Face Detection in Grey Images Using Orientation Matching

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1 Introduction

Face recognition is a major area of research with numerous potential commercial and industrial applications. The performance of face recognition techniques depends heavily on the accuracy of the detected face position within the input image - once the face position is determined, a rectangular box will be extracted from that area, normalized in both scale and orientation, and passed onto the face recogniser.

A natural approach to face detection is to use a colour model to locate skin-like areas in the image [1][2][3]. Image pixels can be labelled as skin or non-skin pixels according to the values of the pixels with respect to the colour model. The problem with this approach is that skin colour varies under different lighting conditions and other objects or even the background may have the same colour as the skin. A widely used approach is to model faces and non-faces as two separate classes. A typical such system is Rowley's neural network-based face detector [4]. The detector consists of a set of neural networks trained by a large training set of face images and non-face images. Pixel values of 20x20 subwindows are input to the neural networks, and outputs from these networks are put through an arbitrating process to arrive at the final decision as to whether a subwindow is a face image. Feraud's face location methods [5] are also based on neural networks and the size of the subwindows is 15x20.

Another popular approach to face detection is based on matching facial features. This approach aims to find the arrangement of certain features such as the eyes, nose, and the mouth in the image, which forms a face pattern. Since it is quite difficult to locate these facial features accurately in light of image variations in illumination and facial expression, some feature extraction methods perform wavelet analysis [7] on the image. For real time applications detection speed is very important. Viola et al [9] proposed a rapid object detection algorithm using a basic and over-complete set of Haar-like features and a cascade of classifiers. These classifiers were combined to produce a more powerful one. The multi-stage classification procedure reduces the processing time substantially and yet achieves almost the same accuracy as the single stage classifier. Rainer and Jochen [10] extended the basic set of Haar-like features by a set of 45^0 rotated features. In addition, they performed a new post-optimisation procedure for the boasted classifier and improved the performance significantly. A hit rate of 82.3% on the CMU face set is reported. But the method is sensitive to head pose - only nearly frontal faces ($\pm 10^0$) can be detected. To address the over-fitting problem due to lighting conditions, poses and complex backgrounds, R.Y. Qiao and Y. Guo proposed a soft margin AdaBoost algorithm [11]. A regularisation term was introduced and the most effective weak classifiers are selected. Experimental results showed an improved performance over the original AdaBoost algorithm.

Instead of using the original image, experiments have shown that it is possible to locate face patterns in the edge orientation image. Fröba and Küblbeck [6] extract the edge orientation map from a face model and use this to match against the edge orientation map extracted of the input image. To locate faces larger or smaller than the face model a pyramid of edge orientation fields has to be built. Since this method uses only the edge orientation information, false detection usually occurs when image texture or edge frequency is high. In [13], a fast face detection algorithm using skin colour information and orientation map matching is proposed. A colour image is converted to a skin probability image using the Gaussian skin colour model, from which an orientation map is extracted. After that, the orientation map is matched with a pre-generated model. It is indicated in [13] that skin colour information can be used to suppress the background. As a result, false detection at high edge frequency areas can be reduced. Recently, an edge-based shape comparison method [8] was used for face detection. 2D Hausdorff distance (HD) was used as a similarity measure between a general face model and possible instances of the object within the image. After a coarse detection of the facial region, face location is refined in a second phase. Accuracy of 91.8% on BioID database [14] was reported.

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This paper proposed an edge orientation based algorithm for face detection in grey images. Since colour information is not available in grey images, orientation histogram is included for detection. Experimental results show that 93.7% accuracy is achieved for the BioID database, which contains 1521 images with large a variety of lighting conditions and backgrounds. Since the histogram is used to filter the blocks before they are matched with the template, our algorithm is also faster in speed.

