CHIN CONTOUR ESTIMATION FOR FACE RECOGNITION

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ABSTRACT

This paper proposes a novel method for chin contour estimation. First, we estimate several possible chin locations. A modified Canny edge detector is then used to extract edges from the face image. Using these estimated chin edges and chin locations, we obtain a number of curves as candidates of the chin contour. A confidence score that measures the likeliness of a curve being the actual chin contour is used to select the most likely candidate. If the confidence score of the most likely candidate is high enough, then the estimated chin contour may be used as a feature for face recognition. Experimental results show that the proposed algorithm can extract the chin contours of human faces with good accuracy and the reliable estimated chin contours can improve the face recognition rate.

1. INTRODUCTION

Automatic face recognition has been an active research area over the past few years. Most analytic face recognition approaches extract geometric features such as locations and shapes of facial organs [2,3,4] and perform face recognition by comparing the facial features of different faces [1,5]. The shape of a chin is an important feature for a human to recognize a face. Works have been performed to estimate chin contours. For example, [5] estimates a chin contour using active contour models. In [6], a chin contour is estimated by a deformable template consisting of two parabolas. However, few face recognition methods use the shape of chin contour as a geometric feature. One reason is that an estimated chin contour sometimes can deviate wildly from the true contour due to lack of prominent edges between the chin region and the neck region. Another reason is the geometric feature of the chin contour is not robust for face recognition under varying pose.

In this paper, we propose a novel method to estimate chin contour assuming the eye corners, mouth corners, and noses are known. It is found that the location of the lowest point of the chin (called chin point in the following) can be estimated from some facial distances using the least- square-fit approach, which allows a search window to be constructed for estimating the chin contour. A modified Canny edge detector is proposed to extract the chin edges that may have the same direction and location as the chin contour. Using these chin edges and the possible locations of the chin, several pairs of curves, which are not restricted to parabolas, are modeled as the contour candidates. Then a confidence score is introduced to evaluate the reliability of the contour candidates and the best candidate is chosen to represent the chin contour. If two faces have similar poses and the estimated chin contours are reliable, then geometric distance between the chin contours may be used for face recognition. Experimental results show that the proposed algorithm can extract chin contours of human faces with good accuracy and the extracted chin contours are effective to enhance the face recognition.

2. LEAST MEAN SQUARE ESTIMATION OF CHIN LOCATION

There are some interrelations of locations of chin, eyes, mouth and nose in a human face. Hence, we anticipate a high correlation between the lower lip-chin distance, denoted as d, and the facial distances d_1, d_2, d_3 and d_4, as defined in Fig. 1

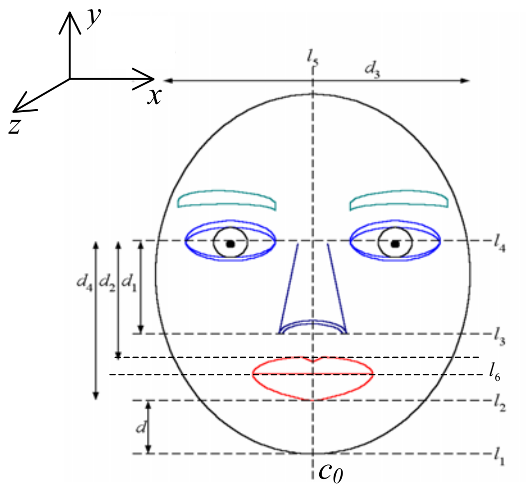


Fig. 1 Definition of the facial distances and chin point c_0.

A high correlation between d and these facial distances allows d to be estimated using these facial distances by minimizing the mean square error,

$$e = E[(\hat{d} - d)^2] \qquad (1)$$

where $\hat{d}$ is an estimate of d. In our algorithm, d_2, d_3 and d_4 is used as the estimation parameters, i.e.

$$\hat{d} = a_1 d_2 + a_2 d_3 + a_3 d_4 . \qquad (2)$$

To evaluate the relationship between d and these facial distances, we have selected a total of 383 images from the Purdue University database as the training data. To facilitate our investigation, the location of eyes, eyebrows, noses and mouths in the training images were carefully and manually located. Thus a_1, a_2 and a_3 can be obtained based on Least Mean Square Estimation. Experimental results show that d is always within $[\hat{d}-3\sigma, \hat{d}+4\sigma]$, where σ is the standard derivation of d.

