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A Review of Face Recognition Technology

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ABSTRACT Face recognition technology is a biometric technology, which is based on the identification of facial features of a person. People collect the face images, and the recognition equipment automatically processes the images. The paper introduces the related researches of face recognition from different perspectives. The paper describes the development stages and the related technologies of face recognition. We introduce the research of face recognition for real conditions, and we introduce the general evaluation standards and the general databases of face recognition. We give a forward-looking view of face recognition. Face recognition has become the future development direction and has many potential application prospects.

INDEX TERMS face recognition, image processing, neural network, artificial intelligence

I. INTRODUCTION

FACE recognition is a subdivision problem of visual pattern recognition. Humans are recognizing visual patterns all the time, and we obtain visual information through our eyes. This information is recognized by the brain as meaningful concepts. For a computer, whether it is a picture or a video, it is a matrix of many pixels. The machine should find out what concept a certain part of the data represents in the data. This is a rough classification problem in visual model recognition. For face recognition, it is necessary to distinguish who the face belongs to in the part of the data that all machines think of the face. This is a subdivision problem.

Face recognition in a broad sense includes related technologies for building a face recognition system. It includes face detection, face position, identity recognition, image preprocessing, etc. Face detection algorithm is to find out the coordinate system of all faces in one image. This is the process of scanning the entire image to determine whether the candidate area is a face. The output of the face coordinate system can be square, rectangular, etc. The face position is the coordinate position of the face feature in the face detection coordinate system. The deep learning framework basically implements some current good positioning technologies. Compared with face detection, the calculation time of face positioning algorithm is much shorter.

In 2016, an artificial intelligence (AI) product called AlphaGo which was developed by a team led by DeepMinda's Demis Hassabis came out. And it beat Ke Jie who was the No. 1 player in Go level in May 2017. In October 2017, the DeepMind team announced the strongest version of AlphaGo, named AlphaGo Zero [1]. The essence of chess playing and face recognition is to find suitable transform function. Although their principles are the same, the complexity of face recognition transformation is far greater than the complexity of finding the optimal solution in the chessboard. We expect to find the ideal transformation function so as to achieve the optimal recognition effect, but the search process is very tough.

From the application layout of face recognition technology, it is most widely used in attendance access control [2], security [3] and finance, while logistics, retail, smartphone, transportation, education, real estate, government management, entertainment advertising, network information security [4] and other fields are starting to get involved. In the field of security, both the early warning of suspicious situations and the trace of suspects can be completed with the assistance of face recognition. It represents a great progress of artificial intelligence technology, which means that we require more accurate, more flexible and more faster recognition technology.

This paper will describe the development stages and related technologies of face recognition, including early algorithms, artificial features and classifiers, deep learning and other stages. After that, we will introduce the research on face recognition for real conditions. Finally, we introduce the general evaluation criteria and general databases of face recognition.

II. THE DEVELOPMENT STAGE OF FACE RECOGNITION AND RELATED TECHNOLOGIES

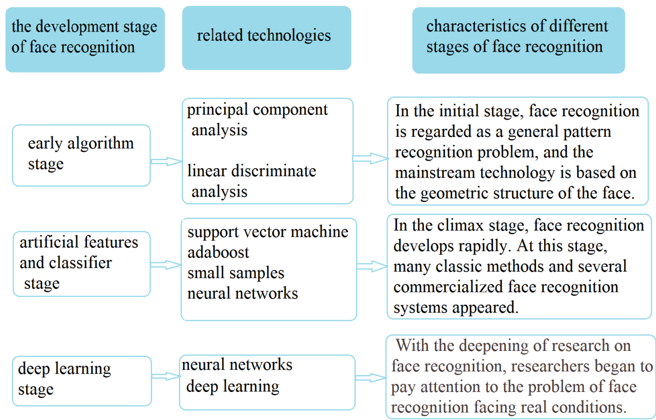

FIGURE 1: The development stage of face recognition, related technologies and characteristics of different stages of face recognition

A. EARLY ALGORITHM STAGE

In the 1950s, people began to study how to make machines recognize faces. In 1964, the applied research of face recognition engineering officially began, mainly using face geometry for recognition. But it has not been applied in practice.

