Scale-Space Color Blob Detection

Ekaterina V. Semeikina, Dmitry V. Yurin
Department of Computational Mathematics and Cybernetics
Moscow State University, Moscow, Russia
esemeikina@graphics.cs.msu.ru, yurin@cs.msu.ru

Abstract

Feature detection in color images frequently consists in image conversion from color to grayscale and then application of one of many known grayscale detectors. This approach has a few disadvantages: some features become indistinguishable in grayscale and features ordering based on grayscale detector response do not accord with features order of importance from human's perception point of view. In this paper the method for direct detection of blobs in color images is proposed. The proposed algorithm is based on scale space approach and estimates blobs sizes. Two modifications of the proposed method are given and compared.

Keywords: *color blob detection, feature points, scale-space, hessian matrix.*

1. INTRODUCTION

Point and linear feature detection is a base problem of image mosaicing, image registration, 3D recovery, pattern recognition, and scene analysis. It has been shown [8] that blobs are the most appropriate point features for the applications which need feature matching. In contrast to corners [4], blobs [8] have more stable location and size. The algorithm for color blob detection will be proposed in the paper.

Feature detection in color images often consists of conversion from color to grayscale mode and application of one of grayscale detectors. This approach has disadvantages described below.

Most of feature detectors [1, 4, 11] consist of three steps. The first of them is application of some transform to image in order to construct Feature Response Image (FRI). Typical examples of FRI are gradient absolute value image (for Canny edge detection [1]), difference of Gaussians (grayscale blob detection [8]), Harris functional (corner detection [4]). The second is extrema detection (or non maxima suppression [1]) in FRI. The third step is thresholding or hysteresis [1]: sufficiently large extrema are considered to be features. Using of thresholds gives rise to the first argument for color image analysis without conversion to grayscale: a possibility of *feature distinguishability reduction*. Equal brightness of a feature and background is a rare situation, but visibility decreasing of some features after conversion to grayscale is typical.

For a wide class of algorithm correct feature sorting in order of their importance is significant. [5] can be considered as an examples of the algorithms which estimate model parameters (homography or essential matrix) using matched pairs of features from different views. Estimation is fulfilled in two stages: using pairs of "most important" features (with high FRI value) and refinement with all feature pairs. If feature ordering is not stable, sets of most important features from different views can contain images of different points of 3D scene and matching will be incorrect.

The corner [10] and edge [2, 3] detectors for color images are known. Unfortunately such approach is not applicable to features dependent on second image derivatives. In this paper two variants of color blob detection are proposed. In our method sizes of blobs are defined adaptively in scale-space. We know the only work [9] on color blob detection, comparative discussion of the proposed method and [9] will be given. Also comparison with detection in converted to grayscale images is presented.

2. SCALE-SPACE

Blobs in image can be described using derivatives of an image brightness function. However, the input image $I(x,\ y)$ is given at discrete pixel mesh in the plane $(x,\ y)$. Scale-space theory [7] proposes to use instead discrete image $I(x,\ y)$ its version $L(x,\ y,\ t)$ blurred with the Gaussian kernel $G(x,\ y,\ t)$:

$$L(x,y,t) = G(x,y,t) \otimes I(x,y)\ ,$$
$$\text{where } G(x,y,t) = \frac{1}{2\pi\sigma^2} e^{-\left(x^2+y^2\right)/2\sigma^2}\ ,\ t=\sigma^2 \qquad \textbf{(1)}$$

Blurred function $L(x,\ y,\ t)$ is infinitely differentiable. Using convolution properties the derivatives of $L(x,\ y,\ t)$ can be calculated via convolution of $I(x,\ y)$ with the corresponding derivatives of Gauss function. Thus image derivatives depend on the blurring parameter $t=\sigma^2$ called *scale* [7].

In blob detection there is no a priory known scale, which should be used for derivatives calculation. A blob should be detected at the scale where it is visible better. Such scale is proportional to the blob size. This leads to consideration of one-dimensional family of images $L(x,\ y,\ t)$ blurred with different t.