3. CHIN CONTOUR ESTIMATION

A novel method to estimate a chin contour that passes through c_0, c_1 and c_2 is proposed. $c_0 = (x_0, y_0)$ is the location of the chin point, $c_1 = (x_1, y_1)$ and $c_2 = (x_2, y_2)$ are the two points on the side of the lower face boundary (see Fig. 2).

3.1. Identification of Search Window

Given an image, the face and neck region is segmented from the background and the facial organs such as eyes, mouth and nose are located, which can be achieved using an algorithm such as [1]. Then d_2, d_3 and d_4 are determined, which are used to obtain c'_0, an initial estimate of c_0 using (2). A rectangle search window B is constructed for the chin contour as shown in Fig.2. The width of B is the distance between the mouth corners. The upper and lower boundary of B is $c'_0-3\sigma$ and $c'_0+4\sigma$ respectively.

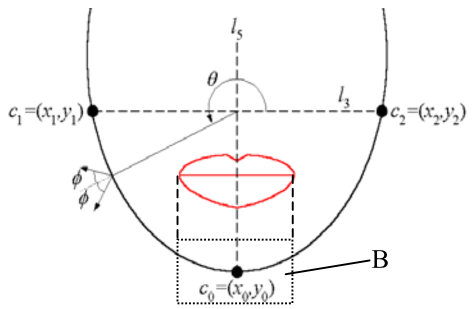


Fig. 2. Location of the control points and the allowable direction range of the potential chin edge.

3.2. Edge Detection Using Modified Canny Edge Detector

A chin contour is the curve that separates the chin region from the neck region. Its location is revealed by long edges that can be connected together to form a continuous curve. In this paper, we call such edges 'chin edges' and propose a modified Canny edge detector to detect the potential chin edges. The original Canny edge detector [7] does not impose restrictions on the gradient directions, but our modified one will exclude some false edges with unfit gradient directions.

With the prior knowledge that the chin edges should approximately be a continuous circular curve, it is reasonable to impose an additional constraint on the potential edge points in order to eliminate edges that do not have a similar direction as the chin contour. To introduce such constraint, the coordinate of the nose tip is firstly chosen as the origin. For each potential edge point, the bearing of its coordinate from the origin is computed and denoted as θ. An allowable range of 2ϕ is established for each edge point for testing as shown in Fig. 2. Any potential edge point having its edge direction in between ($\theta \pm \phi$) will be retained, otherwise it will be discarded. The value of ϕ can be chosen between $30°$ to $45°$. The comparison of the edge map between the original detector and modified detector is illustrated in Fig.3. It reveals that most of the unwanted edges inside the search window are eliminated using the modified Canny edge detector.

(a) (b) (c)

Fig. 3. Comparison of the edge maps between the original Canny edge detector and the modified Canny edge detector: (a) original image; (b) original Canny edge detector; (c) modified Canny edge detector

3.3. Determination of $\hat{c}_0^i$, c_1 and c_2

The next step is to estimate the possible locations of the chin point c_0, which are denoted as $\hat{c}_0^i$, where $i \in [1,N]$. The location of c_0 can be revealed by horizontal projection and edge existence.

Under normal light condition, there is often a sharp intensity drop for pixels along l_1 in region B, producing a U-shape horizontal projection as shown in Fig. 4b. The amount of the intensity drop can be measured by

$$p_1(y) = 2k\sum_{x=m_0}^{m_1} I(x,y) - \sum_{\substack{l=y-k,\\ k\neq 0}}^{y+k}\left(\sum_{x=m_0}^{m_1} I(x,l)\right) \quad (3)$$