1) Principal Component Analysis (PCA)

Principal component analysis (PCA) is the most widely used data dimensionality reduction algorithm. In face recognition algorithms, PCA implements feature face extraction. In 1991, Turk and Pentland of MIT Media Laboratory introduced the principal component analyses into face recognition [5].

PCA is usually used to preprocess the data before other analyses. In the face data with more dimensions, it can remove redundant information and noise, retain the essential characteristics of data, greatly reduce the dimensions, improve the processing speed of data, and save a lot of time and cost [6] [7]. Therefore, this algorithm is usually used for the dimensionality reduction and the multi-dimensional data visualization.

In PCA based feature extraction algorithms, the eigenface is one of the classical algorithms [8]. Figure 2 is a simple process of feature extraction where PCA is combined with face recognition by using K-Nearest-Neighbor (KNN) algorithm. We get the eigenvalues and the eigenvectors of the covariance matrix from sampling data, and select the principal component, which is the eigenvector with the largest eigenvalue.

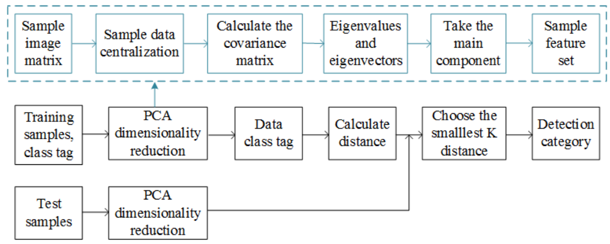

FIGURE 2: PCA is combined with KNN face recognition process

At the same time, the feature matrix of the testing data is obtained by the same dimensionality reduction process. Finally, the face image category of the testing set is detected by the KNN classifier.

Although PCA is efficient in dealing with large data sets [9]. Its biggest drawback is that its training data set must be large enough [10]. For example, the number of original photos in the face recognition system must be at least thousands, so the results of principal component analysis are meaningful. However, when the persons' facial expressions are different, there are obstacles blocking the face, or the light is too strong or too weak, and it is difficult to get good low-dimensional data.

2) Linear Discriminate Analysis (LDA)

For face recognition dataset with labels, we can use linear discriminate analysis (LDA) [11]. It is used to face classification [12]. PCA requires the data variance after dimensionality reduction to be as large as possible so that the data can be divided as widely as possible, while LDA requires the variance within the same category of data groups after projection to be as small as possible, and the variance between groups to be as large as possible [8], as is shown in Fig. 3. This means that LDA has supervised the dimensionality reduction and it should use the label information to separate different categories of data as much as possible.

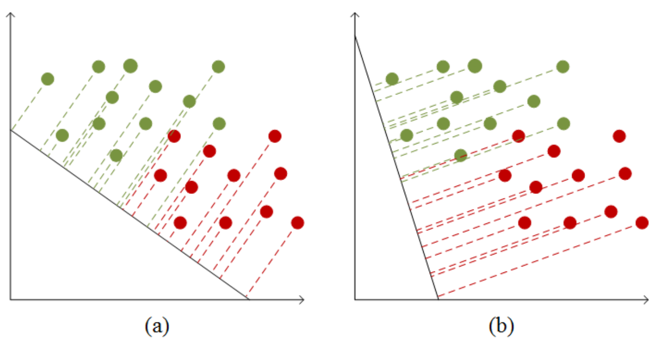

FIGURE 3: (Color online) Comparation between PCA and LDA. (a) PCA, (b) LDA

B. ARTIFICIAL FEATURES AND CLASSIFIER STAGE

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1) Support Vector Machine (SVM)

In 1995, the support vector machine (SVM) was proposed by Vapnik and Cortes. Support vector machine is an algorithm specifically for small sample, high dimensional facial recognition problem [13]. It is a classifier developed from generalized portrait algorithm. Because of its excellent performance in text classification, it soon becomes the mainstream technology of machine learning [14]. In face recognition, we use the extracted face features and SVM to find the hyperplane for distinguishing different faces.

