13—25 Relaxation Algorithm for Detection of Face Outline and Eye Locations

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Abstract

This paper proposes a relaxation-based algorithm for detection of face outline and eye locations. At first, candidates for each facial feature are determined. To select a correct set of facial features from the candidates, probabilities and geometric relationships of each candidate are considered. Relaxation is used for implementation of this algorithm. Simulation results with various test images are presented.

1 Introduction

Detecting human facial features is one of important issues in computer vision. It can be applied to face recognition and video communication. Man can easily distinguish human faces by means of their features. However, it is not easy to implement this human ability into a machine. Many algorithms have been proposed to extract human facial features. Mu *et al.* [1] used morphological filtering and other complex methods for detecting eye and mouth locations. Eleftheriadis and Jacquin [2] used shape information and symmetry of binary edges of a facial image for approximating a face to an ellipse. Kothari and Mitchell's [3] algorithm detects eye locations by using the optical flow gradient vectors that are drawn from inner dark region (iris) to outer white region (sclera) of an eye. On the edges of iris, extrapolated lines toward opposite directions of optical flow intersect at one point. This point is detected as one of several candidates for eye locations. However, only vertical-axis values of candidate points were used for choosing eye locations. So there are some possibilities to choose wrong eye locations. Yuille *et al.* [4] used deformable templates to describe shapes and locations of eyes and mouth. Deformable templates can accurately describe them, however an initial point to fit templates to a facial input image is very important and severely affects the performance. So an additional algorithm to detect their locations is required.

This paper proposes a relaxation-based method for detection of eye and face locations, and face outline that approximates to an ellipse. At first, ellipse candidates for face outline are detected by the fitting algorithm. Position candidates for eye locations are detected by bin incrementing. One set of the facial feature candidates is determined by the proposed relaxation algorithm in the final stage.

2 Proposed Relaxation-Based Algorithm for Detecting Face and Eye Locations

It is impossible for machines to detect the human face and features as man does. However, if a system considers *a priori* information of the facial image, the performance of the system will be improved. So, face outline and eye locations are considered at the same time in the proposed algorithm. The proposed algorithm consists of two parts. The first part is to detect the eye and face location candidates as a preprocessing. Then, their final location is determined by the relaxation algorithm.

2.1 Preprocessing

The preprocessing stage is composed of two parts. One part determines ellipse candidates for face outline and the other part determines position candidates of eye locations. The fitness of the ellipse candidate to a binary edge is considered to determine the ellipse candidates [2]. The shape and contrast of candidate points and neighborhood are considered to determine the candidates of eye locations [3].

2.1.1 Ellipse Candidates for Face Outline

Eleftheriadis and Jacquin [2] used the shape of a binary edge image as an important feature to select the candidates for face outline. A binary edge image is computed by a series of operations: downsampling,

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Sobel edge operation, and thresholding of an input facial image. A downsampled image is desirable as an input to the next stage because it contains global features and can reduce computational complexity. The downsampling factor is set to eight in the proposed algorithm.

An ellipse model is used for approximation of human face outline. It has five parameters for describing its shape and position. Fig. 1 shows the parameters of the ellipse model. Eleftheriadis and Jacquin set θ to zero for simplicity of their algorithm, but in the proposed algorithm, θ is a variable. By changing the five parameters (a, b, x_c, y_c, θ) of an ellipse model, and by considering the fitness of the ellipse model to a binary edge image, the ellipse candidates for face outline are determined. Assume that there is a set of binary edge points, and that whole shape of the set can be approximated by an ellipse model. The model parameters yielding a large fitness value are selected.

For the fitness of an ellipse model to binary edges, Eleftheriadis and Jacquin defined inner and outer contours of an ellipse model. Inner (outer) ellipse contour ε_i (ε_o) is defined by the set of edge points that is L-pixel thick inside (outside) the ellipse model. The normalized average intensities I_i and I_o of the inner and outer contours are defined by

$$I_i = \frac{1}{|\varepsilon_i|} \sum_{(m,n)\in\varepsilon_i} b(m,n), \tag{1}$$

and

$$I_o = \frac{1}{|\varepsilon_o|} \sum_{(m,n)\in\varepsilon_o} b(m,n) \tag{2}$$

respectively, where $b(m,n)$ denotes a binary edge, and $|\varepsilon_i|$ and $|\varepsilon_o|$ are cardinalities of inner and outer ellipse contours, respectively. The fitness R is defined as

$$R = \frac{1+I_i}{1+I_o}. \tag{3}$$

If R is large, the ellipse model is well fitted to the set of binary edges. Fig. 2 shows an example of the best fitted ellipse.

