PAPER

Blob Detection Based on Soft Morphological Filter

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SUMMARY Blob detection is an important part of computer vision and a special case of region detection with important applications in the image analysis. In this paper, the dilation operator in standard mathematical morphology is firstly extended to the order dilation operator of soft morphology, three soft morphological filters are designed by using the operator, and a novel blob detection algorithm called SMBD is proposed on that basis. SMBD had been proven to have better performance of anti-noise and blob shape detection than similar blob filters based on mathematical morphology like Quito and N-Quito in terms of theoretical and experimental aspects. Additionally, SMBD was also compared to LoG and DoH in different classes, which are the most commonly used blob detector, and SMBD also achieved significantly great results.

key words: blob detection, soft morphological filter, mathematical morphology, Quito filter

1. Introduction

The blob normally refers to the region where there is color or grayscale different from surrounding domains. Since one blob represents a region, and it is featured with better stability and stronger anti-noise ability than those of simple corner point. Blob detection is an important technology in computer vision which has been applied in numerous domains including medical image processing [1]–[4], video surveillance [5], [6], robotics [7]–[9], aviation systems [10]–[12], etc.

LoG (Laplacian of Gaussian) [13], as an extremely common blob detector, is effective for the detection of radial symmetric blob, while its time complexity is relatively high. To reduce time complexity of LoG, DoG (Difference of Gaussian) blob detector was proposed [14], where the operation approximation of DoG was used to replace Gaussian Laplace operation of LoG. In order to improve the detection performance of LoG in radial asymmetric blobs, gLoG (generalized Laplacian of Gaussian) blob detector is proposed [15]. gLoG extended the detection to the rotating asymmetric structure with different Gaussian kernels, thereby detecting the blobs with general elliptical structures

in rotational symmetry and asymmetry. Furthermore, Miao et al. [16] proposed a blob detection algorithm based on Rank Order Laplacian of Gaussian (ROLG), guaranteeing the robustness of the filter to noise by setting the rank order sorting operation.

Another commonly used blob detector is DoH (Determinant of Hessian) [13], in which Hessian Matrix is used, where the determinant of the matrix is used to detect blobs on a single scale. In order to extract smaller scale blobs from the image, two blob detectors including HLoG (Hessian-based Laplacian of Gaussian) [17] and HDoG (Hessian-based Difference of Gaussian) [4] are proposed on the basis of DoH.

The above-mentioned blob detection algorithms are not affine invariant. Under this context, the affine co-variant blob detection algorithm was studied, among which the most influential research was the characteristic detection method of maximally stable extremum regions (MSER) proposed by Matas [18]. The watershed idea was used to detect the most stable local region of gray in the image, after which the detected region was rotated and normalized, finally acquiring local features with affine invariance in strict sense. MSER is to find the blob region meeting the measure of “the minimum area change rate” and not to find the blob shape meeting the specified size.

In addition to three classic blob detectors including LoG, DoH and MSER and their variants, there are other types of blob detection algorithms. Though the research to the blob detection has been going on, most of the research destination (especially the research in the recent years) is not to pursue how to detecting the blob shape, rather than obtaining the anchor point by detecting the blob meeting some kind of measure, and these anchor points are often used for follow-up image processing such as image registration and 3D reconstruction of sparse point cloud. Duval-Poo et al. [19] proposed a blob detector SBD (with scale invariance) and the local feature descriptor SLD based on Shearlet (Shearlet is a kind of directional multi-scale framework). After transforming the images into the Shearlet space, SBD will find the local extreme value points in the $3 \times 3 \times 3$ field of the neighboring scale space, and such extreme value points have scale invariance property. That is to say, though SBD is called the blob detector, it is not used to detect the blobs meeting specified size in the image domain, and it is used to find the local extreme value points in Shearlet space. Takacs et al. [20] proposed a kind of RIFF feature detection algorithm based on the radial gradient transformation, which has

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rotational invariance. The position of the feature points is obtained by DOB (difference of boxes), and it is to find out the local extreme value points in the $3 \times 3 \times 3$ field of the neighboring scale space. That is to say, as a kind of feature descriptor, the feature point detecting of RIFF uses DOB algorithm, and though this algorithm is called the blob detector, it is actually used to detect the extreme value points in the local area, rather than to detect the blobs meeting the specified size in the image domain.

In addition to the blob detector described above, there is a type of blob detection filter based on mathematical morphology. Quito Filter, proposed in Ref. [1], has better shape detection capability on radial symmetric blobs. Due to high time complexity of Quito Filter, N-Quito Filter [2] is proposed to improve the calculation speed. But these two algorithms showed two main disadvantages: Firstly, it was weak in anti-noise ability; secondly, although it can be used for locating blobs, and it was poor in detecting the shape of the blobs.

On the basis of studies in Quito and N-Quito blob filter based on mathematical morphology, this paper proposes a soft morphological blob detector (SMBD) in order to improve their deficiencies. Firstly, basic operator dilation in standard mathematical morphology was extended to soft morphological order dilation, then the order dilation operator was utilized to construct two soft morphological filters including SMQ_A and SMQ_B, the former of which was used to locate the blobs, while the later one was used to detect the blob shape. Finally, a complete blob detection algorithm SMBD was designed by utilizing SMQ_A and SMQ_B filters. To verify the performance of SMBD, the experiments were conducted by comparing four methods including Quito, N-Quito, LoG and DoH on two blob image sets to our algorithm in this paper. The experiments showed that SMBD was obviously better both than other four methods in terms of anti-noise and blob shape detection.

