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FaceID: A Face Detection and Recognition System*

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ABSTRACT

A face detection system that automatically locates faces in gray-level images is described. Also described is a system which matches a given face image with faces in a database. Face detection in an image is performed by template matching using templates derived from a selected set of normalized faces. Instead of using original gray level images, vertical gradient images were calculated and used to make the system more robust against variations in lighting conditions and skin color. Faces of different sizes are detected by processing the image at several scales. Further, a coarse-to-fine strategy is used to speed up the processing, and a combination of whole face and face component templates are used to ensure low false detection rates. The input to the face recognition system is a normalized vertical gradient image of a face, which is compared against a database using a set of pretrained feedforward neural networks with a winner-take-all fuser. The training is performed by using an adaptation of the backpropagation algorithm. This system has been developed and tested using images from the FERET⁸ database and a set of images obtained from Rowley, et al⁹ and Sung and Poggio.¹¹

Keywords: face detection, face recognition, template matching, correlation coefficient, neural networks

1 INTRODUCTION

The problem of automatic face recognition in camera images and video segments has received considerable attention over the past several years in part due to a number of important application areas.^{1,4} Despite major recent advances made by several research groups,^{3,9,11,13} reliable detection and recognition of human faces in photographic and video imagery continues to present significant challenges.⁵

The technical issues associated with this problem are inherently difficult due to a lack of structure (for example, variations in pose, facial expressions, lighting conditions, etc.) which makes it non-amenable to traditional pattern classification methods. The most successful face recognition methods are based on customized neural network,^{3,15} or linear¹³ and non-linear⁷ estimation methods. Our primary motivation is to develop a face detection and recognition system employing conceptually simple design principles. We address the problems of: (a) detecting all frontal, upright faces in an image and (b) finding possible matches for each detected face in a given face database.

- (a) **Face Detection:** Face detection for a given image is performed by first generating a vertical gradient image, calculating several statistical characteristics for all template-sized regions of the image, and eliminating the ones whose values deviate significantly from typical values for faces. Then correlation

coefficient is calculated between the face template and a template-sized window centered around each pixel in the surviving regions. The local maxima of high-scoring regions with sufficiently sharp peaks are identified as faces. Faces of different sizes are detected by processing the input image at several scales. A combination of whole-face and face component templates has been used to increase the accuracy and reduce the rate of false detections. Further, a coarse-to-fine strategy is used to speed up the detection process. The most appropriate template was defined as the solution to an optimization problem. The solution was shown to be a weighted average of the gradient images.

- (b) **Face Recognition:** Face recognition is achieved by using a set of feedforward neural networks with a winner-take-all fuser. The vertical gradient image of normalized front views are used as input to the recognition system. The system is trained with a gallery of images using an adapted version of backpropagation algorithm which computes the weights of one neural net for each face. Once trained, a test image is input to the neural network for each face in the database and the neural network that generates the largest output yields the match.

The organization of the paper is as follows. Section 2 describes the face detection subsystem. The face recognition subsystem is described in Section 3.

2 FACE DETECTION

We now describe the various components of our face detection system:

- (a) Analysis of statistical characteristics of faces.
- (b) Template generation.
- (c) Face detection algorithm.

For steps (a) and (b) above, a sample set of 44 front-view face images of different individuals was selected from the FERET database. The images were selected to encompass faces of different sizes, of males and females, and of different skin colors.

2.1 Face image statistical characteristics

Faces were extracted from the sample set of images and preprocessed (as described in the next section) and the following statistical characteristics were calculated:

- The coefficient of variation (CV), which is the ratio of the standard deviation to the average of the pixel values of the image;
- The coefficient of fluctuation (CF), which is the ratio of the fluctuation to the standard deviation, where fluctuation is the average of the absolute values of intensity changes between all adjacent pixels in the image (in horizontal and vertical directions);
- the position of the centroid of the image pixel values.