2 Orientation Extraction

As shown in [13], a block-based orientation extraction method is adopted in our algorithm. Two 3×3 Sobel operators, *Sx* for horizontal filtering and *Sy* for vertical filtering, were convolved with the image I(x, y) to generate two gradient images $G_x(x, y)$ and $G_y(x, y)$.

$$G_x(x,y) = S_x * I(x,y) \tag{1}$$

$$G_y(x,y) = S_y * I(x,y) \tag{2}$$

Similar to the algorithm used in [12], the gradient images $G_x(x, y)$ and $G_y(x, y)$ are divided into a serious of non overlap windows of size w×w, each pixel (x, y) in the same window centred at pixel *(i, j)* is assigned the same orientation value O(x, y) as below:

$$V_y(x,y) = \sum_{u=i-\frac{w}{2}}^{u=i+\frac{w}{2}} \sum_{v=j-\frac{w}{2}}^{v=j+\frac{w}{2}} 2G_x(u,v)G_y(u,v)$$

$$V_x(x,y) = \sum_{u=i-\frac{w}{2}}^{u=i+\frac{w}{2}} \sum_{v=j-\frac{w}{2}}^{v=j+\frac{w}{2}} (G_x^2(u,v) - G_y^2(u,v))$$

$$O(x,y) = \frac{1}{2}\tan^{-1}\left(\frac{V_y}{V_x}\right) \tag{3}$$

After the orientation field of an input image is estimated, the certainty level of edge orientation at pixel (x, y) in the same window centred at pixel (i, j) is defined as below: [12]

$$C(x,y) = \sqrt{\frac{1}{w \times w} \frac{(V_x^2(x,y) + V_y^2(x,y))}{V_e(x,y)}} \tag{4}$$

where

$$V_e(x,y) = \sum_{u=i-\frac{w}{2}}^{u=i+\frac{w}{2}} \sum_{v=j-\frac{w}{2}}^{v=j+\frac{w}{2}} (G_x^2(u,v) + G_y^2(u,v)) \tag{5}$$

A *3 x 3* box filter (or averaging mask) is used to smooth the estimated orientations obtained from previous result so as to remove any abrupt changes in orientation that are caused by noise in the low image quality regions. The edge information on homogenous parts of the image where no grey value changes occur is often noisy and bears no useful information for the detection [6]. A threshold T_c is applied to the certainty level *C(x, y)* to generate an edge certainty level field $C_t(x, y)$.

$$C_t(x,y) = \begin{cases} C(x,y) & \text{if} \quad C(x,y) > T_s \\ 0 & \text{else} \end{cases} \tag{6}$$

Figure 3 (b) shows the orientation map extracted from Figure 3 (a). The edge orientation information can be rewritten as a vector field as below:

$$\mathbf{V}(x,y) = C_t(x,y)e^{jO(x,y)} \tag{7}$$

3 Orientation Histogram

In our experiment, we found that orientation histogram was also a very useful feature for face detection. To apply this kind of feature for detection, a face orientation model was generated at first as described in section 4.1. The histogram of this orientation model is shown in Figure 1. From this figure, we can see that the range of orientation is from 0 to π, the histogram is nearly symmetrical along the axis located at $\pi/2$ for a face with frontal view and upright position. Figure 2 (b), (d) show the orientation histogram from a typical face image and a typical background block from the test database respectively. The orientation histogram of the face image is similar to that of model except that the curve is less smooth. On the other hand, there are much difference between the histogram of background block and that of model.

