Automatic Face Recognition Using Facial Attractiveness

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Abstract

In this paper, we propose a system for automatic face recognition using a novel set of face features derived from facial attractiveness. The motivations for this technique come from psychological studies about the effects of facial attractiveness on human face recognition abilities and the ability of the Golden Mask to define ideal faces. A set of features is calculated from critical points on the face archetype and their corresponding points on the actual face. A neural network model is then used to identify an individual. Experimental evaluations using face images of 70 persons, with certain variations in light, background, image size, and facial expressions result in a recognition rate of 92.86%.

Keywords: *Face Recognition; Facial Attractiveness; Golden Mask.*

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การรู้จำหน้าคนแบบอัตโนมัติโดยใช้ความมีเสน่ห์ของใบหน้า

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บทคัดย่อ

บทความนี้นำเสนอระบบรู้จำหน้าคนแบบอัตโนมัติโดยใช้คุณลักษณะรูปแบบใหม่ที่สกัดจากความมีเสน่ห์ของใบหน้า วิธีการนี้ได้แรงบันดาลใจมาจากการศึกษาทางจิตวิทยาเกี่ยวกับอิทธิพลของความมีเสน่ห์ของใบหน้าต่อความสามารถในการจดจำหน้าของคนและความสามารถของหน้ากาก Golden Mask ในการปรับรูปใบหน้าให้มีความงดงาม ชุดของคุณลักษณะดังกล่าวจะคำนวณจากตำแหน่งอ้างอิงบนใบหน้าจริงและบนใบหน้าที่ได้รับการปรับให้มีเสน่ห์ในอุดมคติ และเครือข่ายประสาทเทียมถูกใช้เป็นตัวแบบในการระบุตัวบุคคล จากการทดลองกับรูปหน้าของกลุ่มตัวอย่างจำนวน 70 คน ซึ่งมีความแปรปรวนของ แสง พื้นหลัง ขนาดของภาพ และอารมณ์ของใบหน้า พบว่าวิธีการที่นำเสนอมีความถูกต้องของการรู้จำถึง 92.86 เปอร์เซ็น

คำสำคัญ: *การรู้จำหน้ามนุษย์ ความมีเสน่ห์ของใบหน้า Golden Mask*

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Introduction

The performance of automatic face recognition depends on several factors and involves several processes. One of the most important processes is feature selection. The choices of features selected highly impact the effectiveness of the recognition.

Psychological studies show that facial attractiveness plays a significant role in human face recognition abilities (Zhao *et al.*, 2003). In addition, facial attractiveness can be defined (Schmidhuber, 1998), measured (Marquardt, 2009a), and learned by machines (Eisenthal *et al.*, 2006).

In this research, we introduce a system for automatic face recognition using a novel set of features derived from facial attractiveness according to the Golden Mask (Marquardt, 2009a). We focus on face images in near frontal views, which are applicable to mugshot style images, e.g. criminal databases, drivers licenses, identification cards, etc. Minor facial and environmental variations, such as illumination, head pose, facial expression, aging, etc., are supported.

The rest of this paper is organized as follows: Section 2 provides related work on face recognition and facial attractiveness. Section 3 presents the details of the proposed system, including the Golden Mask, facial attractiveness extraction, automatic feature localization, and the face recognition model. Section 4 describes experiments conducted to evaluate the effectiveness of the system. Section 5 provides concluding remarks on the research.

Related Work

Face recognition began its early days in the psychological studies of the 1950s. Some of them included work on facial expressions and facial profile-based biometrics (Zhao *et al.*, 2003). Research on automatic face recognition began in the 1970s (Kelly, 1970; Kanade, 1973). Since then, a lot of work has been proposed for solving issues surrounding this problem. Algorithms have been performed in various ways using different sensing modalities, such as visible spectrum, infrared camera, sketches, and others, e.g., sonar (Yoong and Mckerrow, 2005). Research has focused its range from single still images and multiple still images to video sequences. Despite the large number of commercial systems and forensic applications, face recognition is still far from perfect, especially under unconstrained conditions where practical interferences from facial expression, illumination, and pose variations have to be counteracted (Zhao *et al.*, 2003).