The values of the above characteristics for these preprocessed face images were observed to lie within a fairly narrow range. Therefore, during the face detection process all template-sized subimages of the input image whose characteristic values lie outside a preset range are eliminated from further processing.

Figure 1: Face images at each stage of normalization process

2.2 Template Generation

Face detection is based on calculating a measure of similarity (correlation coefficient) between face templates and all candidate regions of a given image. The following procedure was employed in generating the templates from the sample set of face images.

- (a) **Geometric Normalization of Faces:** In each image, the centers of the eyes and the center of the upper boundary of the upper lip were marked manually. A rotational transform was applied such that the eyes would lie on a horizontal line. The image was then scaled so that the inter-ocular distance would be a predetermined constant. A pixel region of predetermined size centered at the midpoint between the eyes and the center of the upper lip from each face was extracted. These transformations yielded geometrically normalized face images, i.e. all faces (and facial features) had comparable orientation, size and position. The parameters for the normalization were selected such that the normalized image would capture the region of a face extending vertically from a few pixels above the eyebrows to a few pixels below the lower lip; and, extending horizontally a few pixels beyond both eyes.
- (b) **Pixel Intensity Preprocessing:** Each geometrically normalized image was then modified to compensate for the effects of possible uneven illumination of the face due to extreme lighting conditions, using a technique adapted from the face detection systems of Sung and Poggio,¹¹ and Rowley, et al.⁹ A linear regression function of a plane which best fit the variation in the intensity across the face image was determined and subtracted from the original image. Then, histogram equalization was performed to improve the contrast and to compensate for differences in camera response curves.
- (c) **Gradient Images:** Absolute values of horizontal and vertical derivatives of pixel intensities were calculated for each normalized face image, using the Sobel gradient operators.⁶ Derivatives were used instead of original gray level values to make the process more robust against variations in lighting conditions and skin color. Face templates for horizontal and vertical derivatives were generated by calculating a weighted average of the gradient images. Figure 1 shows several face images after each of the above processing stages and the resulting templates.

The templates were generated using the horizontal and vertical gradient images. However, significantly better results were obtained using the vertical gradient template, and therefore, only those results are

reported in this paper.

We now provide a justification for the above template used in computing the correlation coefficient. In general, all human faces have similar global structure, with some variations in size and shape of the face, and variations in individual features, namely, eyes, nose, lips, cheeks and chin. A normalized face image X can be considered to be a vector of dimensions $m \times n$. A template is also a vector of dimensions $m \times n$ which would produce a high "measure of similarity" when compared to other face images and low measure when compared to non-face images. Here we derive a specific template which is a weighted average of the normalized faces of the database.

Consider the problem of choosing an appropriate template based on a finite sample set of faces $\mathcal{F}_0 \subset \mathcal{F} \subset \mathbb{R}^{mn}$, where $\mathcal{F}$ is the set of all faces. For a function of similarity $\rho : \mathcal{F} \times \mathcal{F} \mapsto \mathbb{R}$, any template $X_0 \in \mathcal{F}$ is ρ -optimal if

$$\max_{Y \in \mathcal{F}} \frac{1}{|\mathcal{F}_0|} \sum_{X \in \mathcal{F}_0} \rho(X, Y) = \frac{1}{|\mathcal{F}_0|} \sum_{X \in \mathcal{F}_0} \rho(X, X_0),$$

where $|\mathcal{F}_0|$ is the number of faces in $\mathcal{F}_0$. In other words, the optimal template represents the most significant similarities between the faces in the sample set. In our case, $\mathcal{F}_0$ is a set of N vectors $\{X_1, X_2, \dots, X_N\}$, $|\mathcal{F}_0| = N$, where $X_i = (x_{i,1}, x_{i,2}, \dots, x_{i,mn}) \in \mathbb{R}^{mn}$, represents a sample face. For vector X_i we define $\bar{x}_i = \frac{1}{mn} \sum_{k=1}^{mn} x_{i,k}$ and $\sigma_i = \sqrt{\frac{1}{mn} \sum_{k=1}^{mn} (x_{i,k} - \bar{x}_i)^2}$, $i = 1, 2, \dots, N$. Correlation coefficient (a measure of similarity) between two face vectors X_i and X_j is defined as

