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A New Face Database of Asian Faces with Multiple Angles and Lighting Variations

Fanyu Diao

Beijing University of Posts and Telecommunications, Beijing, 100876, China

diaofanyu@bupt.edu.cn

Abstract. With the rapid development of face recognition technology, the demand for face databases in constructing various face-related models is increasing, along with higher requirements for database completeness and quality. However, the number of available databases containing Asian faces is limited, and the proportion of Asian faces in these databases is generally low. This situation somewhat restricts the accuracy of various models in applications involving Asian face recognition. Therefore, this paper proposes a face database specifically designed for the Asian face recognition. To achieve this goal, this paper meticulously setup shooting scenarios and recruited enough volunteers to participate in face image collection. Therefore, this paper collects successfully a new database that covers multiple angles and combinations of lighting variations of Asian faces. Experimental results show the potential of this database in Asian face recognition.

Keywords: Face Recognition, Deep Learning, Database, Computer Vision, Asian face recognition.

1. Introduction

The face, as one of the unique and defining features of the human body, contains a wealth of information and plays an important role in identity recognition and status assessment. In recent years, with the rapid advancement of imaging and artificial intelligence technologies, face recognition technology has revolutionized traditional identity verification methods. By enabling automatic detection and tracking, it allows for more efficient, convenient, and accurate analysis. Today, face recognition technology is widely applied across various aspects of daily life, from personal camera operation to identity verification in national security systems. It plays an increasingly vital role in safeguarding social security and providing convenient services, making it an indispensable part of modern society. Meanwhile, as social demands expand, face recognition technology continues to improve and evolve, gradually becoming an even more crucial technological component.Through in-depth research on face recognition technology and meticulous analysis of existing face databases, this paper summarizes the characteristics of existing databases and their acquisition methods, and on this basis, it exploratively constructs a new database specifically for Asian faces, adapting to different combinations of light and angle.

2. Literature Review

2.1. Theoretical framework

As early as the last century, many researchers began studying face recognition technology. However, due to limitations in image resources and network transmission, most of these studies focused on algorithmic development. Entering the 21st century, with the ongoing development and maturation of machine learning, several high-accuracy algorithms have emerged [1]. With advancements in image quality and expanded data availability, face recognition technology, leveraging deep learning, has achieved significant accuracy improvements. Currently, deep learning-based face recognition technology can be categorized into static and dynamic recognition. Building on static recognition, developments in dynamic recognition have further enhanced the scope and reliability of face recognition in complex real-world conditions [2].

The face recognition process based on deep learning mainly includes steps such as face preprocessing, feature learning, and feature comparison, with the feature learning phase being particularly critical. Through learning and extracting complex facial features from large volumes of face images, deep learning models can adapt to various challenging conditions and environments. This enhances recognition accuracy, improves robustness, and broadens the scope of application scenarios, making face recognition systems more stable and reliable in practical applications [3]. Unlike static objects, face recognition is affected by a series of uncontrollable factors such as age, posture, expression, and lighting. Therefore, selecting appropriate evaluation criteria is essential for advancing deep learning-based face recognition technology. This typically involves multiple facial features, including but not limited to the position and shape of the pupils and other facial features [4].

With the continuous advancement of deep learning-based face recognition technology, research trends have shifted from using multiple deep convolutional neural networks to extract features to employing a single efficient network. Representative models of this shift include VGGNet, GoogLeNet, and ResNet. VGGNet [5] successfully built deep convolutional neural networks with 16 to 19 layers by exploring the relationship between network depth and performance. This achievement demonstrated that increasing network depth can significantly enhance performance, effectively reduce error rates, and extend these improvements to other image datasets. The primary contribution of VGGNet lies in showing that using small convolution kernels can construct deeper network structures. By employing multiple small convolution kernels, VGGNet reduces the number of parameters while increasing nonlinear mappings, which greatly improves the network's fitting capacity. GoogLeNet [6] addresses the issue of excessive network parameters by enhancing the sparsity of the network structure. Its unique inception parallel structure allows feature matrices to be processed simultaneously across multiple branches, which are then concatenated by depth to produce the final output. Additionally, GoogLeNet incorporates 1×1 convolution layers within branches for dimensionality reduction and mapping, thus reducing the model's parameters and computational load. The network also introduces two auxiliary classifiers to assist training and replaces fully connected layers with average pooling layers, further decreasing model parameters. ResNet [7] employs a core strategy of adding cross-layer connections to directly learn the residuals between layers. It introduced an innovative residual learning structure, successfully building ultra-deep networks with over 1000 layers. This design enables ResNet to learn more complex and deeper image features, which is advantageous for detecting diverse and intricate objects in images. Furthermore, its residual structure effectively mitigates the vanishing gradient problem in deep networks, leading to greater stability during training. These architectural improvements have significantly enhanced accuracy on various datasets.

