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Modified Grey-level Models for Active Shape Model Training

Shuo Dong, Shuqian Luo*

College of Biomedical Engineering, Capital University of Medical Sciences, Beijing, China.

Abstract – **Active Shape Model (ASM) is a popular statistical shape model for objects localization. It combines a Point Distribution Model (PDM) and local grey-level model of each landmark point to achieve reliable and accurate result in image interpretation. However, in 2D images, the one-dimensional profile grey-level models will lose information in other directions. In this paper, we modeled the grey-level information of the $k \times k$ square neighbor region around each point, hoping to take more information into account. Yet, further works should be done in order to compare the searching results obtained by square grey-level models with those by one-dimensional profile grey-level models.**

Keywords – **shape localization, Active Shape Model (ASM), local grey-level modeling.**

I INTRODUCTION

Accurate extraction and alignment of target objects from images are required in many computer vision and pattern recognition applications.

Active Shape Model (ASM), proposed by Cootes et al. [1, 5], is a popular statistical model for objects localization. It is derived from the famous Snake algorithm, which defines contour as an energy-minimized curve. The inner force from the curve itself and the outer force from image data are used to drive the snake curve to approximate the edge of interests.

Active Shape Model employs prior knowledge, which makes it more robust than Active Contour Model (i.e. Snake). It consists of a point distribution model and a set of grey gradient distribution models. The former presents the shape variations of object instances. And the latter describes local texture of each landmark point. The major advantage of ASM is that the model can only deform in the ways leant from the training set. That is, it can accommodate considerable variability, and at the same time, maintain the specificity to the class of object it intends to represent.

*Corresponding author: sqluo@ieee.org

II METHOD AND MATERIAL

1. METHOD

The basic algorithm of Active Shape Model consists of three steps: obtaining a true shape representation by aligning the training set, capturing the statistics of the set of aligned shapes and searching for the shape instance in images.

To obtain a true shape representation means to filter out the location, scale and rotational effects from the object [3]. In ASM, we represent a shape by a set of points called landmarks. A landmark is a point of correspondence on each object that matches between and within populations [4]. A commonly used alignment procedure is Procrustes Analysis [2].

Alignment brings the set of shapes into a frame of reference. The next work is to describe the variation of shapes within that frame, i.e. to capture the statistics of the aligned shapes.

Consider the case of having N shapes consisting of n points each, where each shape is represented as [3]:

$$x = [x_1, x_2, \cdots, x_n, y_1, y_2, \cdots, y_n]^T \tag{1}$$

The mean shape of these aligned shapes is calculated using [1, 3]:

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{2}$$

Equation (3) is used to calculate the shape covariance matrix [3].

$$\Sigma_x = \frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})(x_i - \bar{x})^T \tag{3}$$

The eigenvalues λ_i and unit eigenvectors p_i of this covariance matrix are used to describe the variance modes of the shapes.

$$\Sigma_x p_i = \lambda_i p_i \tag{4}$$

Since computing in 2n-dimensional space is relatively complicated, simplification method is in requiring. And the popular Principal Component Analysis (PCA) algorithm is used to accomplish this purpose.

The variance explained by each eigenvector of the covariance matrix is equal to the corresponding eigenvalue. Most of the variation can usually be explained by a small number of modes, t. This means that the 2n-dimensional ellipsoid is approximated by a t dimensional ellipsoid, where t is chosen so that the original ellipsoid has a relatively small width along axes $t+1$ and above [1].

Therefore a shape in the training set can be approximated using [1, 2]:

$$x \approx \bar{x} + \phi b \tag{5}$$

where $\phi = (p_1, p_2, \cdots, p_t)$ is the matrix of the first t eigenvectors corresponding with the first t maximal eigenvalues, and $b = (b_1, b_2, \cdots, b_t)^T$ is a vector of weights.

This equation allows us to generate new examples of the shapes by varying the parameters (b_k) within suitable limits, so the new shape will be similar to those in the training set. Suitable limits are typically of the order of [1]:

$$-3\sqrt{\lambda_k} \le b_k \le 3\sqrt{\lambda_k} \tag{6}$$

Given a shape model and an image containing an example of the object modeled, interpretation involves choosing values for each of the model parameters (b_k) so as to best fit the model to the image.

