Automatic Facial Feature Points Detection

Vitoantonio Bevilacqua[1,2], Alessandro Ciccimarra[1], Ilenia Leone[1], and Giuseppe Mastronardi[1,2]

[1] Dipartimento di Elettrotecnica ed Elettronica Politecnico di Bari
Via Orabona, 4 70125 – Bari, Italy
bevilacqua@poliba.it
[2] e.B.I.S. s.r.l. (electronic Business in Security), Spin-Off of Polytechnic of Bari,
Str. Prov. per Casamassima Km. 3-70010 Valenzano (BA), Italy

Abstract. This paper presents an algorithm which detects automatically the feature points in a face image. This is a fundamental task in many applications, in particular in an automatic face recognition system. Starting from a frontal face image with a plain background we have effected an image segmentation to detect the different facial components (eyebrow, eyes, nose, mouth and chin). After this we have searched for the feature points of each face component. The algorithm has been tested on 320 face images taken from the Stirling University Face Database [10]. The points extracted in this way have been used in a face recognition algorithm based on the Hough transform.

Keywords: facial features points; face recognition.

1 Introduction

In this paper we present an algorithm which detects automatically the feature points in a frontal face image. This is a very simple task for a human being who has no difficulty in localizing, for example, the eyes in a face. On the contrary, this is a very difficult task for a computer which can only do arithmetic and logic operations.

These feature points are important in many applications, mainly in an automatic face recognition system. Nowadays the increasing need for security makes these systems very useful. If we think of the 11th September 2001 and of all the other terrorist attacks which we hear every day, we can easily understand how important it is to identify automatically, for example, the presence of a terrorist in an airport or in a station.

The proposed algorithm can be divided into two parts. First of all we have a face segmentation in which we localize the various face components (eyebrows, eyes, mouth, nose and chin). After this, in each component, we detect 18 features points: the two pupils, the four eye corners, the four eyebrow corners, the two nostrils, the nose tip, the two mouth corners, the upper and lower lip extremity and the tip of chin.

We present the experimental results of the feature points detection in 320 images taken from the Stirling University Face Database [10].

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The usefulness of the detected points is tested using a face recognition algorithm based on the Hough transform.

2 Face Segmentation

In a previous work Bevilacqua et al. showed that those five features are used in different kinds of algorithms used in face identification and addressed that problem in a face recognition system based on Pseudo 2D HMM applied to neural network coefficients [20].

The first stage of the proposed algorithm is the face segmentation, that is to say the search for the eyebrows, the eyes, the mouth, the nose and the chin. The input to this step is the face region extracted by the Kienzle, Bakir, Franz e Scholkopf library [9].

2.1 Eyes Detection

The most important step of the face segmentation is the eye band detection. To do this, the image is firstly divided into three clusters using the competitive learning algorithm developed by Mavrinac [4]. The darkest cluster contains face features such as eyes, mouth, nostrils and eyebrows. We create a binary image containing the darkest pixels. This image is eroded using a 3x3 square as a structuring element. We find the regions that probably contain the eyes by means of a template matching with an eye template. The similarity between the template and the different regions of the image is calculated using the Normalized Cross-Correlation [5]. In order to verify the real presence of the eyes in the located region, we use a Support Vector Machine classifier. The training set has 400 images, 200 containing eyes and 200 containing other parts of the face. The choice of the images which don't contain eyes is very important to improve the SVM performance.

We have first put in the training set images containing facial components which look like eyes, such as the eyebrows. The other training images have been selected following the bootstrap method described in [13] which gives the possibility to add useful examples in an incremental way.

The SVM model contains 372 support vectors. The gamma parameter of the radial basis function is 0.03125. Then we try to localize the two eyes in a more precise way: we create an eye map with the pixels belonging to regions darker than the surrounding ones [12]. Subsequently we detect the connected components matching the expected eye dimensions.