Let us notice that since Gauss function is used as the blurring kernel, then function $L(x,\ y,\ t)$ satisfies diffusion equation [7]:

$$L_t = \frac{1}{2}\cdot\left(L_{xx}+L_{yy}\right). \qquad \textbf{(2)}$$

3. GRAYSCALE BLOB DETECTION AT A FIXED SCALE

Let us consider Taylor series (3) of image brightness at the point $(x,\ y)$ in order to explain popular blob [8] detection techniques basics.

$$dL(x,\ y,\ t_0) = \vec{\mathbf{g}}^T(x,y)\begin{pmatrix} dx \\ dy \end{pmatrix} + \frac{1}{2}\begin{pmatrix} dx \\ dy \end{pmatrix}^T \mathbf{H}(x,\ y)\begin{pmatrix} dx \\ dy \end{pmatrix} + \ldots,$$

where $\mathbf{H}(x,\ y) = \mathbf{H}(x,\ y,\ t_0) = \begin{pmatrix} L_{xx} & L_{xy} \\ L_{xy} & L_{yy} \end{pmatrix}$ is Hessian matrix, scale $t=t_0$ is fixed. **(3)**

In the middle of a blob first derivatives (gradient) are small and the second term becomes the main. Image brightness $L(x, \ y, \ t_0)$ defines the surface and eigenvalues λ_1, λ_2 ($|\lambda_1| \geq |\lambda_2|$) of Hessian matrix characterizes curvature of this surface in direction of eigenvectors $\vec{v_1}$, $\vec{v_2}$. If both curvature values have the same sign and similar magnitudes then the feature is blob. Thus grayscale blob detection procedure consists of FRI construction $\lambda_2(x, \ y)$ and local extrema detection.

In order to avoid square root calculation Laplacian (4) is frequently used as FRI for blob detection:

$$trace(\mathbf{H}) = L_{xx} + L_{yy} = \lambda_1 + \lambda_2 . \quad \textbf{(4)}$$

Another popular FRI for blob detection is determinant of Hessian matrix $\det(\mathbf{H})$.

4. COLOR BLOB DETECTION AT A FIXED SCALE

4.1 Color variation vector and Hessian matrix for color image

Feature detection using Hessian matrix eigenvalues cannot be directly applied to color images. Usually in order to solve this problem grayscale image is constructed as a projection of color image to some direction in color space, for example, $(0.299, \ 0.587, \ 0.114)$. In this work we propose to select color projection direction adaptively in every image point as a direction in color space of the fastest color change.

In order to introduce vector of the fastest color change let us apply Laplace operator to each of image color channels and let us introduce auxiliary vector $\vec{C}$:

$$\vec{C} = \frac{1}{3} \cdot \left[R_{xx} + R_{yy}, \ \ G_{xx} + G_{yy}, \ \ B_{xx} + B_{yy}\right]^T . \quad \textbf{(5)}$$

Application of the Laplace operator, i.e. convolution with second derivatives of Gauss function, means difference between weighted mean $\vec{C}_- = \frac{1}{3} \cdot [R_-, \ G_-, \ B_-]^T$ over the point neighbourhood of radius r_0 and weighted mean $\vec{C}_+ = \frac{1}{3} \cdot [R_+, \ G_+, \ B_+]^T$ over outer ring neighbourhood (Figure 1). Here $r_0 = \sigma\sqrt{N_G}$, where N_G is the dimensionality of used Gaussian function, in our case $N_G = 2$. So we can say that $\vec{C} = \vec{C}_+ - \vec{C}_-$ is a *color variation vector* in the feature neighbourhood.

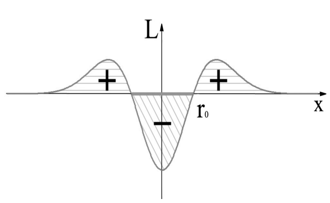

Figure 1: Second derivative of the 1D Gauss function.