Suppose there is a two-dimensional space with many training data. SVM should find a set of straight lines to classify the training data correctly. Due to the limitation of the number of training data, the samples outside the training set may be closer to the segmentation line than the data in the training set. So we choose the line furthest from the nearest data point, namely the support vector. Such a segmentation method has the strongest generalization ability, as is shown in Fig. 4. The above method distinguishes the data on two-dimensional plane, but this theory can also be applied to three-dimensional or even higher-dimensional space, only the boundary to be found becomes a plane or hyperplane.

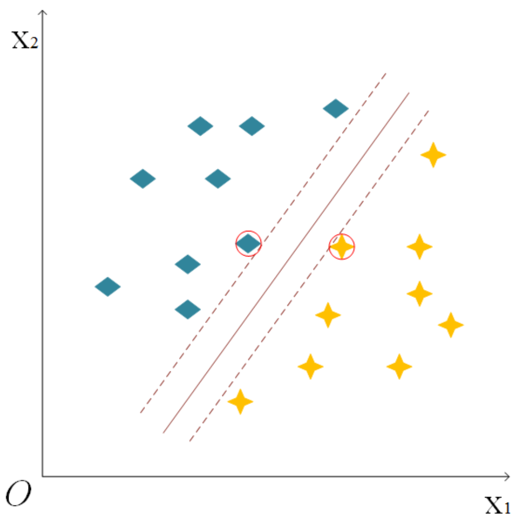

FIGURE 4: Support vector

2) Adaboost

The original boosting algorithm was proposed by Schapire. It is used for face detection. Boosting algorithm can improve the accuracy of any given learning algorithm. The main idea is to integrate different classifiers into a stronger final classifier through some simple rules so that the overall performance is higher [15].

There are two problems for face recognition in the boosting algorithm. One is how to adjust the training set, and the other is how to combine the weak classifier to form a strong classifier. Adaboost [16] has improved these problems, and it has been proved to be an effective and practical boosting algorithm in face recognition. Adaboost uses the weighted training data instead of randomly selected training samples to focus on the relatively difficult training data samples. Adaboost uses the weighted voting mechanism instead of the average voting mechanism which makes the weak classifier with good classification effect have larger weight [17].

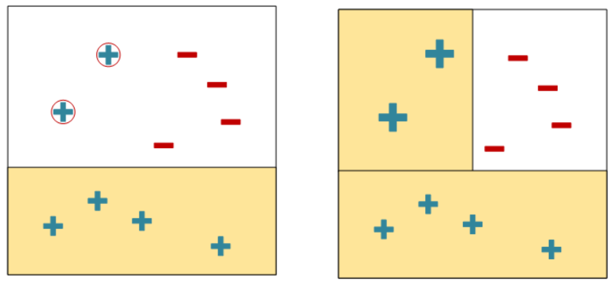

FIGURE 5: (Color online) Adaboost adjusts the sample weight. (a) The result of the first classification, and wrong samples are marked with red circle. (b) The classifier which is retrained after adjusting the weight of the first misclassification sample.

Adaboost classifier can be understood as a function (please see Fig. 5). It inputs the characteristic value x and returns the value $G(x)$. In the adaboost classifier, multiple weak classifiers G_i are combined into a strong classifier, and each weak classifier has weight w_i , which is shown as follows

$$G(x) = sign(\sum_{i=1}^{n} w_i * G(x_i))$$

In face recognition, using the adaboost algorithm should take Haar features for each image. This feature reflects the gray level change of the image [18].

Haar classifier is a cascading application of the adaboost algorithm [19]. The structure of the cascade classifier is shown in Fig. 6. Each cascading classifier contains several weak classifiers, and the structure of each weak classification is also a decision tree. Figure 7 shows a weak classifier in the form of decision tree to determine whether a picture is a face.

3) Small samples

The small sample problem refers to the fact that the number of training samples for face recognition is too small, which causes most face recognition algorithms to fail to achieve their ideal recognition performance [20].