$$\rho(X_i, X_j) = \frac{\frac{1}{mn} \sum_{k=1}^{mn} (x_{i,k} - \bar{x}_i)(x_{j,k} - \bar{x}_j)}{\sigma_i \sigma_j}.$$

A ρ -optimal template can be obtained by maximizing the objective function

$$L(X) = \frac{1}{N} \sum_{i=1}^N \frac{1}{mn} \sum_{j=1}^{mn} \frac{(x_{i,j} - \bar{x}_i)(x_j - \bar{x})}{\sigma_i \sigma},$$

where $X = (x_1, x_2, \dots, x_{mn})$, $\bar{x} = \frac{1}{mn} \sum_{j=1}^{mn} x_j$, and $\sigma = \sqrt{\left(\frac{1}{mn} \sum_{j=1}^{mn} (x_j - \bar{x})^2\right)}$. Replacing the order of summation, we get

$$L(X) = \frac{1}{mn} \sum_{j=1}^{mn} \left(\frac{x_j - \bar{x}}{\sigma} \right) \left(\frac{1}{N} \sum_{i=1}^N x_{i,j} / \sigma_i - \frac{1}{N} \sum_{i=1}^N \bar{x}_i / \sigma_i \right).$$

Denoting $y_j = \frac{1}{N} \sum_{i=1}^N x_{i,j} / \sigma_i$, and $Y = (y_1, y_2, \dots, y_{mn})$, we have $L(X) = \rho(X, Y)$, since

$$\frac{1}{mn} \sum_{j=1}^{mn} y_j = \frac{1}{N} \sum_{i=1}^N \frac{\bar{x}_i}{\sigma_i}.$$

According to Cauchy-Schwartz inequality, $L^2(X) \leq 1$ and the equality is achieved by $X = (x_1, x_2, \dots, x_{mn})$ when $x_j = \alpha y_j + \beta$, $j = 1, 2, \dots, mn$, for arbitrary $\alpha, \beta \in \mathbb{R}$. Thus, the ρ -optimal template is a weighted average of the chosen feature for the face samples with weights reciprocal to the standard deviation of the values of the chosen feature for each face image. For our detection algorithm we chose $\alpha = 1$ and $\beta = 0$, and, the horizontal and vertical components of gradient as the features. The correlation coefficient $\rho \in [-1.0, 1.0]$, and is independent of scale changes in the amplitude of the input vectors.

2.3 Face detection algorithm

Face detection for a given image is performed in two steps:

- (i) Several statistical characteristics for different regions of the image are computed. Regions whose characteristics deviate significantly from typical range of values for faces are eliminated from further processing.
- (ii) A correlation coefficient is calculated between the vertical gradient face template and a template-sized window centered around each pixel in the surviving regions. The local maxima of high-scoring regions having sufficiently sharp peaks are identified as faces.

Faces of different sizes are detected by processing the input image at several scales. A combination of whole-face and face component templates has been used to increase the accuracy and to reduce the rate of false detections. The face component templates used are the eye-pair template and the nose-lips template. A coarse-to-fine strategy is used to speed up the detection process. The input image is first processed at a lower resolution to obtain an initial list of likely face regions and then only those regions are considered while processing the image at full-resolution.

The face detection process is described below in detail.