2.2. Existing Literature

As a data-driven method, deep learning-based face recognition relies heavily on large training datasets. The quality and development direction of the training set largely influence the progress of face recognition technology. Several mature face databases, such as CMU Multi-PIE, FERET, and AR, currently exist. To meet the requirements of various models and specific real-world applications, these

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databases emphasize different aspects such as facial expressions, facial occlusion, time span, and posture, and are widely used in face recognition research. While 2D face recognition technology is relatively advanced, challenges arise in 3D contexts where variations in facial angles and lighting conditions can significantly alter factors like facial shading and the actual positions of facial features, potentially leading to substantial accuracy drops in recognition [8]. However, existing databases are generally lacking in terms of comprehensive combinations of angles and lighting direction, and the associated models often lack adequate evaluation criteria and training under these variations. This may result in practical applications where areas with high brightness, shadows, or other lighting-induced changes on the face fail to be correctly detected by the recognition system or lead to misidentification [9]. Moreover, most current face databases predominantly feature Caucasian and male faces. Research has identified a "cross-race effect" in facial recognition algorithms [10], wherein Western algorithms recognize Caucasian faces more accurately than Asian ones, while Asian algorithms recognize Asian faces more accurately than Caucasian ones. This suggests that algorithms developed in different regions may lack generalizability, potentially resulting in lower accuracy for face recognition in certain populations. Consequently, there remain significant challenges in improving face recognition algorithms to handle complex lighting and angle variations and in recognizing Asian faces [11].

2.3. Research Content and Its Importance

Based on these findings, the construction of this database focuses on a comprehensive combination of facial angles and lighting directions, aiming to establish a face database specifically for Asian faces with balanced gender representation. This database is designed to enhance research on changes in facial appearance under varying lighting and angles to address current limitations in facial recognition algorithms regarding angle and lighting perception. A dedicated setting was built and personnel were recruited to carefully control variables such as time span, facial occlusion, and posture. By varying facial angles and lighting directions, realistic scenarios were simulated, resulting in a non-commercial collection of facial data.

The successful construction of this database compensates to a certain extent for the current lack of independent face database resources for Asian groups. The core of its innovation lies in the fact that it provides a novel solution to address the facial recognition challenges in complex natural scenes through well-designed multi-dimensional combinations of different lights and angles, and provides rich data support for the validation of face recognition algorithms' adaptability to the complex light and angle changes in daily life. Meanwhile, the clear research direction of this database provides a strong data base and reference for solving specific challenges in this field in the future.

3. Existing Face Databases

At present, there are many relatively mature databases designed to meet various requirements in terms of lighting, facial occlusion, facial expressions, and face angles. Notable examples include the CMU Multi-PIE face database, FERET face database, and AR face database.

3.1. CMU Multi-PIE Face Database

The CMU Multi-PIE face database [12] was developed at Carnegie Mellon University in the United States as an upgraded and expanded version of the original CMU-PIE database. Under strictly controlled conditions, the database utilizes a uniform static background and monitors subjects in real-time (see Figure 1). Over the course of four data collection sessions, it recorded facial states of 337 subjects in a static environment, capturing a range of factors including different lighting conditions, camera angles, facial expressions, and time variations.