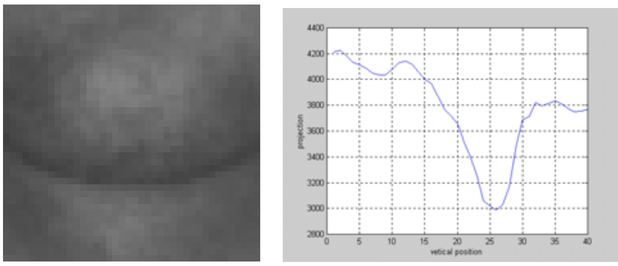
where $I(x,y)$ is pixel intensity at the location (x,y), m_1, m_0 are locations of the right and left mouth corner. The pixels along l_1 in region B should have many edge points. This can be measured by

$$p_2(y) = \sum_{x=m_0}^{m_1} T(x,y) \quad (4)$$

where $T(x,y)$ is the edge map obtained by the modified Canny edge detector. $T(x,y)$ is 255 if there is an edge point at (x,y), and 0 otherwise. Based on computed values of $p_1(y)$ and $p_2(y)$, we can assign a score to each row in region B such that

$$s(y) = p_1(y) + p_2(y). \quad (5)$$

Let y_{max} be the value of y that maximizes $s(y)$. l_1 is then given by the equation $y = y_{\max}$. The chin location c_0 is chosen as the intersection between l_1 and the l_5. However, in some cases, $s(y_{max})$ may not be significantly higher than other $s(y)$. This implies that the c_0 suggested by $s(y_{\max})$ may not be the real c_0. To tackle this problem, we select multiple candidates for c_0. A pixel along l_5 and within region B is chosen as $\hat{c}_0^i$ if $s(y) > s(y_{\max})/2$. We assume that the face and the neck have been segmented from the background. Since c_1 and c_2 are face boundary points passing through by l_3 (see Fig. 1), they can be found easily.



(a) (b)

Fig. 4. (a) Chin image; (b) Horizontal projection intensity in each row of region B.

3.4. Chin Contour Modeling

We shall model a chin contour by two curves. The left curve passing through c_0 and c_1 models the chin contour on the left face and the right curve passing through c_0 and c_2 models the chin contour on the right face. The following discussion will concentrate on the right face, which can be easily extended to the left face. The right curve that models the right chin contour is given by

$$y = b_k \cdot x^k \tag{6}$$

with c_0 as the origin and k= 2, 3, 4 or 5. For each of the $\hat{c}_0^i$, $i \in [1,N]$ which are the candidates of c_0 estimated in the previous step, we are to find the values of b_k and k that can produce a curve that best fits the right chin contour. Note that the value of b_k is fixed when k, c_0 and c_2 are known.

Now we need to define a criterion that measures how well a curve fits a chin contour. The criterion allows us to determine the optimal values for k and c_0. Intuitively, a curve that has the most chin edges in proximity is a good candidate. We shall first define the proximity of a right curve in region F by a set R_R that contains all pixels on the curve and pixels adjacent to the curve (see Fig. 5). Hence, for all pixels in R_R, we define P_R as the percentage of pixels that are chin edges. The percentages P_R are computed for all possible values of k and c_0. Similarly, we define R_L and compute P_L. A chin curve consists of a left curve and a right curve passing through the same c_0. We now choose the chin curve that has the highest confidence score, which is defined as:

$$s_C = (P_L + P_R) / 2 \tag{7}$$

A high score means that the estimated chin contour is likely the real chin contour.

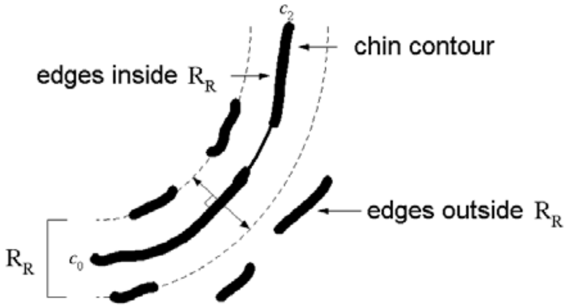


Fig. 5 Curve range R_R.