The blob detection algorithm SMBD we proposed is not to detect the anchor point based on some kind of measure criterion, and it is used to detect the blob shape meeting the specified size. SMBD is a kind of improvement to the existing Quito and N-Quito, and it is established on the foundation of mathematical morphological theory. Therefore, SMBD should be compared with the algorithm of the same kind. Besides, as is pointed out in the Ref. [21], LoG and DoH are the most widely-used algorithms in the application field of blob detecting of medical images, therefore, it is necessary to compare SMBD with these two representative algorithms although they have different principles. For the reasons above, we have selected four kinds of algorithms above, and haven't compared the other blob detecting methods proposed in the recent years.

Filter principles of Quito and N-Quito will be analyzed in Sect. 2, after which our blob detection method will be detailed in Sect. 3 and the results of the comparison will be given in Sect. 4, and finally, the conclusions of this paper will be drawn in Sect. 5.

2. Quito Filter and N-Quito Filter

To detect isolated cancer shadow in the lungs, Yamamoto et al. [1] proposed a Quito filter based on mathematical morphology as follows:

$$h(x, y) = f(x, y) \oplus D_{(x,y)} - f(x, y) \oplus R_{(x,y)} \quad (1)$$

$$g(x, y) = h(x, y) \oplus D_{(x,y)} - h(x, y) \oplus R_{(x,y)} \quad (2)$$

$$D(u, v) = \begin{cases} 0, & \text{if } u^2 + v^2 \leq r_1^2 \\ -\infty, & \text{otherwise} \end{cases} \quad (3)$$

$$R(u, v) = \begin{cases} 0, & \text{if } r_2 \leq u^2 + v^2 \leq r_3^2 \\ -\infty, & \text{otherwise} \end{cases} \quad (4)$$

Where, $f(x, y)$ represents the input image, $D(u, v)$ and $R(u, v)$ respectively denote disc and ring structural elements, r_1 denotes the radius of disc structural element, r_2 and r_3 respectively represent inner and outer radii of ring structural element, $h(x, y)$ represents the image after locating blobs, and $g(x, y)$ denotes the image acquired by the shape restoration of the blob via the located point.

The principle of Quito Filter can be illustrated in Fig. 1. When the dilation processing is applied to process the isolated convex region (bright blob), the disc may only be anchored at its apex instead of falling off if the structural element is a disc (Fig. 1 (a)). If the convex region is subjected to the dilation processing with ring structural element, the circular ring may fall to the bottom when it fits into the convex region (Fig. 1 (b)). Therefore, the isolated convex region may be detected by calculating these two difference images. The region which is the convex region and fails to be harnessed into or is long convex region (Fig. 1 (c)) will not be detected due to extremely slight difference between the disc and the circular ring in the difference image. In other words, only the isolated convex region trapped by the circular ring may be detected by Quito Filter.

The detection of isolated bright region by Quito Filter is composed of two morphological transformations, where, the first morphological transformation anchors the bright blob, and the second morphological transformation restores the shape of the blob. When the bright blob takes on a hemispherical shape, the restored shape is also hemispherical, and the shape of the blob is not ideally restored if the blob is not hemispherical. Quito Filter mainly suffers from three defects: (1) Relatively poor anti-noise ability; (2) Relatively poor blob shape recovery; (3) Relatively high time complexity.

Fig. 1 Schematic diagram for Quito filter.

In order to improve the processing speed of Quito Filter, Miwa et al. [2] proposed the N-Quito Filter. It is assumed that the bright blob is featured with rotational symmetry and highly monotonic decreasing, the dilation filtering of single-point structural element may replace the dilation filtering of disc structural element, consequently greatly shortening the processing duration. The definition of N-Quito Filter is shown as follows:

$$h(x, y) = f(x, y) - f(x, y) \oplus R_{(x,y)} \quad (5)$$

Where $f(x, y)$ denotes the input image, R represents ring structural element, and $h(x, y)$ denotes the resulting anchor image of the blob. N-Quito is only better than Quito in terms of the filtering speed, and it has the disadvantage of failure to overcome its noise sensitiveness like Quito. Additionally, N-Quito Filter is only able to anchor the position of the blob and is incapable of detecting the shape of the blob.

For particular blob with rotational symmetry and highly monotonically decreasing, the method for automatically determining the filter size by conducting the binary distance transform (BDT) on the input image is given in Ref. [2]. Furthermore, the gray weight distance transform (GWDT) is proposed in Ref. [2] to act a method of preprocessing with the aim of improving the processing performance of N-Quito filter on the overlapping region between isolated shadow and linear shadow (e.g the cancer shadow near blood vessel or cancer shadow traversed by blood vessel). As the preprocessing of abovementioned two distance transforms is included in the processing of special image, generally they are not considered to be a part of N-Quito filter.

