SEARCHING AND FITTING STRATEGIES IN ACTIVE SHAPE MODELS

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Keywords: Active Shape Model, shape parameter, self-adjustment, active searching, image fitting, outlying points.

Abstract: The Active Shape Model (ASM) is an ever-increasingly important method for object modelling, shape recognition, and image localization. However, when the target is not clarity, or the initial model placed very far from the target, ASM may have problem to locate on an acceptable result. In this paper, a new strategy is proposed on the ASM searching and fitting procedure, which forms an active searching method. Using this new strategy, the influence of the clarity of the target and initial position of the model is reduced and the result of the fitting is more accuracy. Experiments and results show that the new strategy are effective for improving the performance of the image fitting.

1 INTRODUCTION

The Active Shape Model (ASM), firstly proposed by Cootes et.al. (Cootes et.al, 1995), is an important method for modelling of a deformable model, image fitting, shape recognition, and shape localization.

For the traditional ASM, it performs successfully when the target image is clear and the initial position of the model closes to the target. However, when the target is not clarity, for example, the beard in a facial image or a weak boundary in medical images, or the initial model placed very far from the target, ASM may have problem to locate on an acceptable result. Fig. 1 illustrates a few situations of these scenes.

Figure 1: Problems occurred in ASM fitting to an image (the left is the initial pose and the right is the fitting result).

Some improvements were put forward to ASM in recent years. (Bruijne et al. 2001,Wan et al. 2005,Wang et al. 2002). However, ASMs still need an appropriate initial position and clear target images. Li and Chutatape presented the self-adjusting weight in the transformation from shape space to image space and the exclusion of outlying points in obtaining shape parameters (Li and Chutatape 2003). This modification is more robust and converge faster than the conventional ASM in the case where the edge of optic disk is weak or occluded by blood vessels, but it is uneasy to extend to other cases.

In this paper, a novel method is presented that avoid the influence of the targe and initial position of model by using the minimize square error(MSE) obtained by an equation as defined like (Cootes et al.1995):

$$f(d) = (h(d) - \bar{y}_j)^T C_{y_j}^{-1} (h(d) - \bar{y}_j) \tag{1}$$

If the MSEs of some points are too large, we ignore these points when the shape and pose parameters are attained. The organization of the remainder paper is as follows. Section 2 outlines the standard ASM procedure. Some new strategies are developed and described in Section 3. Practical experimental and results are given in Section 4 and a conclusion is followed in Section 5.

2 THE ACTIVE SHAPE MODEL

ASM have been helpful for image fitting, shape recognition, and shape localization. Because models are built by the training set, instance of an ASM can only deform in the ways found in its training set. The local structures are also considered by ASM through modelling the gray-level information of each landmark.

2.1 The Point Distribution Model (PDM)

PDM is built to describe both typical shape and typical variability by disposing a training set which we have chosen. Firstly, landmarks are labelled on each image in the training set by hand.

After all images in the training set have been labeled, they must be aligned with respect to a set of axes. The required alignment is achieved by scaling, rotating, and translating the training shapes in order that they agree as closely as possible.

And then we capture the statistics of the set of aligned shape. In previous steps, labeling and aligning shapes, the mean shape is obtained by the equation which defined as following:

$$\bar{X} = \frac{1}{N}\sum_{i=1}^{N} X_i \tag{2}$$

where the N is the number of the shapes in the training set. The X_i is a vector which represents the coordinates of landmarks in the i-th shape:

$$X_i = [x_{i1}, y_{i1}, x_{i2}, y_{i2}, \ldots, x_{im}, y_{im}] \tag{3}$$

In Eq.(3), m is the number of the points on one shape. Afterwards, we calculate the covariance of the training set as following:

$$S = \frac{1}{N-1}\sum_{i=1}^{N}(X_i - \bar{X})(X_i - \bar{X})^T \tag{4}$$

And then the eigenvectors ϕ_i and corresponding eigenvalues λ_i are computed. Now we can approximate any shapes in the training set, X, by using

$$X \approx \bar{X} + \Phi b \tag{5}$$

where $\Phi = (\phi_1 | \phi_2 \ldots | \phi_n)$ and b is a N dimensions vector which can be given by

$$b = \Phi^T (X - \bar{X}) \tag{6}$$

For reducing the dimensions of the model and variations, the Principal Components Analysis (PCA) is employed. Thus we get the t dimensions vector b. Eq (5) can be modified as following:

$$X \approx X' = \bar{X} + Pb \tag{7}$$

where b is the t dimensions vector, and P is the corresponding eigenvectors. And now we can present a new shape that is similar to the shape in the training set as the following:

$$X = \bar{X} + dX_i \tag{8}$$

where $dX_i = Pb$. And

$$b = P^T (X - \bar{X}) \tag{9}$$

2.2 Extract Gray-level Information and Image Fitting

After the PDM is built, the new points are found by modelling gray-level appearance on the target image which present the object and transform the model into a new better location.

We consider the gray-level values along a line passing through the landmark in perpendicular to the boundary formed by the landmark and its neighbours. Gray-level profile g_{ij} is extracted from n_p pixels that are centred at the landmark for each landmark point j in the image i of the training set. We get the gray-level profile g_{ij} as following:

$$g_{ij} = [g_{ij0}, g_{ij1}, \ldots, g_{ij\,np-1}]^T \tag{10}$$

$$dg_{ij} = [g_{ij1} - g_{ij0}, g_{ij2} - g_{ij1}, \ldots, g_{ij\,np-1} - g_{ij\,np-2}]^T \tag{11}$$

Here, the mean values are calculated as following :

$$\bar{y}_{ij} = \frac{1}{N}\sum_{i=1}^{N} dg_{ij} \tag{12}$$

Now the gray-level information has been modelled, and for each landmark, there is a certain profile $\bar{y}_j$. To transform the mean shape into target object , the target points responded to the points in the model must be found, according to the modelled grey-level information, then the model transforms to the new model that form by target points, but this transformation is restricted by the shape parameters b which is defined in Eq(9). In this way, the new shape will not bring too large distortion to represent the object shape in almost situation. However, in the standard ASM, there are some instances that the new shape will occur the too large distortion and this distortion will lead the fitting process to a failure result (Ghassan Hamarneh).