In order to effectively retain image information, maintain the relationship between samples, reduce the impact of noise, and further enhance the face recognition effect, many studies have been done. Howland et al. proposed a method which combined the linear discriminant analysis with generalized singular value decomposition (GSVD) to solve the small samples size problem [21]. He et al. presented a way to improve the performance of linear discriminant analysis methods on small samples by using the Householder QR decomposition process in different spaces [22]. Wang

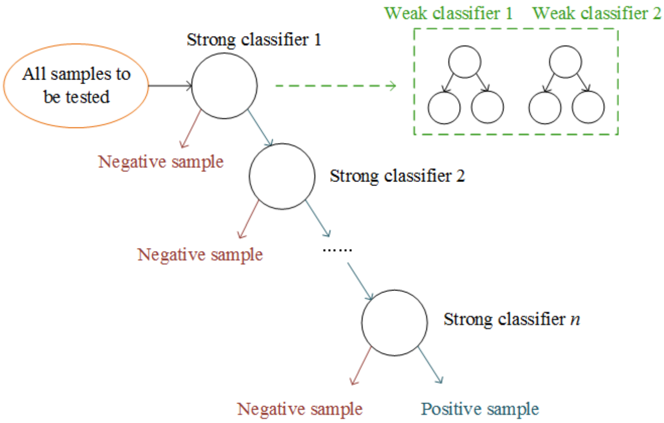

FIGURE 6: Adaboost cascading structure

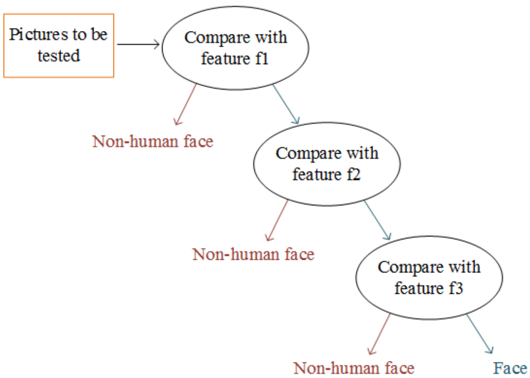

FIGURE 7: Tree structure of the weak classifier

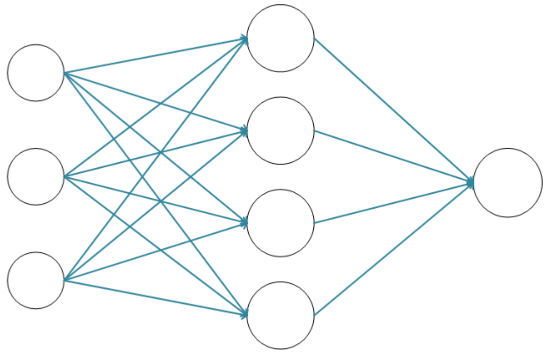

FIGURE 8: (Color online) Structure of single layer hidden layer neural network. The left is the input layer, the middle is the hidden layer and the right is called the output layer. Here, the output layer has only one output neuron or multiple output neurons.

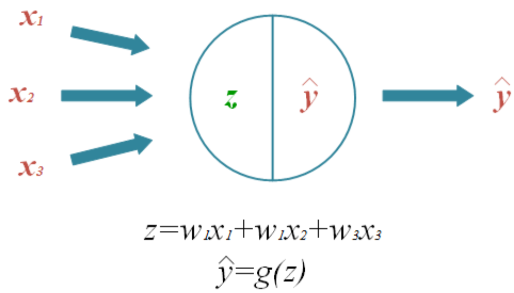

FIGURE 9: The neuron of neural network. The linear function here refers to that each neuron links the transmitted signal with weight $(z(x) = wx + b)$, while the activation function deals with the output of the neuron. The ideal activation function will map the result to '0' or '1'. Early, the Sigmoid function is more popular, and it can squeeze the output in a large range into the range of [0,1]. Now the most commonly used function is the rectified linear unit (ReLu).

et al. proposed a exponential locality preserving projections (ELPP) method for the small sample problem faced by the locality preserving projections (LPP) technology [23]. Wan et al. proposed a generalized discriminant local median preserving projection (GDLMPP) algorithm based on DLMPP [24], which can effectively solve the small sample size problem. These studies have greatly improved the performance of facial recognition.