Direction of $\vec{C}$ is a vector of the fastest color change (6):

$$\vec{c} = \left[c_R \quad c_G \quad c_B\right]^T = \frac{1}{\sqrt{3}} \vec{C} \Big/ \left|\vec{C}\right| \quad \textbf{(6)}$$

In order to form Hessian matrix, derivatives of the adaptively projected image should be constructed. Derivatives calculation in the point (x_i, y_i) via convolution with Gaussian derivatives would require forming of separate image L_i, using the fixed coefficients $\vec{c}(x_i, y_i)$ in all points of L_i.

$$\begin{aligned} L_i \ (x, y) &= c_R(x_i, y_i) \cdot R\ (x, y) + \\ &+ c_G(x_i, y_i) \cdot G\ \ (x, y) + \ c_B(x_i, y_i) \cdot B\ (x, y) \end{aligned} . \quad \textbf{(7)}$$

Fortunately we can avoid building of this image set $\{L_i\}$ and calculate derivatives in all points directly from color components derivatives:

$$\begin{aligned} \hat{D}(L(x, y)) &= c_R(x, y) \cdot \hat{D}(R(x, y)) + \\ &+ c_G(x, y) \cdot \hat{D}(G(x, y)) + c_B(x, y) \cdot \hat{D}(B(x, y)) \end{aligned} , \quad \textbf{(8)}$$

where $\hat{D}(\ldots)$ is differentiation operator.

Since only adaptive image derivatives are needed for blob detection, *the proposed method does not contain image conversion from color to grayscale*.

4.2 Detection at a fixed scale

Hessian matrix can be formed using derivatives (8). Further blob detection is analogous to detection in grayscale images using eigenvalues λ_1, λ_2 ($|\lambda_1| \geq |\lambda_2|$) of Hesse matrix.

Let us chose threshold β characterizing maximum allowed oblongness of a blob. Local extrema of FRI $\lambda_2(x, y)$, where $\lambda_2 / \lambda_1 > 1/\beta > 0$, are detected as blobs. These local extrema can be detected via scanning by 3×3 frame and comparing central pixel on FRI with its 8 neighbour pixels. In our experiments $\beta = 8$ have been used.

In the previous work [6] $|\lambda_2(x, y)|$ was used as FRI and local maxima needed to be detected. Detection of maxima instead of maxima and minima slightly saves computation time but leads to artifacts.

4.3 "Continuity" and "compatibility" properties

Like classical color extensions of corner [10] and edge [2, 3] detectors the proposed method obeys an important "*continuity*" property: small changes in RGB channel values results in small FRI changes. It also obeys property of "*compatibility*" with grayscale detector: when image color components are equal:

$$R(x, y) \equiv G(x, y) \equiv B(x, y) , \quad \textbf{(9)}$$

formulae used to construct FRI of color image come to formulae used for grayscale images. Thus the results of detection using color and grayscale algorithms are the same when (9) is true.

5. TWO VARIANTS OF SCALE-SPACE BLOB DETECTION

Unlike edge detection, where incorrect scale selection frequently leads only to some change of the edges shape, blobs will be missed if incorrect scale is used for detection. In the current section the method for scale-space detection which allows to detect feature at the scale where it is better visible is proposed.

For blob detection in scale-space we construct Hessian matrices (3) for a set of sequential scales t_j using derivatives (8). Then we construct a set of FRIs $\lambda_2(x, y, t_j)$ and detect local extrema via scanning with window $3\times3\times3$.

This scale-space blob detection method can be modified if simultaneous blob and ridge detection is needed. Ridge detection [6] uses Hessian matrix $\mathbf{H}(x, y, t)$, characterizing brightness curvature in 3D space (x, y, t):

$$\mathbf{H}(x,y,t)=\begin{pmatrix} L_{xx} & L_{xy} & L_{xt} \\ L_{xy} & L_{yy} & L_{yt} \\ L_{xt} & L_{yt} & L_{tt}\end{pmatrix}=\{\textit{diffusion equation}\ (2)\}=$$

$$=\begin{pmatrix} L_{xx} & L_{xy} & \dfrac{L_{xxx}+L_{xyy}}{2} \\ L_{xy} & L_{yy} & \dfrac{L_{xxy}+L_{yyy}}{2} \\ \dfrac{L_{xxx}+L_{xyy}}{2} & \dfrac{L_{xxy}+L_{yyy}}{2} & \dfrac{L_{xxxx}+2L_{xxyy}+L_{yyyy}}{4}\end{pmatrix} \quad \textbf{(10)}$$