A previous technique allows an initial guess for the best shape, orientation, scale and position to be refined by comparing the hypothesized model example with image data and using differences between model and image to deform the shape [5].

Since this technique uses only strong edges during search, statistical models of local grey-level appearance were then incorporated, leading to improved reliability and accuracy. Reference [6] concentrated on one-dimensional profiles normal to the arcs passing through each landmark point.

In this paper, we consider a $k \times k$ square neighbor region around each point.

We borrow the method of building statistical model of grey-level appearance in Active Appearance Model [7].

First we warp each example image so that its landmarks match the mean shape. After interpolation, we sample the grey level information g_{im} from the shape-normalized image over the $k \times k$ square neighbor region around each point.

Similar to the shape processing method described above, we apply PCA to the grey-level data of each landmark point and obtain a linear model as follow [7]:

$$g \approx \bar{g} + P_g b_g \tag{7}$$

where $\bar{g}$ is the mean grey-level vector, P_g is a set of orthogonal modes of variation and b_g is a set of grey-level parameters.

2. MATERIAL

We used a training data set consists of 40 still images of 40 different frontal human faces, all without glasses and with a neutral expression. The gender ratio is 1:1. All these images were acquired in 1280×960 JPEG color format using a digital camera of SONY Cyber-Shot DSC-F707. To save the memory and computing time, we shrank the image size to 640×480.

III RESULTS

The following facial structures were manually annotated using 56 landmarks in total: eyebrows, eyes, nose, mouth and jaw. Refer to Fig. 1 for an example annotation. The foundation of the shape models is the 56 facial landmarks shown in Fig. 2.

Plotting the scatter of all 40 face annotations yields the rather confusing plot in Fig. 3. The aligned shapes obtained are shown in Fig. 4.

The mean grey level of each landmark point is shown in Fig. 5.

Table 1 shows the most significant eigenvalues of the shape covariance matrix.

Table 2 and Table 3 show the most significant eigenvalues of the covariance matrix derived from the grey level of 11×11 neighbor region around landmark 20 and landmark 42.

IV DISCUSSION AND CONCLUSION

Active Shape Model is a powerful method for locating known structures in images. During image search we wish to locate the best position for each model point. This can be done by finding the area near to the current position where the image best matches the grey-level environment model for the point. In traditional ASM method, one-dimensional profiles normal to the arcs passing through each point are modeled to achieve the order described above. However, images to be interpreted are two dimensional, and these one-dimensional models will lose information in other directions.

In general, we can consider a region of any shape around each point. We tried a grey-level model of the $k \times k$ square neighbor region around each point, hoping that the reliability and accuracy of ASM searching can be improved. Yet, we need more future work to compare the searching results obtained by square grey-level models with those by one-dimensional profile grey-level models.

V ACKNOWLEDGEMENT

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Table 1 Eigenvalues of the shape covariance matrix

Eigenvalue	$\frac{\lambda_i}{\lambda_T} \times 100\%$
λ_1	29%
λ_2	25%
λ_3	9%
λ_4	7%
λ_5	5%
λ_6	3%

Table 2
Eigenvalues of the covariance matrix derived from the grey level of 11×11 neighbor region around landmark 20

Eigenvalue	$\frac{\lambda_i}{\lambda_T} \times 100\%$
λ_1	90%
λ_2	3%
λ_3	2%
λ_4	1%
λ_5	0.8%
λ_6	0.6%

Table 3
Eigenvalues of the covariance matrix derived from the grey level of 11×11 neighbor region around Landmark 42

Eigenvalue	$\frac{\lambda_i}{\lambda_T} \times 100\%$
λ_1	81%
λ_2	8%
λ_3	3%
λ_4	2%
λ_5	1%
λ_6	0.8%