3. SMBD

3.1 Order Dilation Operator

Koskinen et al. [22] extended the dilation operator of standard mathematical morphology to soft dilation, which is mainly characterized with less sensitive to additive noise and the change in the shape requiring filtering. The definition of soft dilation is shown as follows:

$$f \oplus [B, A, K](x, y) = k^{th} \text{ largest value of multiset } \{k * f(a) : a \in A_{(x,y)}\} \cup \{f(b) : b \in (B - A)_{(x,y)}\}. \quad (6)$$

The above operator in soft morphology is defined on the basis of sorting statistics, the structural element of standard mathematical morphology is replaced with the structural system $[B, A, k]$. The structural system consists of three parameters: For the sets of finite planes A and B , $A \subset B$ is satisfied, a natural number k satisfies $1 \leq k \leq \min\{\frac{|B|}{2}, |B - A|\}$, and $|\cdot|$ represents total number of elements in the sets. B denotes the structural set, A represents the hard center of B , $B - A$ generates corresponding soft contour, and k represents the order index specified. The symbol $*$ indicates repeated operation, and is defined to be $k * x =$

$\underbrace{x, x, \dots, x}_{k \text{ times}}$, for example $\{2 * 1, 2, 3 * 3\} = \{1, 1, 2, 3, 3, 3\}$. Obviously, when $A = \phi$ and $k = 1$ are satisfied, the soft dilation degenerates into a standard dilation.

In order to design Quito Filter in soft morphology, the order dilation operator based on the soft dilation operator is defined firstly.

Definition of order dilation:

$$f \oplus [B, k](x, y) = k^{th} \text{ largest value of multiset } \{f(b) : b \in B_{(x,y)}\} \quad (7)$$

Where, B denotes a structural element, k represents the natural numbers satisfying $1 \leq k \leq \frac{|B|}{2}$, and the order indexes are sorted from the maximum to the minimum. Equation (7) actually turns the hard center A in the structural system $[B, A, k]$ in Eq. (6) into the empty set, thereby causing the structural system to degenerate into $[B, k]$. It means that image f is subjected to morphological dilation by use of soft contour $B - A$ and hard center A converts to the morphological dilation of image f merely by Soft Contour of structural element B .

3.2 Soft Morphological Quito Filters

By utilizing the order dilation operator, three Quito filters in soft morphology is firstly defined as follows.

(1) SMQ Filter:

$$SMQ(D, R, k_D, k_R, f, x, y) = f \oplus [D, k_D](x, y) - f \oplus [R, k_R](x, y) \quad (8)$$

(2) SMQ_A Filter:

$$SMQ_A(D, R, k_a, k_b, k_c, k_d, f, x, y) = \frac{1}{k_b - k_a + 1} \sum_{i=k_a}^{k_b} f \oplus [D, i](x, y) - \frac{1}{k_c - k_d + 1} \sum_{j=k_c}^{k_d} f \oplus [R, j](x, y) \\ \text{where, } k_a, k_b = 1, 2, \dots, |D|/2; \\ k_c, k_d = 1, 2, \dots, |R|/2; k_a \leq k_b, k_c \leq k_d. \quad (9)$$

(3) SMQ_B Filter:

$$SMQ_B(D, R, k_m, k_n, f, x, y, u, v) = f(u, v) - \frac{1}{k_m - k_n + 1} \sum_{i=k_m}^{k_n} f \oplus [R, i](x, y) \quad (10)$$

Where, f denotes the image of filtered object, $k_m, k_n = 1, \dots, |R|/2$, $k_m \leq k_n$, R denotes ring structural element, D denotes disc structural element, and $(u, v) \in D_{(x,y)}$ (where $D \notin R$ is satisfied, and D and R are homocentric). The working principle of the above three Quito filters in soft morphology will be described as below.

Working principle of SMQ Filter: Intuitively, Quito Filter actually moves concentric disc and ring to Object

Point P , and then finds maximum value V_D of the disc domain and maximum value V_R of circular ring domain respectively. The Object Point P is determined to be included in the blob region or not via the value of $V_p = V_D - V_R$. SMQ Filter is similar to Quoit Filter except that it finds its own specified order index in the disc and ring domain respectively rather than maximum value, consequently avoiding the effects of changes in the noise and shape effectively. SMQ is degenerated into Quoit Filter when k_D and k_R of SMQ Filter are set to be 1, and it degenerates into N-Quoit Filter if D is set to one element. The robustness of SMQ to noise and morphological change may be adjusted by adjusting the order indexes including k_m and k_n . SMQ Filter is mainly used for locating blob.

Working principle of SMQ_A Filter: According to the introduction to the principle of SMQ above, it is concluded SMQ is a morphological filter, in which the order index is specified, and SMQ_A denotes an extension of SMQ. When SMQ_A morphologically filters the blob with a disc and a ring structural element, it is based on the mean value of gray values corresponding to certain segment of order indexes rather the gray value corresponding to a certain order index. Therefore, theoretically SMQ_A exclusively delivers better shape robustness than SMQ based on a certain order index. When the order indexes including $k_a = k_b$ and $k_b = k_d$ are satisfied, SMQ_A degenerates into SMQ. SMQ_A Filter is mainly used for locating blob.