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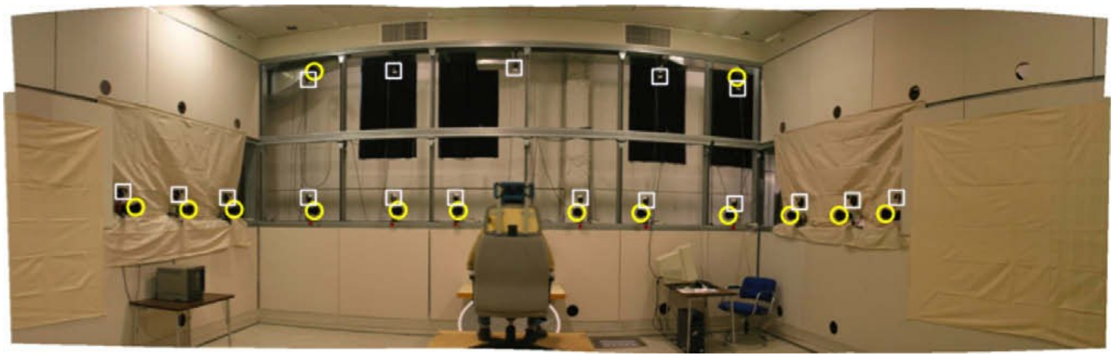

Figure 1. Data Collection Environment for the CMU Multi-PIE Face Database

The database focuses on capturing high-resolution facial images, which document subjects under varying expressions, angles, lighting conditions, and at different points in time (see Figure 2). To achieve this, the system is equipped with fifteen cameras and eighteen flashlights, all connected to a set of Linux PCs. Additionally, a separate computer serves as the main controller, responsible for manually adjusting camera positions and calibrating camera colors to ensure visual consistency across the images produced.

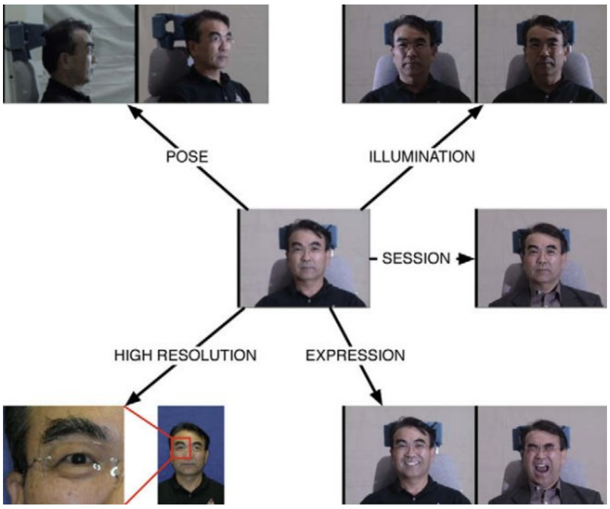

Figure 2. Content Captured in the CMU Multi-PIE Face Database

Ensuring that all images meet high-resolution standards, the database has accumulated over 750,000 images. Among the subjects, approximately 70% are male, about 60% are of European-American descent, and the overall average age is 27.9 years. This composition has demonstrated strong performance in model testing.

3.2. PERET Face Database

The PERET face database [13] is a project funded by the U.S. Defense Advanced Research Projects Agency (DARPA) focused on developing and evaluating automated face recognition algorithms and technologies. Today, it has become one of the most widely used face databases in the field of face recognition.

This database includes images of faces from both front and side views, with various expressions, multiple postures, and under different lighting conditions (see Figure 3). Each image is accompanied by a detailed identifier containing specific information about the conditions at the time of capture, such as the date and angle. Additionally, each photo in the database has been normalized, converted to grayscale, and standardized to a resolution of 80×80 pixels.

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Figure 3. Image Example from the PERET Face Database

The database includes 14,051 photos from 200 different individuals, with each individual photographed under seven different conditions. It is important to note that the majority of subjects are of Western descent, which somewhat limits the database's generalizability.

3.3. AR Face Database

The AR face database contains over 4,000 images [14], capturing 126 individuals under varying facial expressions, lighting conditions, and with facial obstructions (e.g., wearing sunglasses or scarves) (see Figure 4) . This database plays a crucial role in face recognition, deep learning model optimization, and image processing technology evaluation.

Figure 4. Single Subject Example from the AR Face Database

4. Setup for the Face Database

4.1. Shooting Environment Setup

Given that this database focuses on variations in facial angles and lighting angles, creating a high-quality shooting environment is crucial. For this purpose, a temporary face photo collection area was set up indoors. A white cloth was hung as the background, greatly reducing the influence of the background on facial lighting effects and minimizing potential interference with model training (see Figures 5 and 6).