Existing face recognition techniques are roughly classified into holistic approaches and local approaches. The representative holistic approaches include Eigenface (Turk and Pentland, 1991) and Fisherface (Belhumeur *et al.*, 1997). Deriving feature information from the whole face image for classification, holistic approaches usually suffer from environmental variations in practice. The local approaches, such as Elastic Bunch Graph Matching (EBGM) (Wiskott *et al.*, 1997) and Local Binary Pattern (LBP) (Ahonen *et al.*, 2006) extract information from local facial features, which are less sensitive to alterations, e.g., points at the eyes, sides of the nose and the mouth, and points surrounding the cheekbones, to distinguish faces and have the advantage of robustness in relation to environmental changes.

Facial attractiveness has received attention for centuries. Pythagoras, a Greek philosopher, believed that he had discovered a mathematical code for beauty, not only in humans but also for the universe. He found that plants and animals grow according to a formula based on a geometric ratio, called the perfect ratio (or golden ratio), which is 1:1.618. The closer an object is to this proportion, the more likely it will be found attractive. This ratio has been proven to work in nature, e.g., in the formation of shells, human DNA, etc. Man-made objects are often more pleasing to the eye if they follow this ratio (Dale, 2004).

The ranking studies on the significance of facial features by Bruce (1988) and Shepherd *et al.* (1981) show that attractiveness plays a significant role in face recognition and they conclude that the more attractive a face is, the more easily it will be recognized, followed by the least attractive faces, then by moderately attractive faces.

Johnston and Franklin (1993) produced an attractive female face using a genetic algorithm, which evolved a "most beautiful" face according to interactive user selection. Additionally, Schmidhuber (1998) created an attractive female face from fractal geometry of rotated squares and the powers of two.

Eisenthal *et al.* (2006) presented a study of the notion of facial attractiveness in a machine-learning context using different techniques for learning facial attractiveness, for example, feature-based measures and Eigenface representation. The results show that facial beauty is a universal concept and can be learned by machines.

Some studies indicate that beauty is held in a set of features that is universal across different faces. For example, a study by Marquardt (2009a) took a series of 18 photos of women with a range of facial attractiveness and showed them to people of all ages from a variety of cultural backgrounds. Ninety-seven percent of the participants placed the women in the same order of attractiveness. This finding indicates that there are no, or few, cultural differences in the physical rules of what is considered beautiful and that there is a set of universal rules for what makes a person beautiful. This indicates that cultural deviation is not important in recognizing beauty, and that beauty is due to a set of key biological features (Dale, 2004).

Proposed Methodology

In this section, we provide a detailed description of our proposed system, including the Golden Mask, facial attractiveness extraction, automatic feature localization, and the face recognition model.

The Golden Mask

Marquardt (2009a) finds that the parameters of an attractive face and orientations of those features collectively recognized in an attractive face can be described using a collection of lines and points selected from a composite of pentagons whose sizes are related to? the golden ratio. He thus creates the Golden Mask, also referred to as the “Beauty Mask” (see Figure 1), where the better a face fits the mask, the more attractive or beautiful it is. This mask reflects the ideal positions and proportions of the features of an attractive face. In this paper, we use this mask as the ideal face template for extracting the facial attractiveness of individuals.

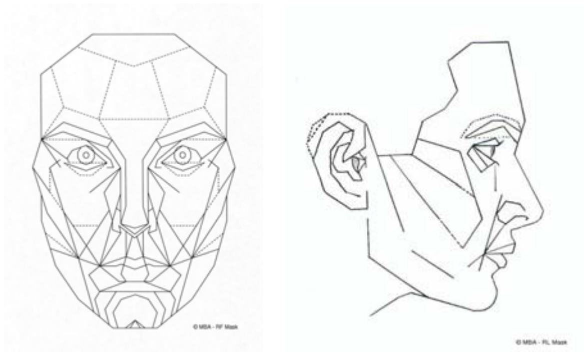


Figure 1: Repose frontal & lateral Golden Mask (Marquardt, 2009a)

Automatic Face Recognition

In general, a fully-automated face recognition system is composed of four basic steps:

1) *Face region detection*: The first step for face recognition is to locate the face in an input image, which can be a single still image or a sequence of images from a video.