N candidates for face outline are determined according to the value $R(l)$, where l, $0 \leq l \leq N-1$, is an index of candidates.

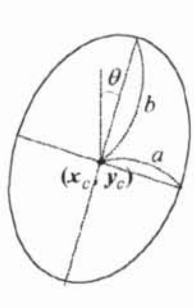


Figure 1: Ellipse model.

2.1.2 Candidates for Eye Locations

To detect eye locations, Kothari and Mitchell [3] considered the fact that an eye region shows a large contrast and the shape of iris is ellipsoidal. Optical flow on the edge of iris radiates outwards. If lines are extrapolated along the opposite direction of the optical flow on the edge points of iris, lines intersect at a point. They defined *bins* which are accumulators in two dimensional array. When a line passes through a set of pixels, the values of *bins* corresponding to those pixels are increased. If many lines pass through a pixel, the *bin* corresponding to this pixel has a large value. The value of the *bin* is equal to the number of lines that pass through this pixel. If the value of a *bin* is large, the point corresponding to the *bin* satisfies the contrast and ellipsoidal conditions of eyes. M candidates for eye locations are determined according to the values of *bins*. M pixels having the largest *bin* values are selected as the candidates of eye locations, and the fitness $B(l)$ is defined by these values of *bins*, where l, $0 \leq l \leq M-1$, is an index of candidates.

Fig. 3 shows the result of *bin* incrementing, where a test image is the first frame of the Miss America sequence. The darkest pixel represents the largest *bin* value.

2.2 Proposed Relaxation Algorithm for Detecting Face Outline and Eye Locations

After determining the candidates of face outline and eye locations, a relaxation algorithm is employed to select correct face outline and eye locations. In the relaxation algorithm, each candidate has the probability value of this candidate being a correct feature. The probability value is updated iteratively. If a candidate satisfies the condition for correct features, the probability of this candidate will be larger as iteration proceeds. Good condition means that there are other features satisfying the ge-

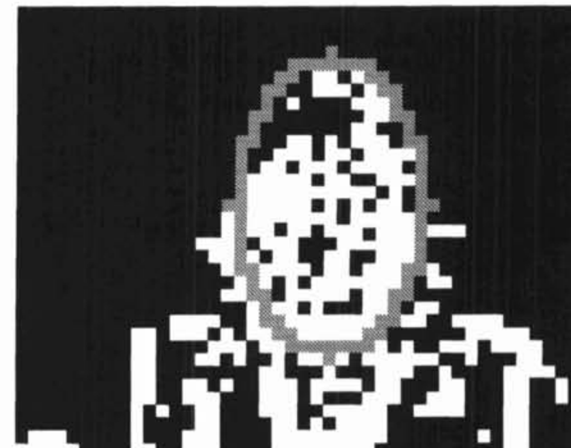


Figure 2: Example of a best fitted ellipse.

ometric relationship with this feature. Fig. 4 shows the geometric features that are used for relaxation, where an ellipse and two filled squares signify elements (face outline and eye locations, respectively) of the model, and d_{i+1} and d_{i+2} denote distances between model eyes and candidate eyes. For example, if there is a candidate set for facial features (one face outline and two eyes), and the set of three features satisfies the geometric relationship for facial features, the probability for the correct candidate set of facial features will be the largest value at the end of iterations.

Fitnesses R and B cannot be used directly for assigning the initial probability, because relaxation uses probability for the compatibility measure of the candidates. The initial probability is defined by

$$P_i^0(l) = \frac{F_i(l)}{\sum_{l'} F_i(l')} \tag{4}$$

where $F_i(l)$ denotes the fitness of the l^{th} candidate and the subscript i signifies the feature index, with $i = 0, 1$, and 2 (0: face outline, 1: left eye, and 2: right eye). $F_0(l)$, $F_1(l)$, and $F_2(l)$ are defined by $R(l)$, $B(l)$, and $B(l)$, respectively. The probability at the $(k+1)^{\text{th}}$ iteration is denoted by

$$P_i^{k+1}(l) = \frac{P_i^k(l)[1 + q_i^k(l)]}{\sum_{l'} P_i^k(l')[1 + q_i^k(l')]}, \tag{5}$$

and the probability update term at the k^{th} iteration is denoted by

$$\begin{aligned} q_i^k(l) &= \frac{1}{a_{i+1} + d_{min_{i+1}}} P_{i+1}^k(l^{i+1}) \\ &+ \frac{c}{a_{i+2} + d_{min_{i+2}}} P_{i+2}^k(l^{i+2}) \end{aligned} \tag{6}$$

where a and c are constants, i is the feature index, and l^{i+1} and l^{i+2} are the indexes of candidates which satisfy the conditions $d_{i+1} = d_{min_{i+1}}$ and $d_{i+2} = d_{min_{i+2}}$, respectively. Note that $d_{min_{i+1}}$ and $d_{min_{i+2}}$ are the minimum values of d_{i+1} and d_{i+2}, respectively. P, q, and k denote probability, probability update term, and iteration index, respectively [5] [6].