Working principle of SMQ_B Filter: Both SMQ and SMQ_A are exclusively used to locate the blob rather than detecting actual shape of the blob due to that the only thing to be considered is morphological change in the point rather than morphological changes in other points in the disc domain when the object point is subjected to morphological filtering. To solve this problem, SMQ_A is modified, and formerly Structural Element D of the disc is decomposed into the structural element with only a single element (the dilation processing based on structural element of single elements is the image itself), and SMQ_A is applied to make morphological filtering on every point (u, v) in the disc domain (R is always kept to exclusively filter Object Point (x, y) in such a structural element). In other words, when SMQ_B Filter filters Object Point (x, y) , the difference between gray value of point (u, v) and response value (the right part of Eq. (10)) of point (x, y) based on soft morphological filtering of R is calculated within the range where the point (x, y) is the center of the circle and is covered by D , consequently SMQ_B may detect the shape of the region of Object Point (x, y) covered by D when the object point (x, y) is morphologically filtered. The point (x, y) is subjected to the processing of soft morphological filtering (right part of Eq. (10)) by structural element R of circular ring within the range of the order indexes $k_m \sim k_n$, essentially, the filtering effects on the shape of the blob are changed by adjusting the response value of the filter at the point. Since the mean between order indexes $k_m \sim k_n$ acts as response value of morphological filtering, theoretically, it is stable compared to morphological filtering based on single order index.

3.3 The Blob Detection Algorithm

SMQ is a Quoit Filter designed based on order dilation operator in this paper, and it involves Quoit Filter and N-Quoit Filter, while SMQ_A and SMQ_B are extensions to SMQ. The bright blob detection algorithm SMBD based on SMQ_A and SMQ_B filters is shown below. To detect dark blobs, it will work to reverse the gray scale of the input image.

Algorithm 1 SMBD Algorithm

Step 1: Parameter settings of filter

- (1) Set the parameters $D_A, R, k_a, k_b, k_c, k_d$ of SMQ_A Filter, where D_A denotes disc structural element of SMQ_A Filter.
- (2) Set the parameters of SMQ_B Filter D_B, R, k_m and k_n , where D_B denotes the disc structural element of SMQ_B Filter.
- (3) Set the threshold of locating blob to be Th_{A1} and the threshold of blob region to be Th_{A2} , these two thresholds are mainly used to control the number of blob candidates.

Step2: SMQ_A Filtering

The input image $I(x, y)$ is subjected to the blob filtering by using the SMQ_A Filter, acquiring the image $L(x, y)$ of location point candidates:

$$L(x, y) = SMQ_A(D_A, R, k_a, k_b, k_c, k_d, I, x, y).$$

Step3: Generating the mask image $M(x, y)$

```

if  $L(x, y) > Th_{A1}$  then
     $M(x, y) = 1$ 
else
     $M(x, y) = 0$ 
end if

```

Step4: SMQ_B Filtering

Set $I_2(x, y)$ to be the image filtered with SMQ_B. Firstly initialize $I_2(x, y)$ with 0, then traverse each effective pixel (x, y) in image $I(x, y)$, and perform the following filtering processing steps with SMQ_B. Where, $v(u, v)$ denotes the filtered value of SMQ_B under the precondition of $(u, v) \in D_{B(x, y)}$.

