Based On Edge Extraction of ASM Automatic Landmark Placement

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Abstract

In the Active Shape Model, the most time consuming and scientifically unsatisfactory part of building shape models is the labeling of the training images. Manually placing hundreds (in 2D) of points on every image is both tedious and error prone. To reduce the burden, the combination of the image edge information and the traditional manual calibration methods have been developed. This method improves the calibration accuracy, and obtains more accurate statistical shape model and local texture model. Aiming at the characteristics of ASM modeling, this paper adopts a multiscale wavelet transform modulus maximum method of edge extraction, using the maximum variance method to obtain a threshold, after the use of connectivity judgment for each scale edge fusion. The simulation results show that, this algorithm can effectively reduce the burden, improve the modeling accuracy.

Keywords: *ASM, multiscale, wavelet modulus maxima, maximum between-cluster variance*.

1. Introduction

Active shape model [1] is a statistical model based on image search method, can be flexible matching the contour of the target, and to a certain extent maintaining its own topology. Point distribution model [2] is a powerful shape description technique. In order to obtain a target object to the point distribution model requires containing the target object of various changes in form of a group of image collection, image to each of the target feature point for calibration way, to show the target object shape information.

Because the standard fixed-point set determines the model contains all the a priori knowledge [3].So the point selection and calibration accuracy is directly related to the performance of the model. As for the different target segmentation and different application, we need to adopt the different training image calibration, therefore cannot get a put things right once and for all image training set. Each image contains a great deal of feature points, and the position of the calibration is very accurate and representative. So the calibration image also became a huge amount of work. At present, most of the calibration work done by manual, and in some areas also must rely on expert knowledge to achieve accurate calibration.

2. Based On the Edge Extraction of ASM Feature Point Location

Based on the above reasons, this paper put forward the image edge information is used in the ASM positioning feature points in the process, the edge is the most basic features of the image. The so-called edge refers to the image gray scale intensity have dramatically changed those pixels set, many feature points in the edge information of strong position. Based on the ASM algorithm modeling features, image preprocessing, required for each image of a target area to be extracted, we want to model objects to reduce unnecessary trouble and effort, then the extracted object. On the other hand, as the physical and light and other reasons, each image in the edge is usually produced in a range of different scales, the formation of different types of edge, and this information is unknown. In this paper, using multi-scale wavelet transform modulus maximum edge extraction to obtain the edge information [4]-[5], using the edge information to improve ASM search process, to reduce workload, accelerate speed modeling.

2.1 Multi Scale Wavelet Modulus Maxima of the Edge Detection Principle

Images at different scales of the wavelet transform provide certain edge information. When the small scale, the image edge information is more abundant, the edge location precision is higher, but susceptible to noise interference; large scales, image edge stability, good noise immunity, but poor positioning accuracy. In practical applications there are often contradiction between noise removal and accurate positioning of the contradiction. Multi scale edge detection's [6] main idea is of along the gradient direction, respectively, with several different scale edge detection operators in the corresponding point on the detection of modulus maxima of the transform, and through to the threshold, and then at different scales were integrated to get the final edge image, can better solve the contradiction between noise and positioning accuracy.

Set $\theta(x,y)$ Binary smoothing function, often taking practical

$$\theta(x,y)=\frac{1}{2\pi\sigma^2}e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{1}$$

Apparently it meets

$$\iint_{R^2}\theta(x,y)dxdy=1$$
$$\lim_{\substack{x\to\infty\\ y\to\infty}}\theta(x,y)=0 \tag{2}$$

Note

$$\psi^{(1)}(x,y)=\frac{\partial\theta(x,y)}{\partial x}=\frac{-x}{2\pi\sigma^4}e^{-\frac{x^2+y^2}{2\sigma^2}}$$
$$\psi^{(2)}(x,y)=\frac{\partial\theta(x,y)}{\partial y}=\frac{-y}{2\pi\sigma^4}e^{-\frac{x^2+y^2}{2\sigma^2}}$$

(3)

Obviously

$$\iint_{R^2}\psi^{(1)}(x,y)dxdy=0$$
$$\iint_{R^2}\psi^{(2)}(x,y)dxdy=0 \tag{4}$$

So $\psi^{(1)}(x,y),\psi^{(2)}(x,y)$ are the two-dimensional admissible wavelets

$$\theta_s(x,y)=\frac{1}{s^2}\theta\left(\frac{x}{s},\frac{y}{s}\right) \tag{5}$$

$$\psi_s^{(1)}(x,y)=\frac{1}{s^2}\psi^{(1)}\left(\frac{x}{s},\frac{y}{s}\right)=s\frac{\partial\theta_s(x,y)}{\partial x}$$
$$\psi_s^{(2)}(x,y)=\frac{1}{s^2}\psi^{(2)}\left(\frac{x}{s},\frac{y}{s}\right)=s\frac{\partial\theta_s(x,y)}{\partial y} \tag{6}$$