Using of second eigenvalue of Hessian matrix $\mathbf{H}(x, y, t)$ (10) as FRI gives result equivalent to result of detection with $\mathbf{H}(x, y)$ (3): sets of detected local extrema are almost the same (see example in Figure 2) and contrasts of the corresponding extrema are close. To compare extrema contrast two values have been calculated: in case of local maxima $c_1=\lambda_{mean}/\lambda_{\max}$ and $c_2=\lambda_{pre\max}/\lambda_{\max}$, where $\lambda_{\max}$ is detected maximum value, $\lambda_{pre\max}$ is maximum value among $\Lambda_{3\times3\times3}$ - neigbourhood of $\lambda_{\max}$ of size $3\times3\times3$, λ_{mean} is mean value among $\Lambda_{3\times3\times3}$. Analogically in case of local minima: $c_1=\lambda_{mean}/\lambda_{\min}$ and $c_2=\lambda_{pre\min}/\lambda_{\min}$. Mean values over the test base, containing synthetic and natural images, are $\langle c_1\rangle\approx2.3$ and $\langle c_2\rangle\approx1.02$.

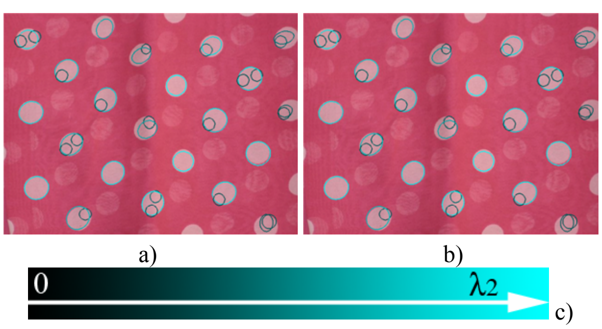

Figure 2: The blobs detected (response threshold 1.25): a) using $\mathbf{H}(x, y)$, b) using $\mathbf{H}(x, y, t)$, c) color of ellipses correspond to blob response.

Figure 3 illustrates eigenvalues of $\mathbf{H}(x, y)$ and $\mathbf{H}(x, y, t)$ at a set of scales. For a figure in the left part four FRI sets have been calculated: $\lambda_1(x, y, t)$ and $\lambda_2(x, y, t)$ of $\mathbf{H}(x, y)$ and $\mathbf{H}(x, y, t)$. Each diagram in the right part of Figure 3 contains the same row of FRI taken at sequential scales. Rows y_{cc} and y_{ec} of FRIs are shown, where circle blob in the original image has center (x_{cc}, y_{cc}) and elliptic blob has center (x_{ec}, y_{ec}). It can be seen that in the middle of circle or elliptic blob there is evident extremum of $\lambda_2(x, y, t)$ and both eigenvalues λ_1, λ_2 have close values.

6. COMPARISON

Adaptive projection (8) preserves features distinguishability towards background unlike methods using a fixed direction or the adaptive method [9] proposed by Ming and Ma (11):

$$\hat{D}(L\ (x,y))=\frac{R(x,y)}{S(x,y)}\cdot\hat{D}(R\ (x,y))+ +\frac{G(x,y)}{S(x,y)}\cdot\hat{D}(G(x,y))+\frac{B(x,y)}{S(x,y)}\cdot\hat{D}(B(x,y)), \quad \textbf{(11)}$$

where $S(x,y)=R(x,y)+G(x,y)+B(x,y)$.

Unlike the proposed algorithm method [9] take into consideration only the color in current point and do not use background color. Let us consider an example blob of color $(255, 0, 0)$ against a background of color $(255, 0, 5)$. In formula (11) red component, which does not distinguish feature and background, has the highest contribution while the most important blue component is suppressed, so projection direction is $(0.98, 0, 0.02)$. In our method (8) a component has the higher weight the higher change between feature and background for this component. The color variation vector is proportional to $(0, 0, 1)$ for the above example.