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Figure 5. Face Image Collection Environment

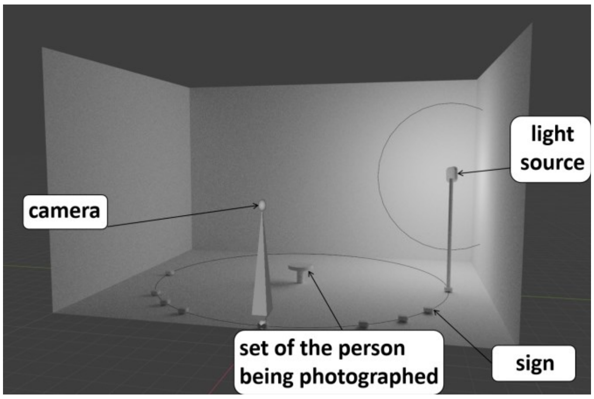

Figure 6. 3D Diagram of the Shooting Environment

Based on an in-depth study of existing face databases and a clear direction for building this database, 20 participants with Asian facial features were recruited for image collection.

To ensure a fixed position for each participant, a circle with a radius of 130 cm was marked around the participant, starting from the direct left side of the participant. Nine angles were marked on this circle at 0°, 30°, 45°, 60°, 90°, 120°, 135°, 150°, and 180°, enabling precise control over shooting and lighting angles (see Figure 7). A Canon EOS 800D camera was used with a focal length set to 35 mm, tailored to the collection environment to minimize facial distortion. During the shoot, photos were taken at seven horizontal angles (0°, 30°, 60°, 90°, 120°, 150°, and 180°) relative to the face, as well as four upward and downward angles (left upward, center upward, right upward, and center downward) (see Figure 8). To create varied lighting conditions, blackout cloths were used to block external light, while a single light source was moved to create nine lighting scenarios: front light, left-front light, left side light, left-back light, backlight, right-back light, right side light, right-front light, and top light (see Figure 9). Each participant's photo session lasted one continuous hour. Participants were instructed to sit upright, look forward, and maintain a neutral expression and steady posture throughout, so that any minor changes in facial expression or positioning could be considered negligible. Through different combinations of shooting angles and lighting angles, 39 distinct facial images were collected for each participant.

Figure 7. Actual Marking Diagram

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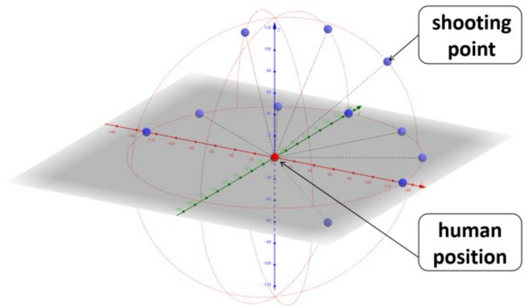

Figure 8. 3D Diagram of Shooting Positions

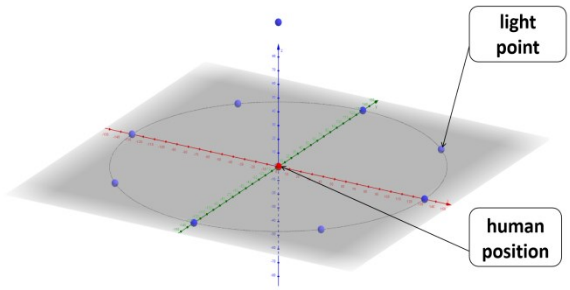

Figure 9. 3D Diagram of Light Source Positions

Among these 39 facial photos, variations can be observed in 11 angles under the same lighting direction (see Figures 10 and 11) as well as variations in 9 lighting directions at the same angle (see Figure 12).

