Algorithm Optimization for the Edge Extraction of Thangka Images

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Abstract. A novel image edge detection algorithm developed to extract object region from a Thangka image by gradient magnitude and two-step gradient. The idea of our image edge detection algorithm is similar to the canny edge detection algorithm, but the implementation is rather different. By using this algorithm, we can realize the object region extraction by four steps. Firstly, the Gaussian algorithm is used to smooth the Thangka image. Then, the second order gradient amplitude and gradient angle for the Thangka image are calculated. Thirdly, non-maximum suppression is used to detect the edge of the Thangka image. At last, the double threshold is performed to achieve the outline of the Tang image extraction.

Introduction

Thangka is a unique form of painting art reflecting Tibetan culture. It is called the Tibetan encyclopedia, and its subject matter involves the history, politics, culture and social life of Tibetan [1, 2]. Compared to other images, Thangka images are complex in texture and color, and the contours are not obvious. The paint of Thangka peeled off with the passing of years. For a better transmission of Thangka, we studied the structure and texture of Thangka images, and improved the Canny edge detection algorithm for the extraction of a Thangka image.

The contour is defined as the boundary line of a geometric shape, which includes the boundaries of target and the boundaries of interest. The boundaries of interest are usually defined by gray, color, or texture mutations. Image edge detection has been widely used in many computer vision and pattern recognition applications including image segmentation, object detection, and object recognition for image content analysis[3–5]. Nowadays, a great number of image edge detection techniques are being utilized in many special application fields. For instance, Roberts operator, Sobel operator and Prewitt operator are used to convert the image using the local differential filter for the simulated color channel, while the Marr and Hildreth operators are edge-sliced using the Laplace transform of the Gaussian template. John F. Canny proposed image segmentation method is an edge detection operator that uses a multistage algorithm to detect a wide range of edges in images [6].

Knowing that Thangka images of different ages reflect definitely different historical events, it is difficult to extract the exact edge using the original edge detection method. Moreover, amounts of edges might be lost and lots of non-edge contours might be kept when performing the extraction. To solve the above problem, we propose a new edge detection algorithm. In short, the Thangka image is firstly smoothed, and then the second order gradient of the Thangka images calculated. The gradient and angle of the Thangka image are calculated by the second order gradient of the Thangka image. According to the gradient amplitude and the size of the angle of non-maximum suppression. Finally, the double threshold is used to find the image boundary, and the edge detection of the Thangka image is completed.
Experimental Principle
The edge of a Thangka image is fixed. However, patterns or decoration of a Thangka image are complex. Therefore, the original edge detection algorithm is difficult to distinguish all these elements. When using the original edge detection algorithm, the detected edges are shown in a single pixel. Some broken or dark edge of the color would be lost. In order to solve this problem, we develop a new Tangka image rough edge extraction method, which uses the second order gradient as the gradient amplitude for the Thangka image edge detection.

Image Smooth
Firstly, we use a two-dimensional Gaussian function to smooth the image. The function as follows:

\[
G(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right)
\]

among which, \(G(x, y)\) is the two-dimensional Gaussian function, \((x, y)\) determines the pixel position, and \(\sigma\) is the Gaussian filter parameter. Sigma controls the smooth degree. A smaller \(\sigma\) means a higher filter positioning accuracy but a lower signal to noise ratio. We can control the smooth degree by selecting a suitable Gaussian filter parameter.

Second Order Gradient Principle
Compared with the first order gradient amplitude, the gradient calculated by the second order gradient is smoother and can effectively reduce the missing contour. Therefore, we use a second order gradient to calculate the gradient and gradient angles. We start from the gray histogram of the image. The original image of the gray histogram is shown in Fig. 1(a). In this image, the gray-scale accumulates in the middle and the gray value is large. First-order gradient histogram of the image is shown in Fig. 1(b). From this image we can clearly see the image of the gray value of the lower part of the relatively large share. The second order gradient histogram is shown in Fig. 1(c). From this image can be seen, although the gray value is relatively low proportion of relatively large, but the other pixel gray value relative to the number of the gap is not large, equivalent to the effect of histogram equalization.

![Figure 1](image)

Figure 1. (a) The gray histogram of the original image. (b) First-order gradient histogram of the image. (c) Second order gradient histogram of the image.