Comparative examples of blob detection with the proposed algorithm and detection after conversion to grayscale are given in Figure 4. It can be seen that after conversion to grayscale most noticeable from the human perception point of view color features are missed. At the same time these features have been detected by the proposed method with high response.

7. CONCLUSION

Two variants of scale-space algorithm for blob detection in color images have been developed. Up today the color detectors of features dependent on first derivatives (edges and corners) were known. In this paper we have proposed an other approach to using color information. In contrast to previous approach our method can be applied to features dependent on second derivatives, particularly blobs. It has been showed that the proposed method has advantages in comparison with the only previously known color blob detector and with detection after conversion to grayscale.

8. ACKNOWLEDGEMENTS

The work was supported by the Federal Program “Scientific and Scientific Pedagogical Personnel of Innovative Russia” in 2009–2013 and the Russian Foundation for Basic Research, project no. 09-07-92000-HHC_a.

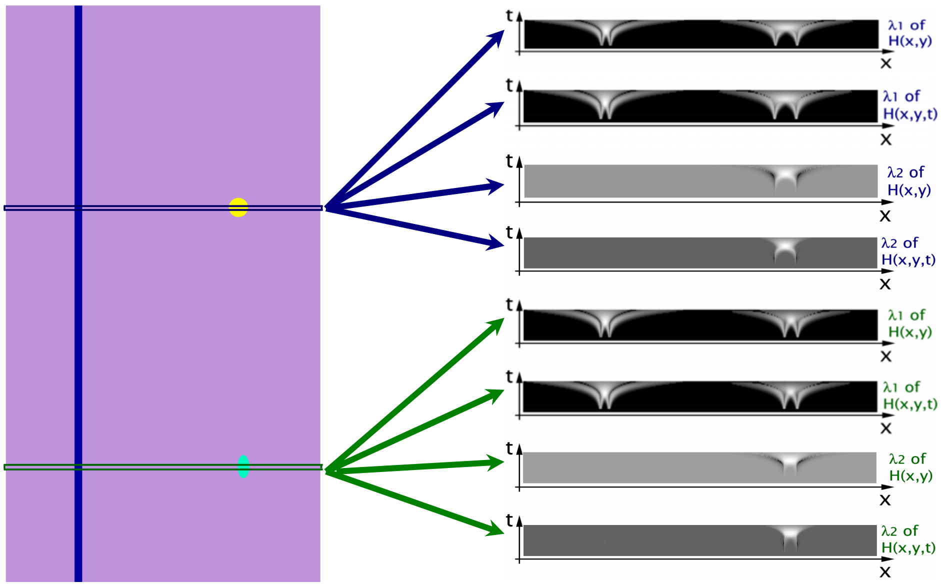

Figure 3: Eigenvalues of $\mathbf{H}(x, y)$ and $\mathbf{H}(x, y, t)$ at a set of scales. For a figure in the left part four FRI sets have been calculated: $\lambda_1(x, y, t)$ and $\lambda_2(x, y, t)$ of $\mathbf{H}(x, y)$ and $\mathbf{H}(x, y, t)$. Each diagram in the right part contains the same row of FRI taken at sequential scales. Shown rows are taken in the middle of circle and elliptic blobs. Values in diagrams are normalized to [0, 255].

Figure 4: Comparison of results obtained from the proposed algorithm ((c) and (d)) and detection after conversion to grayscale ((e) and (f)). Response threshold is 0.75. After conversion to grayscale most noticeable color features are missed.

9. REFERENCES

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About the authors

Ekaterina V. Semeikina is a Ph.D. student at Chair of Mathematical Physics, Faculty of Computational Mathematics and Cybernetics, Lomonosov Moscow State University, Russia.

Her contact email is esemeikina@graphics.cs.msu.ru

Dmitry V. Yurin (PhD) is a senior researcher at laboratory of Mathematical Methods of Image Processing, Faculty of Computational Mathematics and Cybernetics, Lomonosov Moscow State University, Russia. His contact email is yurin_d@inbox.ru