Figure 10. Facial Changes at 7 Horizontal Angles Under the Same Lighting Direction

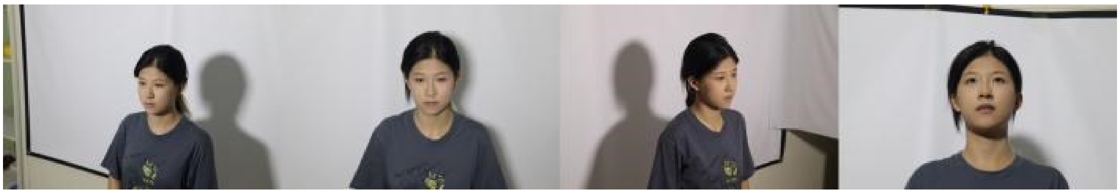

Figure 11. Facial Changes at 4 Different Angles in Space Under the Same Lighting Direction

Figure 12. Facial Changes Under 9 Lighting Directions at the Same Angle

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4.2. Data Collection

In the shooting environment designed above, this study successfully established a face database containing 20 participants with Asian facial features, with each participant having 39 photos, totaling 780 facial images. The 20 participants consist of 10 males and 10 females, with an average age of 31.15 years. The sample is primarily concentrated around the 20-year age range, with an age span from the youngest at 8 years old to the oldest at 73 years.

For each participant, the 39 photos cover the following conditions: under three main lighting conditions—front light, left side light, and right side light—11 different angles were captured, one photo for each angle. Additionally, at a horizontal direction of 90°, six additional photos were taken under specific lighting conditions: left-back light, left-front light, right-front light, right-back light, backlight, and top light.

For ease of management and usage, these 780 photos are stored in a layered folder structure. The first layer consists of 20 individual folders, one for each participant, with folder names following the format "ID-Gender-Age." The IDs are assigned in order, with females listed first, followed by males, organized by ascending age. Within each participant's folder, the 39 photos are named according to the format "Lighting Angle-Position," where "Position" uses a pure numerical value to represent the corresponding horizontal angle, and "P1," "P2," "P3," and "P4" represent the four special angles of left upward, center upward, right upward, and center downward, respectively.

This database is primarily oriented toward Asian populations and can be used for the training and optimization of face recognition systems. In practical applications, it enables face recognition by capturing three-dimensional non-frontal facial angle information, thereby improving the speed and efficiency of face recognition. Additionally, this database can be utilized to enhance techniques for automatic frontal face tracking, ensuring accuracy and quickly capturing 2D images with the most comprehensive facial information.

5. Analysis and Evaluation

5.1. Experimental Results

The face database was comprehensively evaluated using existing platform models, specifically Tencent Cloud's face similarity comparison service. For the evaluation process, five sets of photos were randomly selected from the 20 participants' photo collections for face similarity comparison, using a 100-point scoring scale. The results showed that most comparison scores were above 95 points, although a few individual scores were relatively lower. Specifically, only one participant's average score was slightly below 90, while the overall average score reached 96.1 (see Table 1), indicating that the quality of the self-built face database is generally reliable. Additionally, some interesting patterns were observed during the data comparison analysis. Compared to facial images with smaller angles of deflection and better lighting conditions, random combinations of images with larger face deflection angles or poorer lighting conditions tended to receive lower scores in face similarity comparisons. This finding suggests that further research should focus on face recognition under these specific conditions to improve and enhance current face recognition technology.

Table 1. Face Similarity Comparison Scores

Group	1	2	3	4	5	Average
1 female-19	100	98	100	89	100	97.4
2 female-19	96	54	100	98	93	88.2
3 femal-19	100	100	84	100	100	96.8
4 female-19	90	100	96	100	89	95.0
5 female-20	100	100	75	100	88	92.6
6 female-20	97	100	100	100	98	99.0
7 female-40	100	100	82	100	100	96.4

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Table 1. (continued).

8 female-44	100	97	100	67	97	92.2
9 female-45	100	100	100	98	100	99.6
10 female-73	100	87	100	100	100	97.4
11 male-8	100	100	98	100	91	97.8
12 male-19	98	100	100	100	84	96.4
13 male-19	100	100	75	100	90	93.0
14 male-19	100	100	85	98	100	96.6
15 male-19	98	100	100	88	100	97.2
16 male-20	100	100	100	89	100	97.8
17 male-27	91	100	100	100	100	98.2
18 male-48	100	100	100	71	100	94.2
19 male-56	100	100	91	100	98	97.8
20 male-70	97	100	100	100	94	98.2

Based on the evaluation results of the face similarity comparison(see Figure 13), it can be judged that the overall quality of this database basically meets the requirements of the model application. In order to further verify its quality, a PyTorch-based deep learning model specialized in facial recognition is used in the subsequent experiments. After making necessary adjustments and optimizations to this model, a new database containing Asian faces with multiple angles and light variations is introduced for testing.