2) *Face image preprocessing/normalization*: The aim of this step is to normalize the face images identified in the first step. The images may vary in size, pose (orientation of head), illumination, etc. Preprocessing is required so that robust feature extraction can be achieved. Preprocessing includes, for example, alignment (e.g., transformation, rotation, and scaling) and light normalization.

3) *Feature extraction:* A set of facial features best representing interpersonal discrimination is extracted using methods dependent upon the face recognition technique.

4) ***Face recognition:*** The feature vectors of images enrolled in a database, obtained from the previous step, are matched against the vector of the query image. Matching algorithm may vary; it can be a simple nearest neighbor, a decision tree, a regression model, a neural network, etc.

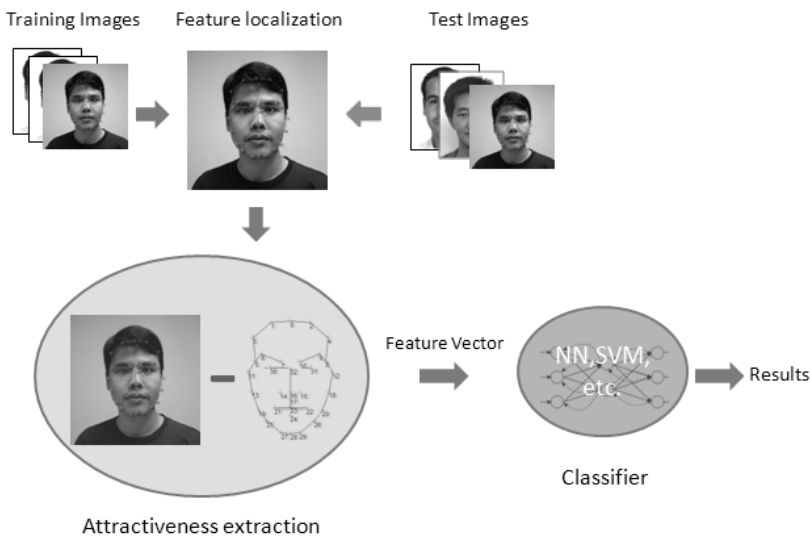
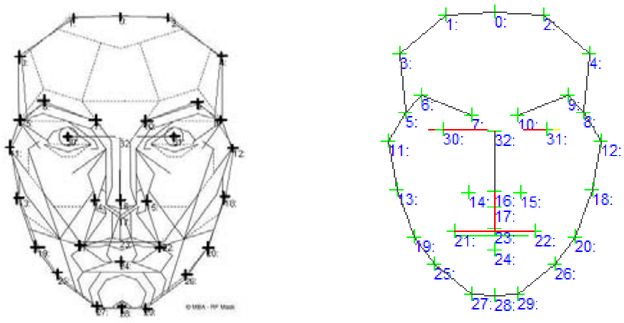


Figure 2: Architecture of the proposed system

In this research, we use the Golden Mask to model attractive faces. All points and lines on the mask conform to the golden ratio. The feature points selected from the mask are used as ideal positions for morphing a face into an attractive one. We employ these points together with additional points: eye centers, middle points between the eyes, mouth corners, and center of the mouth. Figure 3(a) illustrates the feature points on the Golden Mask. In order to apply the mark to automatic face recognition, we select feature points which are less sensitive to variations in environments, ornaments, and emotions, and which can be extracted automatically. The selected points are shown in Figure 3(b).



(a) (b)

Figure 3: a) Feature points on the Golden Mask, b) points selected from the Golden Mask to be used in the recognition

Facial Attractiveness Extraction

In this section, we describe the process used in our face recognition system to extract selected features. The process consists of five steps, as follows:

1. Locate the eyes and mouth corners, and calculate the length of the facial vertical line (the line between the middle of the two eyes and the center of the mouth) of a facial image.