2.2 Localization of Other Face Components

Once detected the eyes, we proceed to the localization of the other facial components using simple anthropometrical considerations.

The eyebrows are detected as the two regions above the two eyes already localized. We look for the mouth in a region below the eyes. We compute the derivative of the Variance Projection Function [11] of the image. The mouth ordinate is the one which

maximizes the VPF derivative. Finally the nose is localized in a region between the eyes and the mouth.

3 Feature Points Detection

Once the face has been detected, we try to localize the different feature points. In particular we look for the two pupils, the eye corners, the eyebrow corners, the nostrils, the nose tip, the mouth corners, the upper and lower lip extremity.

3.1 Pupil

In the grey scale eye image, the iris is a circular dark region. To remove the reflex we process the image with a 5x5 minimum filter and equalize the image to improve the contrast between the iris and the rest of the image. We estimate a rough position of the pupil and the iris radius length working with binary eye images. We erode the image to increase the separation between the connected regions. We proceed labelling the connected components: we calculate the height and the width of the biggest connected component and its centre coordinates. The iris dimensions are calculated on the base of the dimension of this connected component. The pupil is localized more precisely in this way: we look for all circles having radius equal to the estimated iris radius and we find the one having the lowest average pixel value. The pupil position is computed as the average point between the previously located connected component and the centre of the darkest circle. In Fig. 1 there are some results.

Fig. 1. Examples of detected pupils

3.2 Eye Corners

Once we have located the pupil and estimated the iris radium length, we reduce the region where we can search for the eye corners considering a rectangle region centered in the pupil and we look for the eye corners in the first and last 30% of it. The researched point will have many white pixels belonging to the sclera on one side, and darker pixels belonging to the skin on the other side. So its variance will be higher.

Fig. 2. Examples of detected eye corners

We compute the average position of the 20% of the pixels with higher variance. This procedure is repeated for all the four eye corners. Fig. 2 shows some results.

3.3 Eyebrow Corners

The eyebrow is a dark region surrounded by a lighter one (the skin).

We look for the darkest regions and we create a binary image. We proceed analysing the connected components and the corners are located as the extremities of the biggest connected component.

Fig.3 shows some examples of detected eyebrow corners.

Fig. 3. Examples of detected eyebrow corners

3.4 Mouth Feature Points

The first step for the mouth feature points detection is the search for the lip cut. This is the darkest line in the mouth image.

We compute the Integral Projection Function of the mouth image and the lip cut is localized as the ordinate which minimizes the IPF. After that, we cluster the lip cut image and look for the lateral extremity of the darkest region. Then we look for the upper lip extremity: we examine the region above the lip cut, we cluster it searching the feature point in the darkest connected region. In order to find the lower lip extremity we examine the region below the lip cut: we equalize its histogram and we find the extremity of the darkest connected component again.

Fig. 4 shows these mouth feature points.

Fig. 4. Examples of detected mouth feature points

3.5 Nostrils and Nose Tip

Analysing the nose images it's clear that nostrils are two dark regions surrounded by the skin which is lighter. We find the darkest regions and the nostril are located studying the connectivity of the resulting binary image.

The nose tip will be near the nostrils, in particular above them. We examine the region above the nostrils looking for the lightest pixel.

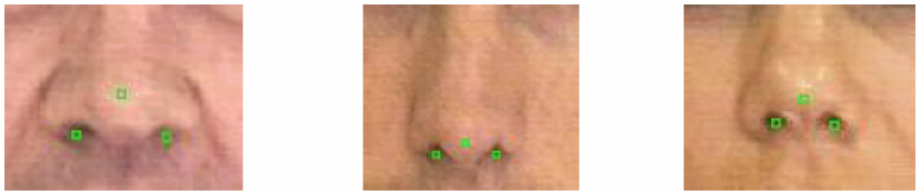

Fig. 5. Examples of detected nose tips and nostrils

In Fig. 5 there are some examples of detected nostrils and nose tips. It is clear that we cannot locate the nose tip very precisely even manually, owing to the low resolution of the examined images.