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if  $M(x, y) = 1$  then
     $v(u, v) = SMQ\_B(D_B, R, k_m, k_n, I, x, y, u, v)$ 
    if  $v(u, v) > I_2$  then
         $I_2(u, v) = v(u, v)$ 
    end if
end if

```

Step5: Extracting the blob shape

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if  $I_2(u, v) \geq Th_{A2}$  then
     $I_3(u, v) = I(u, v)$ 
else
     $I_3(u, v) = 0$ 

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end if

Where $I_3(x, y)$ denotes the blob image detected.

SMBD Algorithm is divided into five steps: (1) Set all the parameters in the algorithm; (2) Conduct the locating processing on the blob in the input image which is smaller than inner radius of specified circular ring with SMQ_A Filter, and smaller radius of the disc may be valued to improve the processing speed. As the calculation quantity will be extremely great if the blob filtering is directly performed by SMQ_B, consequently SMQ_A is firstly utilized to roughly determine the center position of the blob in the algorithm; (3) Filter the candidate for the blob location point to generate the mask image; (4) Take the point valued in 1 as the center of SMQ_B Filter in Mask Image A, and then have Image I subjected to the filtering processing of SMQ_B to acquire the filtered response value image of SMQ_B, namely the response value of detected blob shape; (5) Extract the shape of the blob with the response value greater than the threshold Th_{A2} from Image I according to I_2 , the filtered image of SMQ_B.

3.4 Estimation of SMBD Parameters

SMBD has 12 parameters (please refer to Sect. 4 for naming symbols and descriptions of SMBD parameters), and we give the general method of estimating these parameters first, then we will examine the effect of the variance of such parameters to detecting blob.

The disc structure element of SMQ_A are used to locate the center of the target blob; in general, larger r_{A1} obviously will reduce the confidence of the anchor point of the false target blob (the filtering value of SMQ_A), however, it will also increase the processing time of SMQ_A; according to the experiences, it is proper to make it 20% ~ 50% of the radius of target blob r_T . r_{A2} is the inner radius of the ring structure element, and only it is larger than r_{A1} ; however, on considering of proper tolerance, generally $r_{A2} = r_T + 2$. r_{A3} is the outer radius of the ring structure element, and generally it should warrant that the circle has the width of 2 pixels, i.e., $r_{A3} = r_{A2} + 1$. r_{A4} is the radius of the disc structure element of SMQ_B, and it is used to detect the shape of the target blob, therefore, r_{A4} must equal to r_T .

k_a is the order index of the lower limit of the disc structure element of SMQ_A during the soft dilation, when SMQ_A is searching in the background area, it is mainly used to tell SMQ_A filter: the pixels of which are smaller than the order index k_a in the area covered by SMQ_A ring might be noise. Therefore, k_a can be set as: $k_a = (\text{the disc area of SMQ}_A) \times (\text{the average noise occupation ratio in the unit area})$. k_b is the order index of the upper limit of the disc structure element of SMQ_A during the soft dilation, when SMQ_A is searching in the blob area, it is mainly used to tell SMQ_A filter: the pixels of which are greater than the order index k_b in the area covered by SMQ_A ring might be noise. Therefore, k_b can be set as: $k_b = (\text{the disc area of SMQ}_A) \times (1 - \text{the average noise occupation ratio in the unit area})$.

k_c is the order index of the lower limit of the ring structure element of SMQ_A during the soft dilation, when SMQ_A is located in the background area, it is mainly used to tell SMQ_A filter: the pixels of which are smaller than the order index k_c in the area covered by SMQ_A ring might be noise. Therefore, k_c can be set as: $k_c = (\text{the ring area of SMQ}_A) \times (\text{the average noise occupation ratio in the unit area})$. k_d is the order index of the upper limit of the ring structure element of SMQ_A during the soft dilation, when the ring center of SMQ_A coincides with the blob center, it is used to tell SMQ_A: in the area covered by the ring, the pixels with the order index larger than k_d can most represent the background property surrounding the blob area, and normally $k_d = 3k_c$. k_m and k_n are the order index of the lower limit and upper limit of the ring structural element of SMQ_B respectively, and their effects are the same as those of k_c and k_d , therefore $k_m = k_c$, $k_n = k_d$.

Th_{A1} is the threshold of the anchor point of the blob, and it is used to select the correct candidate positioning for blob; it can be determined according to the average gray scale contrast in the background area in the central area and border of the blob. Th_{A2} is the threshold for extracting the blob shape and it is used to select the correct candidate blob, and it can be determined according to the average grey scale contrast of the blob shape and its surrounding background.

The content above states the general method of estimating SMBD parameters theoretically according to the working principle of SMBD, however, it is not the optimum parameter selection; how to automatically and effectively estimate SMBD parameters is the theme to be researched in the future. The estimation method on SMBD parameters above has been generalized in Table 1. From Table 1 we can see

Table 1 Estimation of SMBD parameters

Parameter	Setting value
r_{A1}	$r_T \times (20\% \sim 50\%)$
r_{A2}	$r_T + 2$
r_{A3}	$r_{A2} + 1$
r_{A4}	r_T
k_a	$(\text{the disc area of SMQ}_A) \times (\text{the average noise occupation ratio in the unit area})$
k_b	$(\text{the disc area of SMQ}_A) \times (1 - \text{the average noise occupation ratio in the unit area})$
k_c	$(\text{the disc area of SMQ}_A) \times (\text{the average noise occupation ratio in the unit area})$
k_d	$3k_c$
k_m	k_c
k_n	k_d
Th_{A1}	It can be determined according to the average gray scale contrast in the background area in the central area and border of the blob.
Th_{A2}	It can be determined according to the average grey scale contrast of the blob shape and its surrounding background.