4. ENHANCE FACE RECOGNITION BASED ON THE DETECTED CHIN CONTOUR

Given a test face image, single view based face recognition is to find an image in a gallery that best matches the test image. Lam [1] proposed an analytic-to-holistic approach for face recognition based on a single front view. It first detects 15 fiducial points in a test face image. Base on a 3D head model, the rotation of the face is estimated using geometric measurement. Then the analytic features and holistic features of the face image are compensated based on the estimated pose to generate the corresponding features for front view. Similarly, the compensated analytic features and holistic features for the front view of each face image in the gallery are obtained. Finally point matching and template matching methods are employed for feature comparison and a similarity list is obtained as the recognition result. The list contains face images in the gallery ranked according to their similarity to the test face image. The candidate that has the highest ranking is the one that best matches the test image.

In this paper, we propose a method to improve the recognition rate of a face recognition algorithm using the estimated chin contour. Experiments based on Lam's face recognition algorithm [1] are used to test the proposed method. All estimated chin contours in the gallery images are manually checked to ensure that they are correct.

Given a test image, the method first generates a list of similar images using Lam's algorithm. The image at the top of the similarity list is the candidate. The method first checks if the test image and the candidate have similar poses. Lam's algorithm provides estimation of θ_t and θ_e which are in-depth face rotation angles of the test image and the candidate respectively. If $|\theta_t - \theta_e| > \varepsilon$, then the pose difference is regarded as too big for the estimated chin contour to be useful. If the test image and the candidate have similar poses, the method will test if the estimated chin contour in the test image is reliable. If both P_L and P_R are lager than a threshold δ, the estimated contour is regarded as reliable and can be used to enhance the face recognition as follows. We compute D_{chin}^{te}, the geometric distance of the chin contours in the test image and in the candidate image. If D_{chin}^{te} is larger than a threshold η, the candidate which is currently at the top of the list will be discarded and the second one will be promoted to the top as a new candidate. Then D_{chin}^{te} will be computed again for the new candidate and compared to η. This process continues until $D_{chin}^{te} \le \eta$.

D_{chin}, the geometric distance between two chin contours, is computed as follows. Sample the section of the chin contour below l_6 (see Fig. 3) by n points with uniform step size to form a chin contour array $p(i) = (x_i, y_i),\ i = 1, \ldots, n$. The chin contour array will be normalized and aligned to the detected point c_0. The geometric distance between the two chin contours is defined as

$$D_{chin} = \sum_{i=1}^{n} \left| A \cdot p'_1(i) - B \cdot p'_2(i) \right| \tag{8}$$

$$A = \begin{bmatrix} \cos\beta_1 & \sin\beta_1 \\ -\sin\beta_1 & \cos\beta_1 \end{bmatrix},\quad B = \begin{bmatrix} \cos\beta_2 & \sin\beta_2 \\ -\sin\beta_2 & \cos\beta_2 \end{bmatrix}$$

where $p'_1(i)$ and $p'_2(i)$ are normalized and aligned chin contour arrays respectively. The rotation matrixes A and B are used to compensate for the effect of face rotation in image plane. β_1 and β_2 (the angles of rotation in image plane) are estimated by Lam's algorithm.

5. EXPERIMENT RESULTS

The chin contour estimation algorithm was tested using 133 images in the Purdue University database and 200 images in the Olivetti face image database, which are all outside the training data. The proposed algorithm succeeded in tracking the chin contour in most of these images. Examples of the extracted chin contours are illustrated in Fig. 6. The results show that the proposed algorithm can track the chin contour with good accuracy.

The use of the chin contour for face recognition is investigated by doing experiments on 200 face images in the Olivetti face image database. 40 frontal view images is used as gallery images and 160 images used as test images. 81 test images are not qualified to use the additional chin contour information because they fail either the reliable chin contour estimation condition or the similar pose condition. For the remaining 71 test images, the estimated chin contour information was used and the recognition rate is increased from 88.7% to 94.3%. For all the 160 test images, the whole recognition rate is increased from 84% to 86%.

6. COCLUSIONS

A new approach of chin contour estimation using a modified Canny edge detector is first proposed. By using the detector, chin edges can be estimated and a curve can be obtained to represent the actual chin contour of a human face. If two faces have similar poses, then geometric distance between two reliable chin contours may be used for face recognition. Experimental results show that the proposed algorithm can extract chin contours of human faces with good accuracy and the extracted chin contours are effective to enhance the face recognition.

Fig. 6. Simulation results of chin contour estimation.

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