2. Adjust the mask size to that of the face image by scaling the mask so that both the input image and the mask have the same length for the facial vertical line.

3. Locate the feature points on the actual face.

4. Compute the distance between each pair of local feature positions and their ideal positions on the mask to obtain a feature vector that represents the face.

5. The feature vector is normalized to the length of the facial vertical line in order to obtain the final feature vector to be used for recognition.

We implement a system that performs fully-automatic feature extraction. The next section describes the algorithms for automatic feature point localization.

Automatic Feature Localization

In real world applications, the selected features used for face recognition must be computed automatically. In our proposed system, we make the following assumptions:

- All facial images are head-shoulder images from frontal or nearly-frontal views with neutral (or minor) facial expression and no face accessories (e.g., sunglasses, scarf, etc.),
- The irises of both eyes are visible.
- Facial images are taken under normal light conditions (i.e., skin color is not changed by light).

The critical steps for our feature localization system are to locate the eyes (center of pupil) and the mouth corners. The set of selected feature points is $\{p_{11}, p_{12}, p_{13}, p_{17}, p_{18}, p_{19}, p_{20}, p_{21}, p_{22}, p_{25}, p_{26}, p_{27}, p_{28}, p_{29}, p_{30}, p_{31}, p_{32}\}$, and the techniques used for automatic feature localization are described as follows:

1. Face Region Detection: Before we can perform any feature localization, the region of the face in an input image must be identified precisely. First, we perform skin-color pixel extraction using the method described in (Chiang *et al.*, 2003); second, the resulting image is converted to a binary image; we then perform vertical (and horizontal) integration projection to estimate the face region. The vertical projection in the region $[x_1, x_2]\times[y_1, y_2]$ of an input image $I(x, y)$ is defined as:

$$V(x) = \sum_{y=y_1}^{y_2} I(x, y)$$

Similarly, the horizontal projection is defined as:

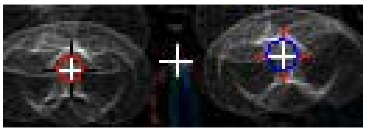
$$H(y) = \sum_{x=x_1}^{x_2} I(x, y)$$

Figure 4: shows the result of the face detection step.

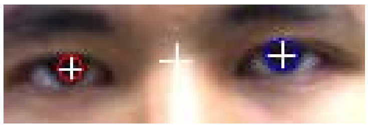
(a) (b)

Figure 4: a) The projection of a facial image, b) the result of facial region detection

2. Eye Detection: In order to locate the eyes, we perform edge detection by applying a 5x5 Laplacian of Gaussian filter and then applying a circular Hough transform within the estimated eye region based on the geometric relationships among facial features in order to limit the search area (i.e., preventing erroneous detection outside the eye region). Previous work using the Hough transform for eye detection can be found in (Kawaguchi *et al*., 2000; Toennies *et al*., 2002; Tian *et al*., 2004). Due to image size variation, the radius of the iris circles in each face image may vary. Therefore, instead of using a constant radius, we varied the radius between 2 and 10 pixels and compared the results in order to determine the best match for the iris circles (i.e., the radius with maximum hits). Figure 5 illustrates the result of the eye detection.



(a)



(b)

Figure 5: a) Circular Hough transform applied to candidate's eye region, b) the result of eye detection

As a result of this step, we obtained the position of points p_{30} and p_{31}, and also that of the middle point between the eyes $p_{32} = ((x_{30} + x_{31})/2, (y_{30} + y_{31})/2)$.

3. Mouth Corners Detection: Integral projection was also applied within the mouth area to detect the mouth corners. Considering the normalized RGB color space, where $r = R/(R+G+B)$, $g = G/(R+G+B)$, and $b = B/(R+G+B)$, we transformed an input image $I(x,y)$ to a gray scale image $I^{'}(x,y)$ using the equation below. In this way we were able to eliminate unwanted pixels from the facial features, such as the beard, which can cause detection errors.

$$I^{'}(x,y) = \begin{cases} 255 \cdot (\dfrac{G}{R+G+B}), if\, (R+G+B) > 0 \\ 0 \qquad\qquad\qquad\quad otherwise \end{cases}$$

where *R*, *G*, and *B* denote the intensity of pixels in red, green and blue channels, respectively. Then, a threshold operation was applied to the transformed image using the following equation.

$$I'(x,y) = \begin{cases} 255 & if(r > 83) \\ 0 & otherwise \end{cases}$$

In this research, a suitable threshold value of 83 (obtained by experiments) was used. Next, integral projections were performed in order to find the x- and y-coordinates of the mouth corners (see Figure 6).