Figure 3: Result of bin incrementing.

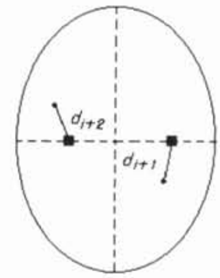
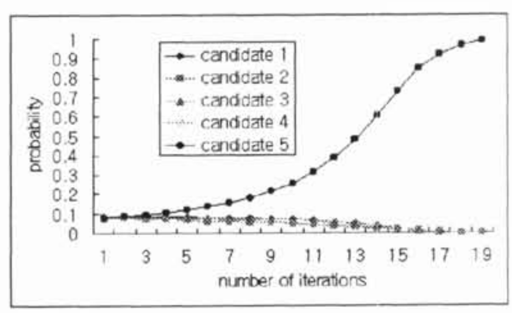


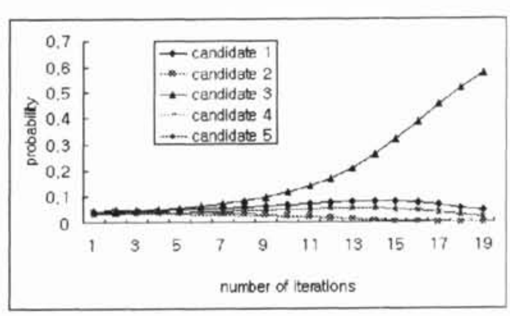
Figure 4: Face model.

3 Experimental Results

Computer simulation of the proposed algorithm is performed with the Miss America sequence and a number of face images from MIT face database[1]. Fig. 5 shows convergence characteristics of five can-



(a) face outline



(b) right eye

Figure 5: Convergence characteristics of five candidates of two facial features.

[1] ftp://whitechapel.media.mit.edu.

didates of two features, with the first frame of the Miss America sequence. In this figure, x-axis denotes the number of iterations and y-axis signifies the probability. After 17 iterations, convergence to a correct solution is observed. Experiments show that 20 is acceptable as the maximum iteration number. In Fig. 5, the dominant candidates for face outline and right eye are the fifth and 23th ranked candidates at the initial stage, respectively. In experiments, $N = 10$ and $M = 30$ are used, where N and M represent the numbers of candidates for face outline and eye locations, respectively. These candidates are chosen with the fitness of each feature (R, B). Outliers and redundancies of these candidates are firstly removed by the geometric relationship, and other candidates are used to select correct features by relaxation. Fig. 6 shows the rejection of outliers and redundancies. Fig. 7 shows the experimental result of the first and 85th Miss America images and other test face images. To show the result, the most probable candidates for face outline and eye locations are superimposed on the input images. Experiments show that the proposed algorithm yields good performance.

4 Conclusion

In this paper, a relaxation-based detection algorithm for face outline and eye locations is proposed. The proposed relaxation algorithm is composed of three stages: detecting face outline, detecting eye locations, and selecting correct ones from a number of candidates. Especially, the selection algorithm is proposed, which uses the fitnesses and geometric relationships of all feature candidates, yielding more reliable results. Further research will focus on the development of the algorithm to detect reliable candidates that yield the high face recognition ratio.

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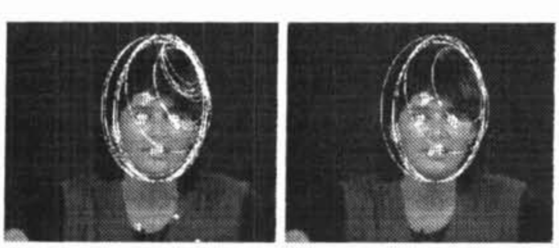

(a) Before rejection (b) After rejection

Figure 6: Rejection of outliers and redundancies.

(a) Test image 1 (b) Test image 2

(c) Test image 3 (d) Test image 4

(e) Test image 5 (f) Test image 6

Figure 7: Experimental results.