Fig. 2 The images on the various intermediate processing procedure of blob detecting with SMBD. (a) is the original image A_2 . (b) is the candidate anchor point of blob obtained after the filtering of SMQ-A. (c) is the image after (b) is processed with binaryzation with the threshold of $Th_{A1} = 60$. (d) is the image of SMQ-B after the blob is processed with morphology filtering at the candidate anchor points. (e) is the real blob shape extracted from the original image of which the morphology filtering value of the blob is larger than threshold $Th_{A2} = 10$.

Fig. 3 The effect of the parameter variation of SMBD on the blob detecting. (a) is the image of the candidate anchor point of blob detected by SMBD at $r_{A1} = 20$. (b) is the image of the candidate anchor points of the blobs detected by SMBD at $k_a = 1$ and $k_b = 5$. (c) is the image of the candidate anchor points of the blobs detected by SMBD at $k_c = 7$ and $k_d = 10$. (d) is the image of the candidate anchor points of the blobs detected by SMBD at $Th_{A1} = 10$. (e) is the image of the blob shape detected by SMBD at $Th_{A2} = 250$.

that, if the size of the target blob is known, we can estimate four parameters of $r_{A1}-r_{A4}$; if the noise distribution of the image is known, we can estimate six parameters of k_a-k_n ; if we know the contrast between the blob center and blob shape and the surrounding background at the blob border, we can estimate Th_{A1} and Th_{A2} .

According to the method estimating SMBD parameters introduced above, we can observe the intermediate procedure of SMBD during the blob detecting. We select image A_2 in Image Set A (please refer to the instruction on Image Set A in 4.1), and it is the image after being applied 5% salt-and-pepper noise on image A_1 (Fig. 2 (a)). Our purpose is to detect the blobs in row 3–4 of image A_2 with the radius of 26 pixels, and the following parameters will be given according to the method of parameter estimation in the Table 1: $r_{A1} = 5$, $r_{A2} = 28$, $r_{A3} = 29$, $r_{A4} = 26$, $k_a = \lceil \pi \times r_{A1}^2 \times 5\% \rceil = 4$, $k_b = \lceil \pi \times r_{A1}^2 \times (1 - 5\%) \rceil = 75$, $k_c = \lceil \pi \times (r_{A3}^2 - r_{A2}^2) \times 5\% \rceil = 9$, $k_d = 3k_c = 27$, $k_m = k_c = 9$, $k_n = k_d = 27$, $Th_{A1} = 60$, $Th_{A2} = 10$.

Figure 2 (b) is the candidate anchor point of blob obtained after the filtering of SMQ-A, from the image we can see that the larger the blob area is, the smaller the corresponding area of anchor point will be. Figure 2 (c) is the image after Fig. 2 (b) is processed with binaryzation with the threshold of Th_{A1} and such processing can eliminate the

wrong candidate anchor points with the filtering value less than Th_{A1} . Figure 2 (d) is the image of SMQ-B after the blob is processed with morphology filtering at the candidate anchor points. Figure 2 (e) is the real blob shape extracted from the original image of which the morphology filtering value of the blob is larger than threshold Th_{A2} .

Finally, we will examine the effect to the blob detecting when the SMBD parameters are improperly set. All the examination testing are based on the image A_2 and its parameters above; when a certain parameter is changed, the other parameters don't change.

Figure 3 (a) is the image of the candidate anchor point of blob detected by SMBD at $r_{A1} = 20$. Compared with Fig. 2 (b), the both are basically the same except for that the filtering value changes. It indicates that we can select r_{A1} , which is far less than the radius of the target blob to obtain the candidate anchor point, and the processing speed of SMQ-A can be increased a lot. Figure 3 (b) is the image of the candidate anchor points of the blobs detected by SMBD at $k_a = 1$ and $k_b = 5$. Because the parameters k_a and k_b are not proper, a lot of noise points are regarded as the candidate anchor points of blobs. The parameters k_a and k_b have large effect to the correct detection of the candidate anchor points of the blobs. Figure 3 (c) is the image of the candidate anchor points of the blobs detected by SMBD at $k_c = 3$ and

$k_d = 10$. Because the parameters k_c and k_d are not proper, some blobs haven't been positioned, and the filtering value of the candidate anchor point is obviously smaller. The parameters k_c and k_d have large effect to the correct detecting of the candidate anchor points of the blobs. Figure 3(d) is the image of the candidate anchor points of the blobs detected by SMBD at $Th_{A1} = 10$. Because Th_{A1} is smaller, some non-candidate anchor points of blob have also been included. Figure 3(e) is the image of the blob shape detected by SMBD at $Th_{A2} = 250$. Because Th_{A2} is larger, some correct blobs have been wrong eliminated.

4. Comparison Experiments

To test the performance of SMBD, two experimental image sets (noisy image set and noiseless image set) are respectively designed, and two algorithms with the same types (Quoit and N-Quoit) and two common algorithms with different types (LoG, DoH) are respectively subjected to comparison experiments.

For the convenience of documenting, named symbols for the parameters used in five algorithms are respectively given. 12 parameters of SMBD: r_{A1} and r_{A4} respectively denote the radiuses of disc structural elements of SMQ_A and SMQ_B; r_{A2} and r_{A3} respectively represent inner and outer radiuses of ring structural element; k_a and k_b respectively denote the order index of the lower and upper limit of the disc structure element of SMQ_A during the soft dilation; k_c and k_d respectively denote the order index of the lower and upper limit of the ring structure element of SMQ_A during the soft dilation; k_m and k_n respectively denote the order index of the lower and upper limit of the disc structure element of SMQ_B during the soft dilation; Th_{A1} denote the threshold of the anchor point of the blob; Th_{A2} The threshold for extracting the blob shape. 4 parameters of Quoit: r_{B1} , r_{B2} and r_{B3} respectively denote the radius of disc structural element, inner and outer radiuses of ring structural element, Th_{B1} represents the threshold of the response of Quoit filtering, being equivalent to Th_{A1} of SMBD. 3 parameters of N-Quoit: r_{C1} and r_{C2} denote inner and outer radiuses of ring structural element, and Th_{C1} represents the threshold of the response of N-Quoit Filter, being equivalent to Th_{A1} of SMBD. 3 parameters of LoG: r_{D1} , r_{D2} and r_{D3} satisfy $r_{D1} < r_{D2} < r_{D3}$. Where, r_{D2} denotes the radius of the target blob to be detected with LoG, and r_{D1} and r_{D3} represent radius ranges of the target blob for which LoG Filter is required to be searched. 3 parameters of DoH: r_{E1} , r_{E2} and r_{E3} satisfy $r_{E1} < r_{E2} < r_{E3}$. Where, r_{E2} denotes the radius of the target blob to be detected with DoH, and r_{E1} and r_{E3} represent radius ranges of the target blob for which DoH Filter is required to be searched.