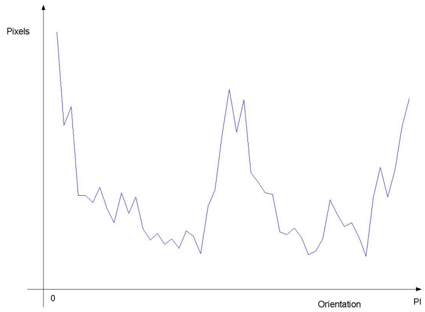


Figure 1 Orientation Histogram of Face Model

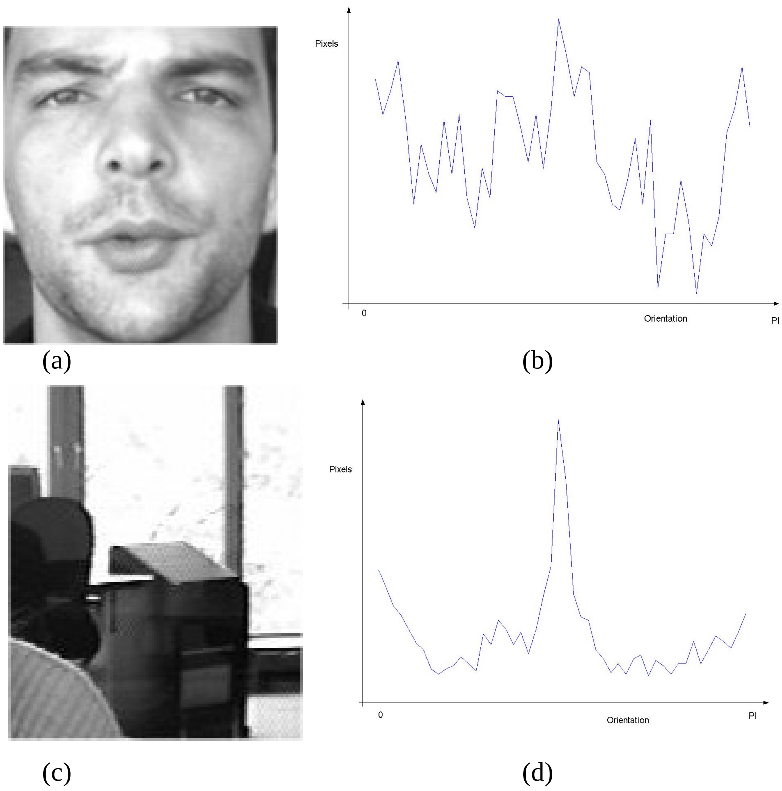


Figure 2 Orientation Histogram of Typical Face Image and Background Block

4 Matching

4.1 Orientation Map Matching

A face model was built from a sample of hand-labeled face images. Ten face images are cropped, aligned and scaled to the size 90×120. Ten orientation maps were extracted from the face images and a model orientation map was calculated by averaging the ten maps. For face detection, the orientation model $\mathbf{V}_m(x, y)$ is slid over the input orientation image and the similarity between the model and the underlying orientation block centred at pixel *(i,j)* is calculated and normalized as below:

$$S_O(i,j) = \frac{\sum_{u=i-\frac{w}{2}}^{u=i+\frac{w}{2}} \sum_{v=j-\frac{h}{2}}^{v=j+\frac{h}{2}} sim(V_m(u,v), V_I(i+u, j+v))}{M} \tag{8}$$

where $\mathbf{V}_I(x, y)$ is the orientation map of the input image, *w* is the width of the model orientation map, *h* is the height of the model orientation map, *M* is the number of orientation vectors with strength > 0 in the model orientation map and

$$sim(\mathbf{V}_1, \mathbf{V}_2) = \begin{cases} \cos(|\arg(\mathbf{V}_1) - \arg(\mathbf{V}_2)|) & if \quad |\mathbf{V}_1|, |\mathbf{V}_2| > 0 \\ 0 & else \end{cases} \tag{9}$$

4.2 Histogram Intersection

Histogram intersection is used in our algorithm to match two histograms *q* and *v*. The similarity score between the model histogram *v* and test histogram *q* is calculated as below:

$$S_H = \frac{\sum_{j=1}^{N} \min(q_j, v_j)}{\sum_{j=1}^{N} v_j} \tag{10}$$

where N is the number of bins used to quantize the orientations. q_j, v_j are the values corresponding to bin *j* in histogram *q* and *v* respectively.

4.3 Face Detection Algorithm

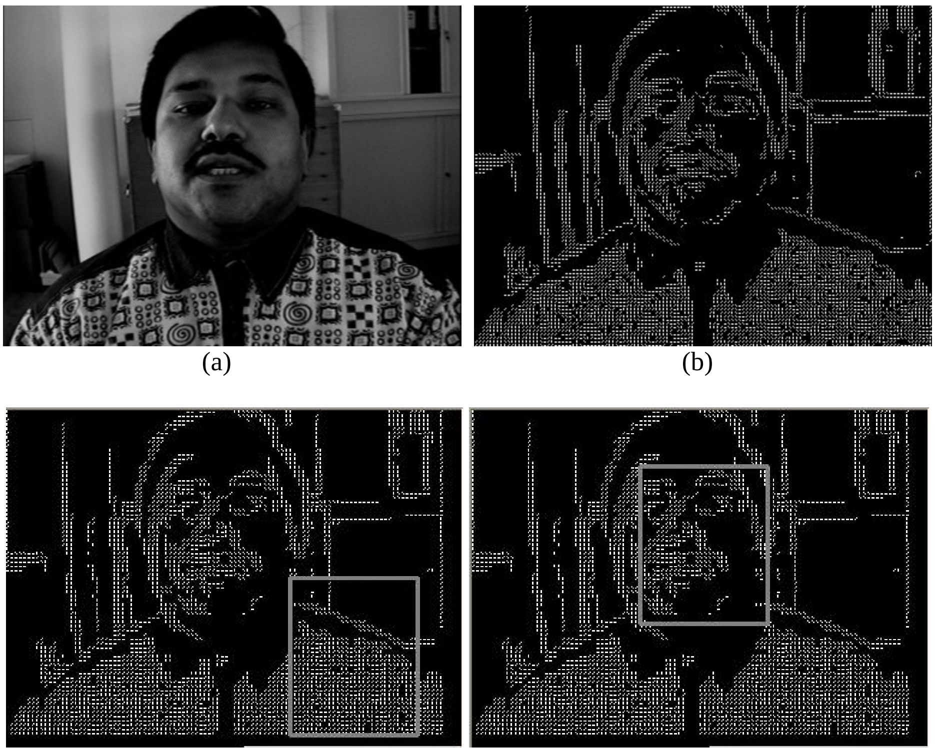
A resolution pyramid of orientation map is used to detect faces of different sizes. The size ration between two resolution levels is set to be 1.25. At each resolution level, the orientation model $\mathbf{V}_m$ is slid over the resized orientation image. When the model is located at pixel *(i,j)* in a resized image of resolution level *l*, the similarity score *S(i,j)* between the underlying block and the model is calculated as below:

$$S(i,j) = \begin{cases} 0 & if \quad S_H < T_H \\ w_o \times S_O(i,j) + w_h \times S_H(i,j) & else \end{cases} \tag{11}$$

where w_o, w_h are two weight values ($w_o + w_h$ =1), T_H is a preset threshold, $S_O(i,j)$ and $S_H(i,j)$ denote the orientation map matching score and the histogram similarity score calculated for the block centred at pixel *(i,j)* respectively. To reduce the effect of low resolution, histogram similarity score is calculated at a higher resolution level. The corresponding block *B* centred at *(i,j)* is retrieved from the image of resolution level 0 (original image) and the orientation histogram of block *B* is then calculated and matched with that of model, using equation (10). A similarity map was generated for each resolution level and from these similarity maps, the pixel with the maximum similarity score is found and a face is detected at location of this pixel.

5 Experimental Results

A test set, BioID database [14], is used in our experiments to evaluate the proposed algorithm. The set consists of 1521 images (384×288 pixel, grayscale) of 23 different persons and has been recorded during several sessions at different places. This set features a large variety of illumination, background and face size. Two algorithms, named as A and B, are evaluated in our experiments. Orientation template matching [6] is used in algorithm A, while both orientation map matching and orientation histogram intersection are applied in algorithm B. Blocks of size 3×3 are used to calculate the orientation map and orientation is quantized to 50 bins. Figure 3 shows the different results when the two algorithms are applied to an image from the database. Figure 3 (c), (d) shows the detection result when algorithm A and B is applied to orientation map (b) respectively. The image block that yields the maximum similarity score is bounded with a rectangle. From this figure, we observe that when only orientation information is used, false detection easily occur where edge frequency, e.g. texture, is high. After the histogram information is involved, false detection for this image is avoided and better detection accuracy can be achieved.



(a) (b)

(c) (d)

Figure 3 Detection Results for Algorithms A & B when applied to a Face Image

Table 1 shows the detection results for these two algorithms after they are applied to the whole database. Accuracy of 93.7% is achieved for the new algorithm B. Since the histogram is also used to filter the blocks before they are matched with the template, less processing time is achieved for algorithm B. The average processing time per image for algorithm B is 1.73 seconds, which is about 17% less than that of algorithm A. When this algorithm is applied to video sequence, the search space can be greatly reduced if the information from previous frame is used. As a result, our algorithm can be easily applied to real-time application.

Table 1 Comparative Results for Algorithm A and B

Algorithm	A	B
Accuracy	89.49%	93.7%
Average Processing Time (Sec)	2.01	1.73

6 Conclusions

In this paper, we have proposed an orientation based algorithm for face detection in grey images. Both orientation map matching and orientation histogram intersection are applied in our algorithm. Orientation histogram is firstly used to filter the blocks before they are matched with the template. After that, the histogram similarity score is weighted together with the orientation map matching score to yield a total matching score for the image block under processing. The test set of BioID database is used to evaluate our algorithm. Experimental results show that 93.7% accuracy is achieved for the database, which contains 1521 images with large variety of lighting and background.

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