3.6 Chin

The tip of chin is identified by a deterministic algorithm based on edge analysis. It can be divided into two steps. We pre-process the chin image and then we look for the chin curve. In the first step, we smooth the chin image and we increase its luminance to highlight the chin curve. Then we detect edges using the Canny edge detector [17]. In the second step we look for a curve with an upwards concavity and an axis of vertical symmetry and located in the central search area. These steps are repeated until the chin curve, and so the tip, is identified. There are cases in which the chin curve identification fails, for example when there is a long beard or in very dark images. In these cases, we identify a hypothetical chin tip on the base on pre-inserted statistic data.

Fig. 6 shows two examples of detected chin tips. It's clear that we cannot locate the chin tip very precisely even manually, due to the low resolution of the examined images and to the presence of the shadow under the chin curve.

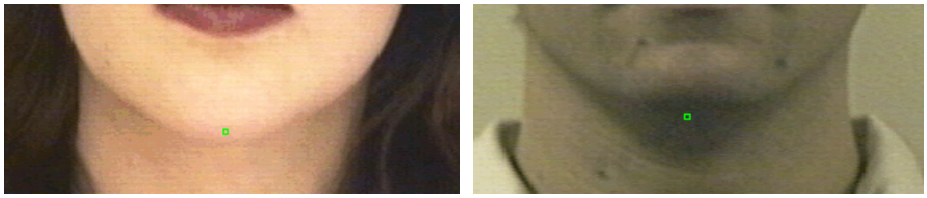

Fig. 6. Examples of detected chin tips

4 Experimental Results

The automatic feature points detection algorithm has been tested on 320 images taken from the Stirling University Face Database available on-line [10].

The errors have been calculated as the distance in pixel between the manually located points and the ones automatically obtained with the developed algorithm. We have also tested the robustness of the algorithm with noisy images (2% salt and pepper noise).

Table 1 presents the errors found and Fig. 7 shows some faces with all the detected points.

Table 1. Errors

Feature point	No noise (px)	Salt and pepper noise 2% (px)
Right eye pupil	2.07	2.67
Left eye pupil	2.60	2.86
Right eye outer corner	3.52	3.76
Right eye inner corner	4.07	5.14
Left eye outer corner	4.58	6.63
Left eye inner corner	4.14	6.14
Right eyebrow outer corner	13.02	14.57
Right eyebrow inner corner	12.08	13.85
Left eyebrow outer corner	10.29	11.93
Left eyebrow inner corner	14.75	13.73
Left nostril	5.50	13.86
Right nostril	4.67	12.53
Nose tip	6.72	13.46
Left mouth corner	4.31	4.67
Right mouth corner	4.39	5.15
Top mouth	5.90	6.12
Bottom mouth	5.45	5.96
Tip of chin	7.23	10.15

The feature points detected in this paper have been used in a face recognition algorithm based on the Hough transform. This algorithm is similar to the classical GHT one. The difference is that the reference table is indexed with the theta angle that the vector of the model point in exam forms with the horizontal axis [14]. We obtained a correct matching in the 80% of the examined cases.

Fig. 7. Examples of detected feature points

Fig. 7. (*continued*)

5 Conclusions and Future Works

In this work we have developed an algorithm to automatically locate the face feature points. This is a very simple task for a human being, but it is extremely complicated for a computer.

We have firstly segmented the face to locate the different components (eyes, eyebrows, nose, mouth) and then we have detected the feature points.

From the results we can see that the most difficult points to localize are the eyebrows corners: this is due to the low resolution of the examined images which does not give the possibility to precisely estimate the beginning and the end of the eyebrow.

A possible future development of this work is the generalization to images with unconstrained background and with partial occlusion like beard and spectacles. We are also going to improve the chin detection.

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