4.1 Comparative Experiment of Image Set A

Image Set A has a total of 10 images named $A_1, A_2, \dots, A_{10}$. A_1 denotes the image of noiseless standard binary blob (the 1st Row, 1st Column in Fig.4), and the remaining 9

pieces are images acquired by applying the salt-and-pepper noise and Gaussian noise to Image A_1 respectively. Image A_1 contains a total of 33 types of binary blob shapes including 11 shapes and 3 sizes, and the blobs of each size have circumscribed circles with the same radius. The rightmost column of Image A_1 contains two small-sized discs, which are connected by a thin line that may be considered as the noise. The radius of the blob between the first and second lines in Image A_1 is 17 pix, the radius of the blob between the 3rd and 4th lines is 26 pix, and the radius of the blob between the 5th and 6th lines is 38 pix. $A_2 \sim A_4$ are images after being applied 5%, 10%, and 15% salt-and-pepper noise respectively. $A_5 \sim A_7$ are images acquired by applying Gaussian noise with variances in 10, 30 and 50 respectively. $A_8 \sim A_{10}$ are images acquired by applying 5% salt-and-pepper noise + Gaussian noise with the variance of 10, 10% of salt-and-pepper noise + Gaussian noise with the variance in 30, and 15% of salt-and-pepper noise + Gaussian noise with the variance in 50. All Gaussian noises have the mean value in 0 and the intensity in 150. The three images in the first column of Fig. 4 are A_1, A_9 and A_{10} respectively.

The purpose of this experiment is to compare the anti-noise ability of SMBD and the other four blob detection algorithms by detecting blobs with the radius of approximately 26 pixels (the blobs in the third to fourth lines in the images in the first column of Fig.4) in Image Set A. The second column of Fig.4 is the result of blob detection of the image of the first column on the left side with SMBD. It can be concluded from the figure that all the target blobs (13 in total) are detected, and the shapes of detected blobs are extremely complete. In addition, other blobs with smaller radiuses are also detected. The parameters of the SMBD in the experiments are $r_{A1} = 17$, $r_{A4} = 26$, $r_{A2} = r_{A4} + 2$, $r_{A3} = r_{A2} + 1$, $Th_{A1} = 60$, $Th_{A2} = 10$, and the remaining parameters k_a, k_b , and k_d take different values depending on the noise situation.

The third column of Fig. 4 represents the results of blob detection on images of the first column on the left side by using Quoit, of which the parameter values of the filter are the same as SMBD. As shown in the figure, the remaining noise images fail to detect the target blob except for the 11 target blobs detected in Image A_1 , which indicates that the Quoit is extremely sensitive to noise.

The image in the fourth column of Fig.4 is the result of blob detection on images of the first column by the N-Quoit. The filter parameters are: $r_{C1} = 26 + 2$, $r_{C2} = r_{C1} + 1$, $Th_{C1} = 60$, and such parameters are similar corresponding parameters of SMBD. It can be concluded from the figure that a considerable number of target blobs are not detected, indicating that N-Quoit is also extremely sensitive to the noise.

Columns 5–6 of Fig. 4 represent the results of blob detection on images of the first column on the left side by LoG and DoH respectively. The filtering parameters satisfy $r_{D1} = r_{E1} = 17$, $r_{D2} = r_{E2} = 26$, $r_{D3} = r_{E3} = 38$. There are many candidates for blob location points (more than 800 blobs per image on average), and only the point candidates

Fig. 4 Some experimental results of image set A. The first column involves three images of image set A, and the columns from the second column to the sixth column are the results of blob detection on the images in the left column with SMBD, Quito, N-Quoit, LoG, and DoH respectively.

Table 2 Detection rate of five detection algorithms for blob

Name of algorithm	Accuracy of Image Set A (total number of blobs is 130)	Accuracy of Image Set B (total number of blobs is 246)
SMBD	100%	98.78%
Quoit	33.84%	86.58%
N-Quoit	30.77%	88.62%
LoG	36.92%	63.01%
DoH	42.31%	59.35%

within the first 100 blobs are taken in the experiment for this reason, the green circle is represented on original drawing with the radius in 26 pix and the candidate location point as the circle center. It can be seen from the figure that considerable parts of target blobs are not detected.

There are a total of 130 target blobs with the radius in 26 pix on Image Set A. The data of comparison experiments of five blob detection algorithms are shown in Table 2. The performance of SMBD Algorithm is better than those of other four algorithms: SMBD is capable of fully detecting all target blobs from different noise images, and the detected blob shape is quite complete. The success of the blob detection is determined by visual inspection as follows: For SMBD and Quito, the shapes of detected blobs are mostly close to original shapes, and most overlapping of original blob region is defined as successfully detected; For N-Quoit, LoG, and DoH, the distance between detected blob position points of blob and the center of target blob less than 40% of the radius of target blob shall be defined as success.

Figure 4 shows the results of blob detection on Image Set A with five kinds of blob detecting algorithm: SMBD, Quito, N-Quoit, LoG and HoG (part of the images). SMBD and Quito output the blob shape to be detected, while N-Quoit, LoG and HoG output the anchor point of the blob

area to be detected. Therefore, in Fig. 4, column 2–3 list the blob shape detected by SMBD and Quito, while column 4–6 list the anchor point of blob detected by N-Quoit, LoG and Hog. N-Quoit can detect many anchor points for a certain blob area; for the sake of convenient observation, we have made the anchor point display on the original figure directly. LoG and HoG can only detect one anchor point for some blob sometimes, if we display the anchor points directly, they might be not very clear; therefore, we set the anchor point as the circle center and draw a circle on the original figure with the radius (of target blob) of 26. Following the same principle, we processed Fig. 6 also in the same way.