4) Neural networks

Neural network is an algorithm designed to simulate human brain for face recognition [25]. As one of the most concerned recognition methods for biometrics, face recognition has become one of the research focuses in the field of neural networks.

A typical neural network structure is shown in Fig. 8. Each neuron is composed of a linear function and a nonlinear activation function, as is shown in Fig. 9.

C. DEEP LEARNING

Deep learning is a branch of machine learning. Deep learning can find out the features needed for classification automatically in the training process without feature extraction steps. That is to force network learning to obtain more effective features for distinguishing different face. The field of face recognition has been completely transformed by deep learning [26]. Deep learning is widely used in face recognition and is divided into the following aspects.

A face recognition method based on convolutional neural networks (CNN) is the first aspect. CNN uses the locality of data and other features to optimize the model structure by combining local perception areas, shared weights, and down-sampling of face images [27]. CNN is very similar to ordinary neural networks. They consist of neurons with learnable weights and bias values. A dot product calculation for each neuron is performed after receiving input data. Then output the scores of each classification. It is the most widely used deep learning framework [28] [29]. Figure 11 [30] clearly delineates the structure of CNN [31].

Deep nonlinear face shape extraction method is the second aspect. Face shape extraction or face alignment plays a very important role in tasks such as face recognition, expression

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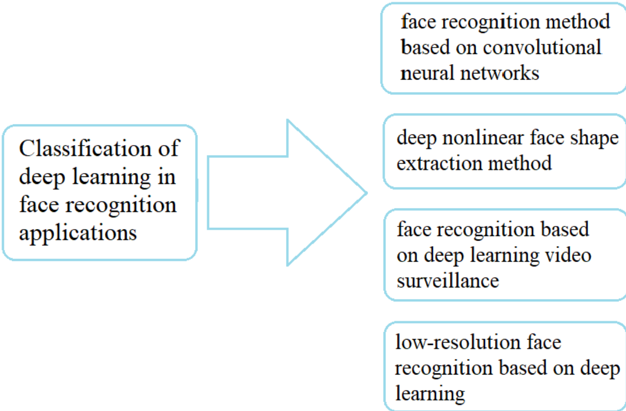

FIGURE 10: Classification of deep learning in face recognition applications.

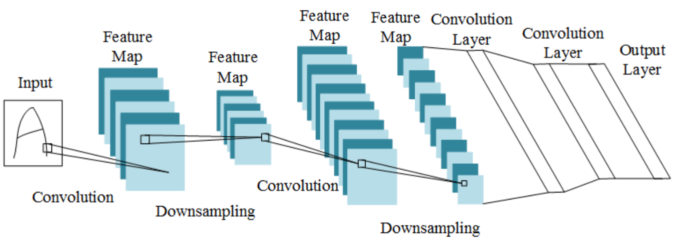

FIGURE 11: (Color online) The structure of CNN. CNN is composed of input layer, convolution layer, pooling layer (lower sampling layer), full connection layer and output layer. And the convolution layer and the pooling layer are alternately set.

recognition, and face animation synthesis. The difficulty in face recognition lies in the high complexity of face shape and texture. In order to further improve the nonlinear regression ability of the algorithm to obtain robustness to changes such as shape, Zhang et al. [32] proposed a deep nonlinear face shape extraction method from coarse to fine (coarse-to-fine auto- encoders networks, CFAN).

Face recognition based on deep learning video surveillance is the third aspect. In an intelligent monitoring environment, the identification of suspicious characters is an important use of face recognition. Recognizing the identity of people in video accurately and quickly is very important for video search and video surveillance. Schofield et al. proposed a deep convolution neural network method, which could automatically detect, track and record human faces in video, and could be used to study the animal behavior [33] [34].

Low-resolution face recognition based on deep learning is the fourth aspect. In practical applications, the collected face images have a variety of posture changes, and the image resolution is low, causing the face image recognition performance to decline rapidly. In [35], the low-resolution face

TABLE 1: Classification of face recognition based on real conditions

classification of face recognition based on real conditions	different influence conditions in face recognition	common techniques
study the factors that affect face recognition	non-ideal condition	PIE problem
the study of using the new feature representation	feature extraction	manual design features, NMF
the study of using new data sources	obtain data sources	GAN

data set was studied, the most advanced supervised discriminant learning method was adopted, and the generative confrontation network pre-training method and full convolution structure were introduced to improve the low-resolution face recognition effect. Many deep learning models focus on the optimization of training methods and processes. However, the accuracy of low-resolution face recognition is constantly improved, and the running time is also reduced accordingly, so that it can be better put into practical applications.