The two-dimensional convolution type of wavelet transform, respectively $W_f^{(1)}(s,x,y),W_f^{(2)}(s,x,y)$

$$W_f^{(1)}(s,x,y)=f*\psi_s^{(1)}(x,y)=f*[s\frac{\partial\theta_s(x,y)}{\partial x}]$$
$$W_f^{(2)}(s,x,y)=f*\psi_s^{(2)}(x,y)=f*[s\frac{\partial\theta_s(x,y)}{\partial y}] \tag{7}$$

The convolution property show

$$W_f^{(1)}(s,x,y)=s\frac{\partial[f*\theta_s(x,y)]}{\partial x}$$
$$W_f^{(2)}(s,x,y)=s\frac{\partial[f*\theta_s(x,y)]}{\partial y} \tag{8}$$

Note for the vector form

$$\begin{bmatrix}W_f^{(1)}(s,x,y)\\W_f^{(2)}(s,x,y)\end{bmatrix}=s\begin{bmatrix}\frac{\partial[f*\theta_s(x,y)]}{\partial x}\\\frac{\partial[f*\theta_s(x,y)]}{\partial y}\end{bmatrix}=s\cdot grad[f*\theta_s(x,y)]$$

(9)

Utility often takes $s=2^j$ ($j=0,1,2,\cdots,J$), $f(x,y)$ two dyadic wavelet transform available

$$\begin{bmatrix}W_f^{(1)}(2^j,x,y)\\W_f^{(2)}(2^j,x,y)\end{bmatrix}=2^j\cdot grad[f*\theta_{2^j}(x,y)] \tag{10}$$

Each scale edge image mode value

$$\sqrt{\left|W_f^{(1)}(2^j,x,y)\right|^2+\left|W_f^{(2)}(2^j,x,y)\right|^2} \tag{11}$$

Argument

$$\theta=\tan^{-1}\left|W_f^{(2)}(2^j,x,y)\right|\Big/\left|W_f^{(1)}(2^j,x,y)\right| \tag{12}$$

2.2 Non Maximum Suppression and Threshold Selection

The $0^\circ\sim360^\circ$ argument into a four direction θ' : 0° , 45° , 90° and 135° .As shown in Figure 1

Thus, direction angle $\left[-22.5^\circ\sim22.5^\circ\right]and\left[157.5^\circ\sim202.5^\circ\right]$ in the range of points are integrated into the direction angle 0° , the other point of view and so on. From ASM point process knowable, the edge is allowed to have only one pixel width, but the operation the edge is irregular. Using Otsu method is effective in reducing the rate of residual edge threshold.

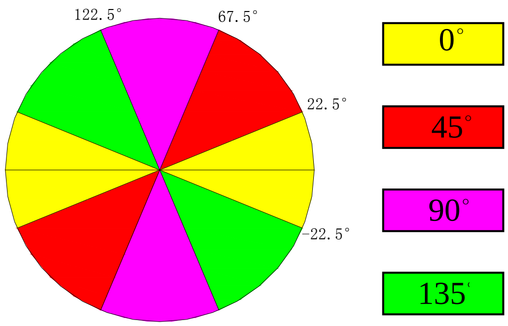

Figure 1 Gradient direction merges.

Non maximum suppression is that those in the gradient direction have a maximum gradient value of the pixel as an edge pixel reservation, the other pixel reservation. Maximum gradient value is usually seen at the edge of the center.

This combination of the above are obtained for each pixel's gradient magnitude and direction, we check around the point (x, y) within the pixel 3×3:

If $\theta'(x, y) = 0^\circ$ then check the pixel $(x+1, y)$、$(x, y) and (x-1, y)$;

If $\theta'(x, y) = 90^\circ$ then check the pixel $(x, y+1)$、$(x, y) and (x, y-1)$;

If $\theta'(x, y) = 45^\circ$ then check the pixel $(x+1, y+1)$、$(x, y) and (x-1, y-1)$;

If $\theta'(x, y) = 135^\circ$ then check the pixel $(x+1, y-1)$、$(x, y) and (x-1, y+1)$;

Comparison of examination of three pixel gradient value, if (x, y) the gradient values are greater than the other two points, so, it is considered to be the edge center and is marked edge, otherwise, not considered edge center removed.

This paper uses the Otsu method to calculate the threshold, adaptive threshold simple and efficient method, the algorithm of input gray image histogram analysis; histogram is divided into two parts. To test this histogram based method, from a discrete probability density function of the normalized histogram, as shown below

$$p_r(r_q) = \frac{n_q}{n} \qquad q = 0, 1, 2, \cdots, L-1 \qquad (13)$$

Among them, n is the total number of pixels in the image, n q is a gray level for the r_q pixel number; L is the image of all the possible gray series. Suppose we now have selected a threshold K, C_0 is a group of gray level for the pixel $[0, 1, \cdots, k-1]$, C_1 is a group of gray level for a pixel $[k, k+1, \cdots, L-1]$.Otsu method for the selection of maximum between-cluster variance σ_B^2 threshold K, C_0 value , C_1 value, probability, probability, total mean, variance is defined as

$$\sigma_B^2 = \omega_0(\mu_0 - \mu_T)^2 + \omega_1(\mu_1 - \mu_T)^2 \qquad (14)$$

In which

$$\omega_0 = \sum_{q=0}^{k-1} p_q(r_q)$$
$$\omega_1 = \sum_{q=k}^{L-1} p_q(r_q)$$
$$\mu_0 = \sum_{q=0}^{k-1} qp_q(r_q)/\omega_0 \qquad (15)$$
$$\mu_1 = \sum_{q=k}^{L-1} qp_q(r_q)/\omega_1$$
$$\mu_T = \sum_{q=0}^{L-1} qp_q(r_q)$$

Calculation of the image histogram, finds σ_B^2's maximum threshold, the threshold for the return of 0 .0 and 1.0 between the normalized value.