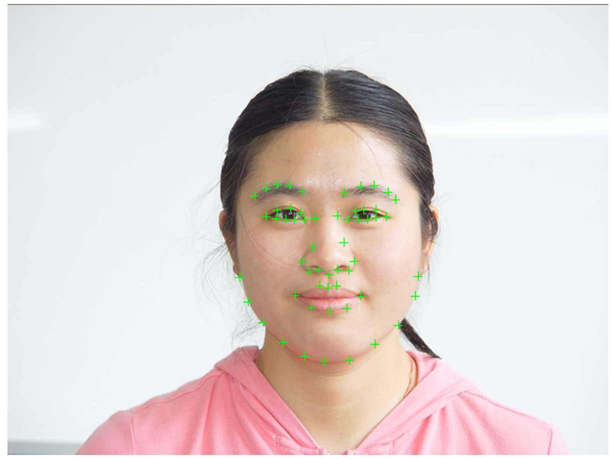


Fig. 1 Example annotation of a face using 56 landmarks

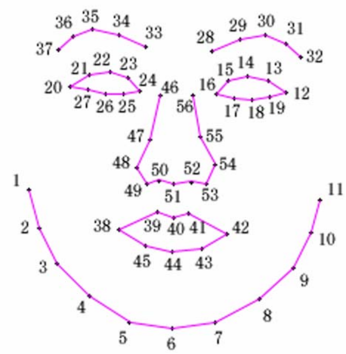


Fig. 2 Facial landmarks

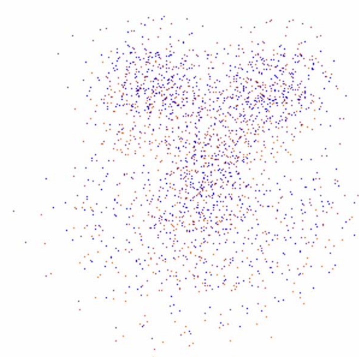
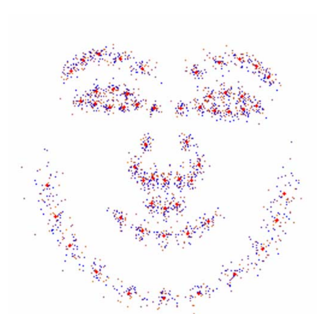


Fig. 3 Unaligned shapes



Fig, 4 Aligned shapes. Red points show the mean shape.

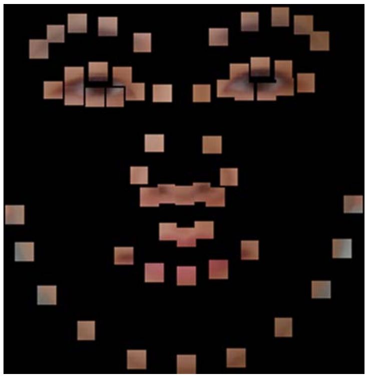


Fig. 5 The mean grey-level model of each landmark point

REFERENCES

[1] T. F. Coots, C. Taylor, D. Cooper, and J. Graham, Active shape models – their training and application, Computer Vision and Image Understanding, 61(1):38-59, January 1995.

[2] T. F. Cootes and C. J. Taylor, Statistical models of appearance for computer vision, Tech. Report, Oct 2001, University of Manchester, http://www.isbe.man.ac.uk/~bim/, Oct 2001.

[3] M. B. Stegmann and D. D. Gomez, A brief introduction to statistical shape analysis, http://www.imm.dtu.dk/~mbs/, 2002.

[4] I. L. Dryden and K. V. Mardia, Statistical shape analysis, John Wiley & Sons, 1998.

[5] T. F. Cootes and C. J. Taylor, Active Shape Models – 'Smart Snakes', in Proc. British Machine Vision Conference. Springer-Verlag, 1992, pp.266~275.

[6] T. F. Cootes and C. J. Taylor, Active shape model search using local grey-level models: a quantitative evaluation, in Proc. British Machine Vision Conference. (Ed. J. Illingworth), BMVA Press, 1993, pp.639~648.

[7] T. F. Cootes, G. J. Edwards, and C. J. Taylor, Active Appearance Models, in Proc. European Conference on Computer Vision 1998. (H. Burkhardt and B. Neumann Ed.s). Vol. 2, pp. 484~498, Springer, 1998.