- (a) **Gradient images and statistical characteristics:** The input image is scaled to several different sizes, with the minimum size being the size of the template, the maximum size being the original size of the image, and the intermediate sizes being at a scale factor of 1.2 with respect to each other. Each scaled image is processed as follows: A vertical gradient image is generated from the gray level image, using the vertical Sobel operator. For every template-sized subimage, the values for CV and CF and the position of the centroid are calculated. If any of these values lie outside the range of acceptable values (determined from the set of sample face images), that subimage is rejected.
- (b) **Correlation Map:** If the subimage passes the above criteria, then template-matching is performed between the subimage and the template using the correlation coefficient (as defined in 2.2) as the function of similarity. Correlation map for an image-template pair is a two-dimensional array of correlation coefficient values calculated for a template-sized subimage centered around each point of the image. It can be observed that the correlation coefficient has a peak near the center of a face and the radial intensity as a function of the distance from the peak decreases monotonically. The same is usually not true for non-face regions. This characteristic is utilized for distinguishing faces from non-face regions. The typical rate of fall in radial intensity for the correlation map in face regions was determined experimentally using the sample set of faces. Figure 2 shows an image being processed at different scales and the corresponding correlation maps.

All points of the image where the correlation coefficient value is greater than an experimentally determined threshold value are selected as potential face candidates. There is likely to be a cluster of points satisfying the threshold condition in each face region. Therefore, a local maxima is determined for each cluster and retained for further processing. If the local maxima does not satisfy the radial intensity criterion, it is discarded. At this point, the pool of likely face candidates is reduced to a very small number.

- (c) **Determining the best scale and position of the face:** The above pool of candidates was determined at an approximate scale. In order to obtain a better estimate of scale and location, correlation map is calculated for a small region around each candidate at several finer scale values. The location with the highest correlation coefficient (and the corresponding scale) for each of the candidates are declared as faces.

Figure 2: Face Detection Results. The figure shows the input image, the face and eye-pair templates, correlation maps for four different scaled vertical gradient images, the face located at the correct scale, and the labeled output image. Also shown is a zoomed view of the sharp peak at the center of the face location.

3 FACE RECOGNITION

The candidates for faces produced by the detection system can be given as input to the recognition system after a process of normalization. We now first describe our solution to the recognition problem and then present experimental results.

3.1 Neural Network Solution

We are given M examples of images of dimensions $m \times n$, each belonging to one of N classes denoted by $1, 2, \dots, N$. Consider a system of N single hidden-layer feedforward sigmoidal networks, where each network is of the form

$$f(W, X) = \sigma \left(\sum_{i=1}^l a_i \sigma(b_i^T X + t_i) \right)$$

where $X \in \mathbb{R}^{mn}$ is the input vector, l is the number of hidden units, $\sigma(z) = 1/(1 + e^{-z})$ for $z \in \mathbb{R}$, is the sigmoidal activation function, and $W = (a_1, a_2, \dots, a_l, b_{1,1}, b_{1,2}, \dots, b_{1,mn}, \dots, b_{l,1}, b_{l,2}, \dots, b_{l,mn}, t_1, t_2, \dots, t_l) \in \mathbb{R}^{l(mn+2)}$ is the weight vector.

Let the M -sample be given by $(X_1, c_1), (X_2, c_2), \dots, (X_M, c_M)$ where $X_i \in \mathbb{R}^{mn}$ is the image and $c_i \in \{1, 2, \dots, N\}$ is its class number. The class j is handled by j th neural network. Each neural network is individually trained with examples of class j as positive examples and all other examples as negative examples. The training sample $(X_1, d_1^j), (X_2, d_2^j), \dots, (X_M, d_M^j)$ for the j th neural network is obtained as follows. For (X_i, c_i) , let $d_i^j = 1$ if $c_i = j$, and $d_i^j = 0$ if $c_i \neq j$. The square error of a neural network with weight W based on the a given training example (X_i, d_i^j) is defined as $(f(W, X_i) - d_i^j)^2$.