3 SELECTION CRITERION

For fitting the images into a good shape model, we must have a good strategy to exclude some outlying points and select good target points. This is done with a MSE criterion. When we calculate the shape and pose parameters, such as the scalars $ds, d\theta, dt$, we need to move our current estimate X_i as close as possible to $X_i + dx_i$. Within this process, however, if some points do not match the target object well or their movements keep away from the target object, it will lead to the bad direction in the image fitting, when current estimate X_i closes to $X_i + dx_i$. For avoiding this situation, we consider to exclude those points which are denoted as the outlying points. The initial shape outlying these dissociated points is denoted as X_i', and the target shape is denoted as $(X_i + dx_i)t$. In this paper, we implement such a strategy as following:

(1) Firstly, the MSE of each point is calculated by eq(1). And the msei is defined as:

$$mse_i = f(d) = (h(d) - \bar{y}_j)^T C_{y_j}^{-1}(h(d) - \bar{y}_j) \tag{13}$$

(2) When the MSE of each point, mse_i, is obtained, we sign the point that the mse_i value is large than h (e.g. h=1.5) times of the mean of all the mse_i. And then we exclude these points and get the new initial shape X_i' and the new target shape $(X_i + dx_i)'$.

(3) Then X_i' is aligned to $(X_i + dx_i)t$ and obtain the shape and pose parameters, $ds, d\theta, dt$.

(4) The shape parameters are calculated without the influence of those dissociated points and they can be used to transform X_i into new shape.

Fig. 2 illustrates that the new shape is affected by excluding the outlying points. It shows that the new shape (green line) with outlying points excluded is obviously improved since the dissociated points do not involved in shape formation anymore.

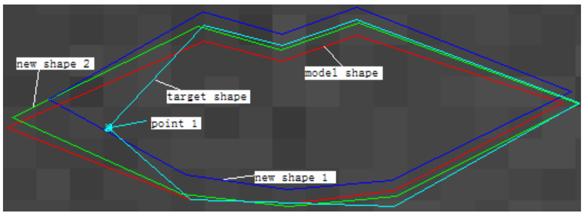


Figure 2: The red line marked by ‘model shape’ is the initial shape. The cyan line marked by ‘target shape’ is the target shape. The green line marked by ‘new shape 2’ is the new shape fitted from no outlying points. The blue line marked by ‘new shape 1’ is the new shapefitted with the outlying points. And the point marked by ‘point 1’ is an example of outlying points that should be excluded.

4 EXPERIMENTS

4.1 Data Set

To evaluate our method, 400 facial images are used to build the PDM in experiments. On facial images, we labelled the lip with eight landmarks for each image. Fig. 4 illustrates these landmarks.

4.2 Experimental Result

In the experiments, we adopt the leave-one-out strategy in order to evaluate the performance more accurately and sufficiently. When each facial image is been fitting, the remaining 399 facial images are utilized to establish the PDM. And the same way is performed in anklebone images. Fig. 4 illustrates the search result of the new strategies and the traditional ASM.

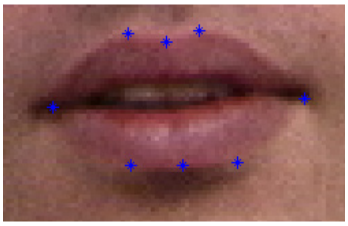
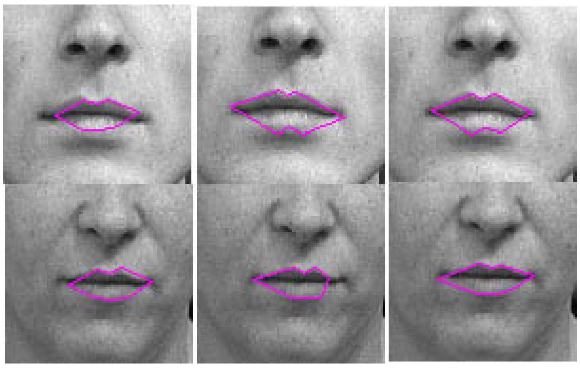


Figure 3: landmarks of the facial image.



(a) (b) (c)

Figure 4: Comparison of the searching results. Column (a) is the standard model and its initial place. (b) Fitting results with the standard ASM. (c) Fitting results with new strategy.

5 CONCLUSION

In this paper, to enhance the robustness and accuracy of image fitting, we propose a new strategy on the Active Shape Model (ASM) method. The main advantages are obvious from observation of practical experiments. For example, according to the MSE that is obtained at the process of the image fitting, the outlying points whose corresponding MSE are too large is excluded for forming a new shape. These outlying points are brought by those target images that are not clarity with some interferential object and the new strategy can avoid effectively the influence of outlying points. By comparison with practical implementation, the proposed strategy works satisfactorily.

ACKNOWLEDGEMENTS

This work is supported by the National Natural Science Foundation of China [NSFC-60405009, 60605013], [ZJNSF-Y105101, Y104185], and a grant for Key Research Items from the Dept of Science and Technology of Zhejiang Province [2006C21002]. S. Y. Chen is a research fellow of the Alexander von Humboldt Foundation, Germany.

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