(a) (b)

Figure 6: Mouth corner detection: a) the original facial image b) x- and y-coordinates found by the integral projections

After the eyes and mouth corners were located, the length of the facial vertical line was determined, and the mask was resized proportionally to that length and placed over the actual facial image, as shown in Figure 7.

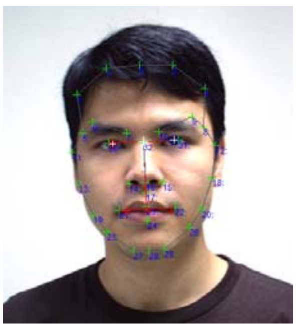
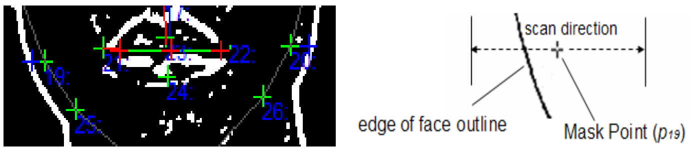


Figure 7: Golden Mask is initialized and placed over the actual facial image

4. Feature Point Detections: From the previous steps, all critical points were located, including the corresponding mask. The remaining feature points selected were detected using the following procedures.

Detecting Points p_{11}, p_{12}, p_{13}, p_{18}, p_{19}, *and* p_{20}*:* These points can be detected by performing pixel-scans in both –x and +x directions until the edge pixels of the face outline are met. Figure 8 shows the detection of point p_{19}.



(a) (b)

Figure 8: a) an edge-threshold image, b) the pixel-scan operation

Detecting Points p_{25}, p_{26}, p_{27}, p_{28}, *and* p_{29}*:* These points lie on the chin curve, which usually is difficult to detect due to its weak contrast with the neck area. A method for chin curve estimation is required. Several methods have been proposed, e.g., (Kampmann, 1997; Wang and Su, 2003). In our environment, where facial images are restricted to the frontal view, the chin curve can be approximated by using a single parabolic function, as follows:

$$y = a(x-h)^2 + k$$

It can be found if the vertex (h,k) and at least one point that the curve passes through are known. From the previous steps, we have determined the two points that lie on the chin curve (p_{19} and p_{20}); thus we only need to find the vertex (specifically point p_{28}) by applying a horizontal integral projection on the estimated chin area to find the y-coordinate, whereas the x-coordinate is computed by substituting y_{28} with the linear equation that passes through points q_{32} and q_{28}. Figure 9 shows the detection of the chin point.

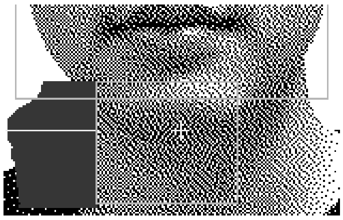


Figure 9: Chin point (p_{28}) detection

Then, substituting the known points p_{19} (or p_{20}) and p_{28} in the above equation, we obtain:

$$a = \frac{(y_{19} - y_{28})}{(x_{19} - x_{28})^2}$$

The parabolic equation for estimating the chin curve becomes:

$$\begin{aligned} y &= a(x - x_{28})^2 + y_{28} \\ &= \frac{(y_{19} - y_{28})}{(x_{19} - x_{28})^2}(x - x_{28})^2 + y_{28} \end{aligned}$$

Therefore, by substituting $y = y'_{25}$ into the parabolic equation, we obtained the x-coordinate for point p_{25}. A similar procedure was applied to the three remaining points: p_{26}, p_{27} and p_{29}.