The learning algorithm is based on a variation of the well-known gradient descent method (similar to backpropagation algorithm), which makes a number of iterations on the training sample. Each iteration consists of M steps, and in each step the example (X_i, d_i^j) is utilized as follows. Let $W_{(r)}^k$ denote the weight vector of the neural network at the r th step in k th iteration. The original vector $W_{(0)}^0$ is randomly initialized. The update rule for each step is given by for $r = 0, 1, \dots, M$

$$W_{(r+1)}^k = W_{(r)}^k + 2\gamma(f(W_{(r)}^k, X_{r+1}) - d_{r+1}) \nabla_W g(W_{(r)}^k, X_{r+1}),$$

where $\gamma \in \mathbb{R}$ is the step size, and

$$g(W, X) = \sum_{i=1}^l a_i \sigma(b_i^T X + t_i).$$

The gradient of $g(\cdot, \cdot)$ with respect to $W = (w_1, w_2, \dots, w_{l(mn+2)})$ is computed as follows: $\nabla_W g(W, X_{r+1})$ is given by $\left[\frac{\partial g}{\partial w_1}(W, X_{r+1}), \frac{\partial g}{\partial w_2}(W, X_{r+1}), \dots, \frac{\partial g}{\partial w_{l(mn+2)}}(W, X_{r+1}) \right]^T$ such that, for $1 \leq i \leq l, 1 \leq j \leq mn$,

$$\frac{\partial g}{\partial t_i}(W, X_{r+1}) = a_i \sigma'(b_i^T X_{r+1} + t_i),$$

$$\frac{\partial g}{\partial a_i}(W, X_{r+1}) = \sigma(b_i^T X_{r+1} + t_i),$$

$$\frac{\partial g}{\partial b_{ij}}(W, X_{r+1}) = a_i \sigma'(b_i^T X_{r+1} + t_i) x_j, \text{ where } X_{r+1}^T = (x_1, x_2, \dots, x_{mn}).$$

For the next iteration $W_{(0)}^{k+1}$ is initialized with $W_{(M+1)}^k$ of the previous iteration, i. e. $W_{(0)}^{k+1} = W_{(M+1)}^k$.

Figure 3: Architecture of the fusion system

After the neural network (with 20 hidden nodes) for each class has been trained for certain number of iterations, the classification of a test input X is computed to be the class number of the neural network that produced the largest output.

A neural network solution similar to the one proposed here was employed in solving the glassware recognition problem,¹² where the traditional neural network methods were not effective. In the present case, our attempts to use a more conventional feedforward neural network¹⁰ was not successful. We applied traditional backpropagation algorithm¹⁴ using the sample $(X_1, c_1), (X_2, c_2), \dots, (X_M, c_M)$. We executed the algorithm with different starting weights and step sizes for more than 10 hours in each case; the percentage of correct classification achieved was less than 60%. Also our efforts to solve this problem using traditional nearest neighbor rules were not successful. Our method is very simple to implement and execute. Figure 3 illustrates the architecture of the face recognition system.

4 EXPERIMENTAL RESULTS

(a) Face Detection:

The face detection system was tested using a subset of FERET database consisting of 250 single front-view face images of different individuals having varying face sizes. The system was able to correctly detect 220 faces, thus achieving a detection rate of 88%. The system incorrectly identified 21 non-face regions as faces. The execution time for processing a 256x384 pixel image (for all scales) using a 33x33 pixel face template on a DEC AlphaStation 250 is approximately 25 seconds.

(b) Face Recognition:

The face recognition system is trained with 44 normalized faces extracted from FERET database. Some of the faces are shown in Figure 1. The vertical gradient of each image is used as input x to the neural networks. These normalized faces are manually generated. In our implementation each example consisted of 64×64 vertical gradient image of the normalized image of an individual face. The number of neurons is 20 which is fixed by a trial-and-error procedure.

After 1,000 iterations, the system was able correctly classify 41 out of 44 pictures of the gallery. After 10,000 iterations, the system was able to correctly classify 43 out of 44 pictures of the gallery. The

same performance is observed when each image was corrupted by uniform random noise with 25% of the original magnitude.