3. The Simulation Results

In recent years based on face recognition is a hot research field, the study of human face recognition has important theoretical value; the technology of face recognition involves multiple disciplines. It involves pattern recognition, artificial intelligence, neural networks, computer vision, computer graphics, physiology, psychology and many other fields. The problem of face recognition research and solve can promote the development of these areas, the related research fields of research work has important influence and significance. Based on this paper adopts the simulation example is the four consecutive changes of face image, as shown in Figure 2.

We want to do is through to the four images of a series of processing, automatic access to face feature points, so as to facilitate the subsequent face recognition, tracking and other processing.

We first performed on the input image pretreatment, face candidate region segmentation, using SMQT method to obtain the corresponding small feature, called LSMQT (Local SMQT) characteristics, and through the SNoW classification to determine the final face location, face detection to achieve work. Figure 3 is shown as follows.

Figure 2 Original image

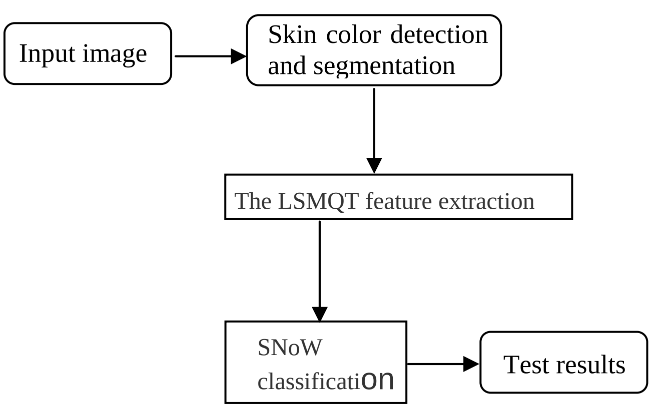

Figure 3 Face detection systems

Treatment results as shown in Figure 4

On the pre processed image, using three scales, the simulation results of three scale edge as shown in Figure 5

Figure 5 Three scale extraction results.

Figure 4 .The result of face detection

From the simulation results, on a large scale, the edge is relatively stable, is not sensitive to the noise, because the sampling shift effect, so that the edge location precision is poor; on a small scale, edge information is relatively abundant, but sensitive to noise. Therefore, the multi-scale edge extraction should play a big, small scale advantages, the scale image edge synthetically, to obtain accurate single pixel edge. This paper uses the multi scale fusion method steps are as follows:

1. Judge j=2 scale edge connectivity (eliminating the scale of isolated chains)
2. By 1 to get the connectivity of the results, to judge the j=1 scales under the candidate edge points are the true edge points, the edge removal, edge points left
3. 2 the edge connectivity judgment, so the two larger scale edge image fusion
4. With 3 of the fusion of judging the minimum scale edge point is the true edge points, then through

connectivity judgment to be the final fusion edge map, the final results as shown in Figure 6

Finally, in order to get ASM algorithm requires calibration point, the edge graph of the results between adjacent points of interpolation, making a smooth curve. Then in accordance with a specific sequence extraction algorithm is needed to ensure that each image point, point of the number and location of the same, thereby accurately to achieve ASM algorithm to automatically mark the feature points. The result is shown in Figure 7.

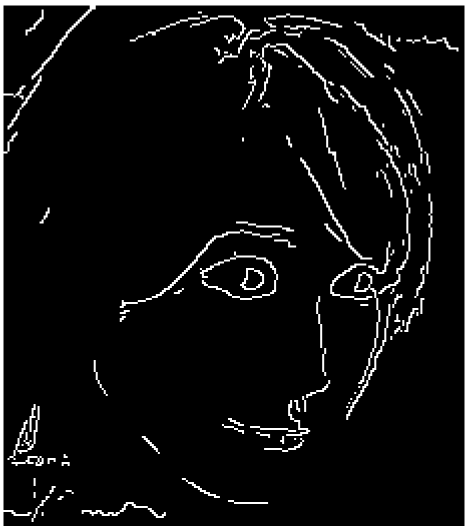

Figure 6 The fusion result

Figure 7 Final results

4. Conclusions

In this paper, through the use of multi-scale wavelet transform modulus maximum method of edge extraction, using the maximum variance method to obtain the threshold, finally using connectivity judgment are the scale edge fusion method is effective to solve the ASM modeling process the fixed-point huge workload issues, and to some extent to ensure the accuracy of calibration points problem. The simulation results show that this algorithm can effectively reduce the workload, improve the modeling accuracy.

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