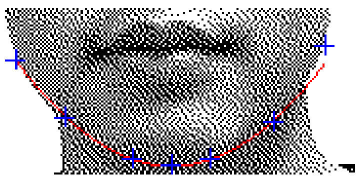


Figure 10: Chin curve estimation for detecting points p_{25}, p_{26}, p_{27} and p_{29}

Detecting Point p_{17} *:* Point p_{17} was detected after the eyes and mouth corners were determined. First, the nose region was estimated using the known eye and mouth corners positions in order to reduce the search area (as shown in Figure 11). Then, a horizontal integration projection was performed to find the y-coordinate of p_{17} , whereas the x-coordinate was exactly x'_{17} .

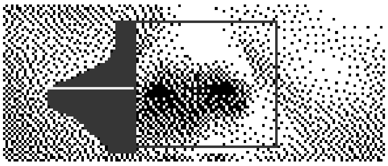


Figure 11: The result of detecting point p_{17}

After all of the selected feature points were located, as shown in Figure 12, a feature vector was calculated from the corresponding points on the actual face and on the mask. The idea was that individual faces are different; each has its own beautiful face. The difference between an original face and the corresponding beautiful face can be measured and thus used in the recognition of faces.

Figure 12: All feature points are located

For each point p_i on the actual face and the corresponding point q_i on the mask, we computed the Euclidean distance between them as:

$$d_i = \sqrt{(x_i - x_i^{'})^2 + (y_i - y_i^{'})^2} \,,$$

where $p_i = (x_i, y_i)$ and $q_i = (x_i^{'}, y_i^{'})$. The resulting feature vector for face representation is represented as:

$$X = [d_1, d_2, d_3, ..., d_{17}]^T$$

Face Recognition Model

A classification model was employed to match the images in the gallery to the query face image. For example, if we have an input image and want to identify this person, we can input the image query into the system. A neural network is a structure of simple processing units, called neurons, connected in a systematic way. In this research, we use a feed-forward neural network, known as a multilayer perceptron (as shown in Figure 13). Neurons in such a network are arranged in layers. There is one layer for input neurons (the input layer), one or more layers of internal processing units (the hidden layers), and one layer for output neurons (the output layer).

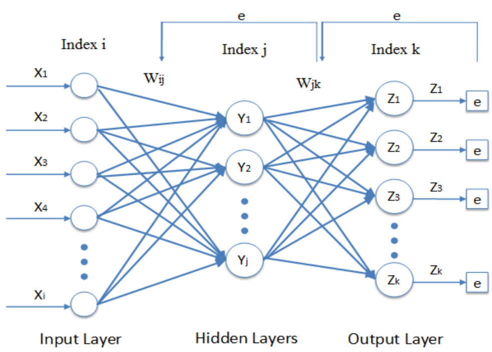


Figure 13: A multilayer perceptron

Each layer is fully interconnected to the preceding layer and the following layer. That is, each neuron in the input layer is connected to every neuron in the hidden layer, and each neuron in the hidden layer is connected to every neuron in the output layer. The connections between neurons have weights associated with them, which determine the strength of the influence one neuron has on another. Information flows from the input layer through the processing layer(s) to the output layer in order to generate predictions. By adjusting the connection weights during the training to match the predictions to the target values for specific records, the network learns to generate better and better predictions.

The training of a multilayer perceptron uses a method called back propagation of error, based on the generalized delta rule (Rumelhart *et al.*, 1986). For each record presented to the network during training, information (in the form of input fields) feeds forward through the network to generate a prediction from the output layer. This prediction is compared to the recorded output value of the training record, and the difference between the predicted and actual output(s) is propagated backward through the network to adjust the connection weights to improve the prediction of similar patterns.

A number of configurations have been studied according to the pruning approach (Thimm and Fiesler, 1995), where a large network is initially created and unhelpful hidden and input layers are pruned to a suitable architecture. We find that a suitable settings and parameters are: 17 input nodes, a single hidden layer with 20 hidden nodes, the number of output nodes equal to the number of people registered in the database, the sigmoid activation function, and the performance change tolerance between consecutive iterations less than 0.001 as the stopping criterion.