This system is trained on SPARC IPX. During training, the execution time for 10,000 iterations was about 8 hours. After training, the processing of a single image took about 36 seconds on DEC Alpha workstation.

5 CONCLUSIONS

The face detection system was able to correctly detect 88% of the faces. Out of the 30 faces which the system missed, 14 had one or more characteristics that our training set was carefully screened against; namely, beards, moustaches and hair partially covering the face; 9 of the remaining missed faces differed substantially from the faces in the training set. There is appreciable variability in structure and features between faces which can not be fully represented by a single template derived from a small database. One focus of our future work will be to improve the performance of our face detection system by using a bank of templates (rather than a single template), with each template representing a distinct class of faces possessing a similar structure. This bank of templates will be generated by employing clustering techniques on a much larger database of faces. Another focus of our future work will be view-based face detection, again using a template-based method similar to the system described here.

For the face recognition problem, future work will involve development of alternative methods (e.g. potential function²) and suitably fusing them with the current neural network method.

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7 REFERENCES

- [1] *Proceedings of Second International Workshop on Automatic Face- and Gesture-Recognition*, Killington, Vermont, October 14-16, 1996.
- [2] M. A. Aizerman, E. M. Braverman, and L. I. Rozonoer. *Extrapolative problems in automatic control and method of potential functions*, volume 87 of *American Mathematical Society Translations*, pages 281-303. 1970.
- [3] J. J. Atick, P. A. Griffin, and A. N. Redlich. Face recognition from live video for real-world applications - now. In *Electronic document*. 1995.
- [4] M. Bichsel, editor. *Proceedings of International Workshop on Automatic Face- and Gesture-Recognition*, Zurich, Switzerland, June 26-28, 1995.
- [5] R. Chellappa, C. L. Wilson, and S. Sirohey. Human and machine recognition of faces: A survey. *Proceedings of the IEEE*, 83(5):705-740, 1995.

- [6] R. C. Gonzalez and P. Wintz. *Digital Image Processing*, pages 337-338. Addison-Wesley Publishing Company, 1987.
- [7] N. Intrator, D. Reissfeld, and Y. Yeshurun. Face recognition using hybrid supervised/unsupervised neural network. *Pattern Recognition Letters*, 17:67-76, 1996.
- [8] P. J. Phillips, P. J. Rauss, and Sandor Z. Der. Feret (face recognition technology) recognition algorithm development and test results. Technical Report ARL-TR-995, Army Research Laboratory, Adelphi, MD 20783-1197, October 1996.
- [9] H. A. Rowley, S. Baluja, and T. Kanade. Human face detection in visual scenes. Technical Report CMU-CS-95-158R, Carnegie Mellon University, November 1995.
- [10] D. E. Rumelhart, G. E. Hinton, and R. J. Williams. Learning internal representations by error propagation. In D. E. Rumelhart and J. L. McClelland, editors, *Parallel and Distributed Processing: Explorations in the Microstructures of Cognition*. MIT Press, Cambridge, MA, 1986.
- [11] K. Sung and T. Poggio. Example-based learning for view-based human face detection. Technical Report A.I. Memo No. 1521, 1994.
- [12] S. Toemoe, N. S. V. Rao, and R. C. Mann. A learning-based method to recognize and localize glassware using laser range images. *Image and Vision Computing*, 14(2):131-134, 1996.
- [13] M. Turk and A. Pentland. Eigenfaces for recognition. *Journal of Cognitive Neuroscience*, 3(1):71-86, 1991.
- [14] P. J. Werbos. Backpropagation through time: What it does and how to do it. *Proceedings of the IEEE*, 78(10):1550-1560, 1990.
- [15] L. Wiskott and C. von der Malsburg. Recognizing faces by dynamic link matching. In *Proceedings of the ICANN'95*, pages 347-352. 1995.