Although the probability distribution of the pixels can be clearly seen from Fig. 1, it is not possible to visually show where the second order gradient has an advantage over the first order gradient. Here we start from the step edge image of the Thangka image, and the gray value of the image \(f(x, y)\) is shown in Fig.2(a). The edge of the Thangka image corresponds to the maximum point of the first order gradient image, as shown in Fig.2(b). And the maximum point of the first-order gradient corresponds to the zero-crossing of the second-order gradient, as shown in Fig. 2(c). It is clear from Fig. 2 that the second order gradient function near the edge of the Thangka image exists from positive to negative steps. This means that the second order gradient image has a more pronounced change in the vicinity of the edge relative to the first order gradient. As the second-order gradient image in the edge near the gradient amplitude changes are more obvious, the image of the background and edge can be distinguished.
Here we use the Sobel operator to calculate the image gradient. The sobel operator is shown in Fig.3.

\[
s_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}, s_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}, K = \begin{bmatrix} a_0 & a_1 & a_2 \\ a_7 & [i, j] & a_3 \\ a_6 & a_5 & a_4 \end{bmatrix}
\]

Figure 3. Sobel operator and the 3 × 3 images. (a) is the convolution of the Sobel operator in the x direction, (b) is the convolution of the Sobel operator in the y direction. (c) Where is the neighborhood dot mark matrix for the \((i, j)\) position to be processed.

\[
G_x = \begin{bmatrix} G_{x0} & G_{x1} & G_{x2} \\ G_{x7} & [i, j] & G_{x3} \\ G_{x6} & G_{x5} & G_{x4} \end{bmatrix}, G_y = \begin{bmatrix} G_{y0} & G_{y1} & G_{y2} \\ G_{y7} & [i, j] & G_{y3} \\ G_{y6} & G_{y5} & G_{y4} \end{bmatrix}
\]

Figure 4. (a) is a first order gradient in the x direction obtained using the Sobel operator. (b) is a first order gradient in the y direction using the Sobel operator.

According to this operator can be used mathematical formula to express the gradient of each point.

\[
G_{sx} = (a_2 + 2a_3 + a_4) - (a_0 + 2a_1 + a_6)
\]

where \(G_{sx}\) is the first order gradient of the x direction.

\[
G_{sy} = (a_0 + 2a_1 + a_2) - (a_4 + 2a_5 + a_4)
\]

where \(G_{sy}\) is the first order gradient of the y direction.

Suppose the first order gradient of the Thangka image is shown in Fig.4. Fig.4 (a) is the first order gradient of the Thangka image x direction. Fig.4 (b) is the first order gradient of the Thangka image y direction. Using the Sobel operator, the second order gradient in the x direction is obtained as follows:

\[
G_{sxx} = (G_{x2} + 2G_{x3} + G_{x4}) - (G_{x0} + 2G_{x1} + G_{x6})
\]

Using the Sobel operator, the second order gradient in the y direction is obtained as follows:

\[
G_{syy} = (G_{y0} + 2G_{y1} + G_{y2}) - (G_{y6} + 2G_{y5} + G_{y4})
\]

Using the sobel operator to obtain x direction, y direction of the partial derivative:

\[
G_{sxy} = (G_{x0} + 2G_{x1} + G_{x2}) - (G_{y0} + 2G_{y5} + G_{x4})
\]

Calculate the average of the second order gradient image as follows:

\[
\text{average} = \frac{G_{sxx} + G_{syy}}{2}
\]

If you only use the second order gradient as the gradient amplitude, there will be bias. So we calculate the bias function by the gradient function, the bias function is:
We determine the size of the gradient amplitude by the sign of the gradient mean. The formula is:

\[
\text{amplitude} = \begin{cases} 
\text{average} + \text{differ}, & \text{average} > 0 \\
\text{average} - \text{differ}, & \text{average} < 0
\end{cases}
\] (9)

We know that when the image is at the edge, the value of the second order gradient image can be positive or negative. Thus, we distinguish the gradient edges by the mean number of symbols. Since the Thangka image is a three-channel image, we finally traverse each element of the three channels and select the maximum value as the current pixel gradient. We calculate the gradient angle based on the second order partial derivative of the gradient and the paranoia of the amplitude and the second order gradient in the x direction. The angle as follow:

\[
\text{angle} = \arctan 2f(\text{amplitude} - G_{sx}, G_{sy}) * 2.0
\] (10)

Then, the gradient angle is normalized to 0-2π. Here the image of the second order gradient is calculated.

**Non-maximal Suppression**

We use the gradient amplitude and the gradient angle of the relationship between the non-maximum suppression. First, we calculate the sine and cosine values based on the radian values of the gradient angle. The sine as follows:

\[
\sin Value = \sin f(\text{angle} * 0.5)
\] (11)

The cosine as follows:

\[
\cos Value = \cos f(\text{angle} * 0.5)
\] (12)

Then we determine the 4 fields we need based on the sine and cosine values. We assume that v00 is the pixel value of the current pixel (i, j). V01 is the pixel value of the pixel (i, j + 1). V10 is the pixel value of the pixel (i + 1, j). V11 is the pixel value of the pixel (i + 1, j + 1). The current contrast as follows:

\[
\text{ret} = (1.0 - \sin Value) \times (1.0 - \cos Value) \times V00 + \\
\sin Value \times (1.0 - \cos Value) \times V10 + \\
(1 - \sin Value) \times \cos Value \times V01 + \\
\sin Value \times \cos Value \times V11
\] (13)

If the current point of the pixel gray value is less than the contrast value that the current point for the background.