The test results show that although the loss value of the model is high and the accuracy is low at the beginning of the training, the loss value gradually decreases and the accuracy is significantly improved as the training progresses. In the end, the loss value of the model was significantly reduced, while the accuracy reached more than 90%. This result shows that, despite some shortcomings, the overall quality of the database is still reliable and has the ability to be applied to various types of model training and detection.

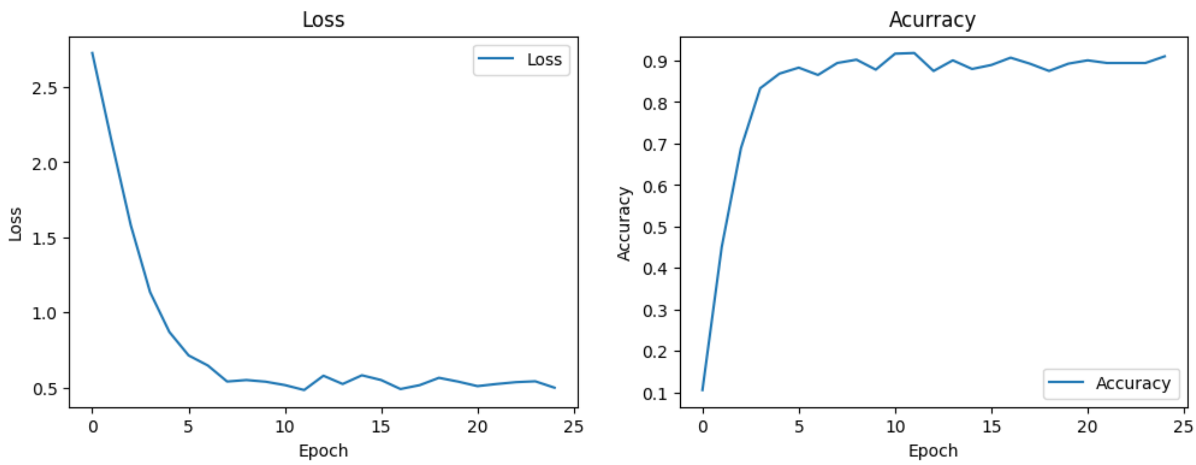

Figure 13. Model test results

5.2. Discussion

Given that this database emphasizes variations in facial images under different angles and lighting conditions, it can be applied in the development and testing stages of facial recognition models, aiming to optimize recognition accuracy for faces with large deflection angles or poor lighting conditions. This enhancement ultimately improves the overall performance of related technologies. The potential applications of this database are extensive, including but not limited to face comparison in surveillance systems, automatic frontal face tracking technology, daily operations of unmanned stores, facial identity verification at entry gates, and smart payment systems. These applications span key areas of social life such as security monitoring, transportation, retail, and education, providing practical convenience and security assurance for people's daily lives and work.

5.3. Future work

Considering the stringent quality requirements for face databases in facial recognition model construction, the database built in this study has certain limitations. Specifically, due to the relatively small sample size, the database is currently best suited for preliminary model testing rather than comprehensive model training. Therefore, in the future, we plan to expand the sample size and improve the overall quality of the database, making necessary additions and optimizations to better meet the practical needs of model development and research.

6. Conclusion

Through an in-depth investigation of existing face databases, this study identified several issues. Specifically, most databases rarely include facial images of Asian faces, and male representation is disproportionately high, which somewhat limits the performance of related models and applications. In response, this study constructed a new database focusing on Asian faces. A dedicated shooting environment was set up for the project, capturing 39 facial images under various lighting and angle combinations for each of 20 volunteers, with a balanced gender ratio of 1:1 and an age range from 8 to 73 years. Experimental results testing this face database demonstrated its effectiveness and accuracy, highlighting its necessity in improving face recognition performance for Asian faces. The study also explored future directions and challenges for this area of development.

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