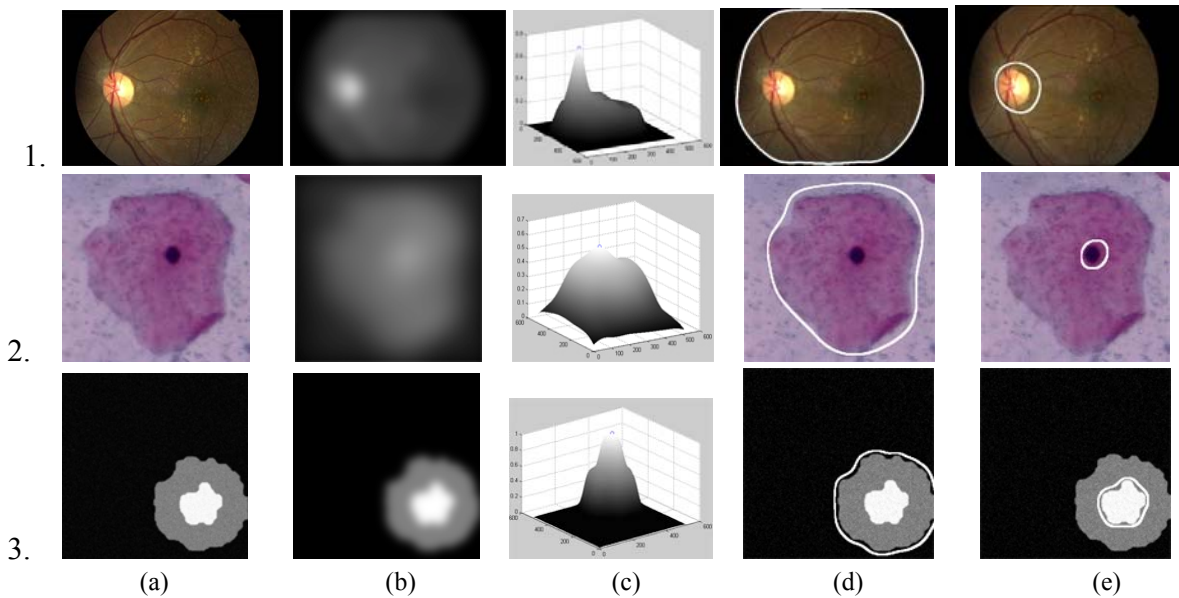
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**Figure 4.** Example of the detection result (a), (b), (c), (d) and (e) on each row represent original image, blurred image with a single blob, 3D surface of the blob, result from traditional scale-space blob detection and result from our proposed algorithm, respectively. Row 1, 2 and 3 shows example of optic disc detection, a nucleus detection and synthesis image.