**Double Threshold Connection**

We uses the double threshold method to detect and connect the final edge from the candidate edge points. The double threshold method first selects the high threshold Th and the low threshold Tl, and then starts scanning the image. (i, j) of the candidate edge image N as a candidate edge point is detected, and if the gradient G(i, j) is higher than the high threshold value Th, the point (i, j) gradient amplitude G (i, j) is lower than the low threshold value Tl, it is considered that the point must not be an edge point. For the pixel whose gradient amplitude is between two thresholds, it is regarded as a suspected edge point, and then it is judged by the connectivity of the edge. If there is an edge in the adjacent pixel of the pixel, The point is also the edge point, otherwise, that the point is non-edge point.
Result of Experiment

Figure 5. Thangka history image edge extraction. (a) The original image. (b) Image after edge extraction using the algorithm developed in this article.

As shown in Fig. 4, Fig.4 (a) is the Thangka history image, Fig.4 (b) is the detection of the Thangka image. It is obvious from the experimental results that the outline of the Thangka history image extracted from this method is very clear and the edge connection is more accurate.

As shown in Fig. 5, Fig. 5 (a) is the Thangka people image, Fig. 5 (b) is the detection of the Thangka image. From Fig. 5 we extracted the Thangka people image is very clear.

Effect Comparison

Remove the False Target

Figure 6. Thangka people image edge extraction. (a) The original image. (b) Image after edge extraction using the algorithm developed in this article.

Figure 7. Contour image results image. (a) Sobel edge detection operator extracted from the Thangka image. (b) Canny edge detection operator extracted from the Thangka image. (c) Laplacian edge detection operator extracted from the Thangka image. (d) This experiment extracts the outline of the Thangka history image.

Below we use the classic edge detection algorithm for Thangka history image contour extraction. We use the algorithm: Sobel edge detection algorithm, canny edge detection algorithm and Laplacian edge detection. Experimental results shown in Fig.7, Fig. 7(a) is the use of Sobel operator to extract the edge of the Thangka. Fig.7 (b) is a Thangkahistory image extracted using the canny edge detection algorithm. Fig.7 (c) shows the Thangkahistory image contour extracted from the Laplacian operator. Fig.7(d) for the experimental algorithm to extract the Thangka image contour. From the comparison results, we can see that the method of this paper is more obvious than the Sobel edge detection algorithm, and there is no loss phenomenon. While the sobel operator extracts the contours
of the triangular area in the middle circle without extracting completely. And through observation we can see that the image extracted a lot of false targets. Using the canny edge detection algorithm to extract the contour image is relatively clear, but the contour is relatively small, a lot of texture will appear in the contour image. It is hard to tell where there is the exact edge. While the Laplacian operator extracts the contours in some regions without extraction without obvious edges. And through the observation we can see that the image extracted a lot of pseudo-target a lot, does not apply to the outline of the Thangkahistoryimage extraction. It can be seen that the algorithm in this paper can effectively remove the false target in the Thangka history image. Extract the outline of the more clear, no extra texture and other decorative things.

Enhance the Edge

In the details of the edge detection as shown in Fig.8. Fig.8 (a) is the edge detected by the sobel operator, Fig. 8 (b) is the edge detected by the Laplacian operator, and Fig. 8 (c) is the edge detected by the canny edge detection algorithm. This algorithm detects the edge of the image. In this experiment we can clearly see that our algorithm can improve the ability of edge detection. Can be detected fine edge, as can be clearly seen from Fig.8, Sobel operator and Laplacian operator detected a lot of the edge are lost. Canny edge detection although the effect is very good, but some of the details of the edge is also lost.

Figure 8. Contour image results image. (a) Sobel edge detection operator extracted from the Thangka people image. (b) Canny edge detection operator extracted from the Thangka people image. (c) Laplacian edge detection operator extracted from the Thangka people image. (d) This experiment extracts the outline of the Thangka people image.

Summary

As discussed above, the Thangka image contour extraction algorithm we developed in this article can effectively extract the edges of a Thangka image. This algorithm removes the false target and keeps the edge information of an image to a much greater extent, and therefore is a very effective image contour extraction algorithm.

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Reference