Experimental Evaluation

In this section, the proposed system is evaluated using actual face databases. The purposes are twofold: to study whether the set of features derived from facial attractiveness is effective in recognizing individuals and to study the performance of the system.

Facial Image Collections

The facial images used in our study are derived from two sources: AR (Martinez and Benavente, 1998) and our own facial database collected from students and staff at the National Institute of Development Administration (NIDA), Thailand. For the AR face database, 20 face images of 10 persons were selected according to our assumptions, as described in Section 3. In addition, 8 images which varied in size, illumination, and head pose were generated for each original image. For the NIDA face database, 600 images of 60 persons (10 images per person) were collected with minor differences in lighting condition, background, facial expression, size, and orientation. Figure 14 shows examples of the facial images used in our experiments.

Figure 14: Examples of facial images used in the experiments

In order to study the applicability of facial attractiveness to machine face recognition, we defined three datasets and performed experiments on each dataset separately. Dataset I contains facial images with relatively the same levels of attractiveness. Dataset II contains images with highly different levels of attractiveness, and Dataset III includes all facial images in the collection. Each dataset was divided into two subsets: the gallery (80%) and the probe (20%) sets. The images in the gallery set were used for training, whereas the images in the probe set were used for testing.

Dataset I: This dataset contains 200 facial images of 20 persons that have relatively the same attractiveness levels, i.e. the attractiveness values within $\pm 5\%$ of the mean value of the dataset, where the attractive value was determined by a norm of the feature vector. The gallery and probe sets contain 180 and 20 images, respectively. Figure 15 shows examples of the facial images in Dataset I.

Figure 15: Examples of facial images in Dataset I

Dataset II: This dataset is diverse in terms of facial attractiveness (distances between actual faces and their corresponding masks are largely different). This dataset comprises 200 images of 20 persons. It was divided into two subsets in the same way as Dataset I. Figure 16 shows examples of the facial images in Dataset II.

Figure 16: Examples of facial images in Dataset II

Dataset III: This dataset contains all of the facial images in the two databases, i.e., the entire collection. It comprises 700 images of 70 persons: 630 images in the gallery set and 70 images in the probe set.

Experimental Results

Table 1 summarizes the performance achieved by the system on different datasets.

Table 1 Recognition rates achieved by the system on different datasets

Data	Total persons/images	Recognition Rate
Dataset I	20/200	90%
Dataset II	20/200	100%
Dataset III	70/700	92.86%

The experiments resulted in a recognition rate of 98.86% for Dataset III, and 100% and 90% for Dataset II and Dataset I, respectively. Dataset II has a higher recognition rate (+10%) than does Dataset I. The results suggest that it is easier to recognize individual faces among those with largely different attractiveness levels than among those with relatively the same attractiveness levels. This supports previous findings, which suggest that distinctive faces are more easily recognized than those of typical faces (Baron, 1981), and attractiveness can help distinguish individuals from others. In Dataset III, where all of the images were used, and images with various attractiveness levels were mixed together, the recognition rate was less than with Dataset II, and the overall performance of the system was 92.86%.

Conclusion

Facial recognition has long captured the interest of various researchers, but both commercial and research systems are still far from perfect. In this paper, we propose a system for automatic facial using a novel set of facial features derived from facial attractiveness. For each facial image, a beautiful archetype was determined by the Golden Mask, which is effectively used in cosmetic surgeries. Features are calculated from the differences between points on an actual face and the corresponding points on the facial archetype. A neural network model was employed to create a facial recognition model. The architecture of the system consists of four main processes: facial region detection, facial image normalization, feature extraction, and the facial recognition model.

Experiments were performed in order to evaluate the effectiveness of the system. The results show that facial attractiveness affects the ability of the system to recognize individual faces, and the proposed system yields an overall recognition rate of over 92%.

Our proposed system works very well in 2D, nearly frontal and frontal mugshot-like applications, with minor variations in illumination, background, and facial expression. The research offers a new perspective on the utilization of facial attractiveness. The idea can be extended to suit more complex environments. In addition, the applicability of facial attractiveness in 3D facial recognition should be explored.

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