4.2 Comparative Experiment of Image Set B

In order to verify the performance of the SMBD algorithm in actual grayscale image, we created Image Set B (Fig. 5). The blob inside the red circle is the target blob expected to be detected, and the sizes of target blobs in the same image are basically equivalent. Image Set B is produced as follows: Select 46 images from the disclosed saliency region test image library, and then cut out the blob sub-images having different sizes and shapes and convert them into grayscale images.

Image Set B includes the small targets (blobs) of various shape. In the experiment, we randomly selected the small targets of different shapes and sizes (such as horse, window and special texture patterns) as the target blobs, with the purpose of examining the performance of blob detecting of SMBD using blobs of different shapes and sizes. Besides, the same image might include several kinds of blobs with different shapes and sizes, and we also randomly

Fig. 5 All images of image set B. The blob inside the red circle is the target blob expected to be detected, and the sizes of target blobs in the same image are basically equivalent.

Fig. 6 Some experimental results of image set B. The first row involves eight images in image set B, and the second to the sixth rows are results of blob detection on images in the first row with SMD, Quoit, N-Quoit, LoG and DoH algorithms respectively.

selected some kind of small targets with basically similar shapes and sizes as the target blob (the area surrounded by red circle in Fig. 5). Such deal is fair for various kinds of blob detecting algorithm, and it means that the more blobs the algorithm can detect from Image Set B, the better performance it will have.

The purpose of this experiment is to compare the performance of SMBD to that of other four blob detection algorithms by detecting actual blobs (in different backgrounds, shapes, sizes, and grayscale changes) in Image Set B. In order to guarantee that experimental results of detection algorithms are comparable to utmost degree, the parameters are set as follows for all the images detected. The parameters of SMBD: $r_{A2} = r_T + 2$, $r_{A3} = r_{A2} + 1$, $r_{A4} = r_T$, Th_{A1} and Th_{A2} are set according to actual image conditions, r_{A1} is much less than r_T , and r_T represents the radius of target blob. The parameters of Quito: $r_{B1} = r_T$, $r_{B2} = r_{B1} + 2$, $r_{B3} = r_{B2} + 1$, $Th_{B1} = Th_{A1}$. The parameters of N-Quoit: $r_{C1} = r_T + 2$, $r_{C2} = r_{C1} + 1$, $Th_{C1} = Th_{A1}$. The parameters of LoG and DoH: $r_{D2} = r_{E2} = r_T$, $r_{D1} = r_{E1} = r_T - 10$ (≥ 1), $r_{D3} = r_{E3} = r_T + 10$.

The first row of Fig. 6 involves eight images in Image Set B, and the second to sixth rows of Fig. 6 are results of blob detection on images of first line of Fig. 6 with SMBD, Quito, N-Quoit, LoG and DoH respectively. As there are numerous point candidates for blob detected by LoG and DoH, only the first 100 candidates for location points of blobs are selected in the experiment, and they are represented in original images by use of green circles.

There are a total of 246 target blobs in Image Set B. The data of comparison experiment on five blob detection algorithms are shown in Table 2. The performance of SMBD algorithm is significantly better than that of other four algorithms. Correct detection rate of SMBD hits 98.78%, and the shapes of blobs detected are extremely complete. In addition, the number of blob candidates detected with SMBD Algorithm is extremely close to the number of target blobs, while the number of blob candidates detected by the other four algorithms is significantly higher than that of SMBD. Whether the blobs in Image Set B have been successfully detected is determined by visual inspection and the criteria is as the same of that of Image Set A.

4.3 The Operating Time of SMBD

We have performed 50 repetitive experiments with 5 kinds of blob detecting algorithms to ten images (1024×1024 gray scale image) in Image Set A. The parameters of the experiments of 5 kinds of blob detecting are the same as those of the comparison experiment in 4.1, and the target blobs to be detected are also the same. Based on the experiments, we have obtained the average detecting time of these 5 kinds of blob detector, as is shown in the Table 3. The program

is realized with C++, and the operation environment for the experiment is: i5-4590CPU, RAM 8GB, Windows 10 Professional. From the Table 3 we can see that, the detecting time of SMBD is similar with that of Quito, and it is slower than N-Quoit, however, it is better than LoG and DoH.

5. Conclusions

The dilation operators of standard mathematical morphology are extended to the order dilation operator, and three soft morphological filters are designed, based on which SMBD Algorithm is proposed. Though SMBD, Quito and N-Quoit are algorithms with the same type based on mathematical morphology, theoretically, SMBD is featured with greater anti-noise capacity than that of Quito and N-Quoit. According to the results of comparison experiment, SMBD not only features with extremely powerful anti-noise capacity but also quite complete blob shape detected compared to other four algorithms, and the number of blob candidates are extremely close to original number of blobs. Theoretically, the blob with the radius within specified range may be detected by two times of SMBD filtering if the target blob is a connected element region. SMBD has 12 parameters, among which 4 parameters of structural element may be easily set according to the size of target blob, whereas the remaining 8 parameters are required to be set according to the image conditions. It is a topic to be explored in the future to realize the adaptive processing of such parameters.

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Table 3 Comparison of detection time

Name of algorithm	SMBD	Quoit	N-Quoit	LoG	DoH
Average detection time (s)	12.98	12.07	0.839	24.97	59.33

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