With the development of more comprehensive deep learning models [36] [37] [38] [39], there are not only deep models that can adapt to large-scale data, but also processing methods that can adapt to the small data set in some specific scenarios. One method is to use synthetic data, the other one is to use the currently popular generative adversarial network to generate the data [40]. However, deep learning also has some shortcomings. For example, it takes long time to train the model, which requires continuous iteration to optimize the model, and it cannot guarantee the global optimal solution. These are also needed to be explored in the future.

III. FACE RECOGNITION BASED ON REAL CONDITIONS

With the deepening of the research on face recognition, the researchers began to pay attention to the face recognition problem in real conditions, mainly including the following aspects of research. First, we analyze and study the factors that affect face recognition. Second, the study of using the new feature representation. Third, the study of using new data sources. As is shown in Table 1.

A. FACTORS AFFECTING FACE RECOGNITION

1) PIE problem

At present, the face recognition technology has been quite mature under the condition of controllable illumination and little intra class change. However, the performance of face recognition in non-ideal condition is still needed be improved. PIE problem [41] is the non-ideal condition that face recognition should solve especially the problem of variable illumination, posture and expression. The researchers proposed a method based on invariant features, which used the features of the face image that did not vary with the change of lighting conditions to process, that is, to find the light insensitive features [42] [43] [44] [45] [46]. At present, the representative method is the quotient image (QI) [46]. In addition, a 3D linear subspace can be used to represent the

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face image with light change without considering shadow. The typical method is the light cone method [47].

Due to the difference of human posture, the facial expression features extracted from the non-positive face image and the positive face image collected by the researchers will also be quite different. If we do not deal with the attitude factors, it will inevitably affect the accuracy. According to different features processed in the attitude normalization, Zhu et al. [48] divided facial expression features into two methods, i,e. feature level normalization method [49] [50] and image level normalization method [51].

There are some new research results recently. In 2017, Xi et al. proposed a multi-task CNN for face recognition based on multi-task learning. They proposed a pose-directed multi-task CNN by grouping different poses to learn pose-specific identity features, simultaneously across all pose [52]. Mahantes et al. proposed a transform domain approach to solve the PIE problem in face recognition [53]. Zhang et al. proposed a supervised feature extraction algorithm named collaborative representation discriminant projections (CRD-P) [54]. Huan et al. proposed an end-to-end network to generate normalized albedo images with neutral expression and frontal pose for the input face images [55]. With the research on the factors affecting face recognition, face recognition technology has been greatly improved.

B. USE NEW FEATURE REPRESENTATIONS

1) Manual design features

In a constrained environment, deep learning can learn face features, which can make complex feature extraction easier, and can learn some hidden rules and rules in face images.

One facial feature is Local Binary Patterns (LBP). Ojala et al. proposed the Local Binary Patterns (LBP) in the research of texture image classification [56]. In 2004, Ahonen et al. [57] used LBP to extract face image features, which started the research of LBP in face recognition. Tan et al. proposed Local Ternary Patterns (LTP) [58] for the noise sensitivity of LBP. Wolf et al. [59] proposed three local binary patterns and four local binary patterns to capture the differences between the local small areas of the face image. LBP based face image features also include poem [60], le [61], lark [62], lhs [63], etc.

Another typical face feature is Gabor feature. Daugman first presented the Gabor wavelet theory in 1985 [64]. Elastic bunch graph matching [65] is the first research work to extract facial features by using Gabor filter. It extracts Gabor filter convolution response at key points, and obtains good expression, posture and noise robustness. Liu et al. [66] also used Gabor filter to extract face image features. This method does not need to detect key points, but directly uses Gabor filter to extract multi-scale and multi-directional features in each pixel position of face image, and obtains better recognition effect. In addition, the famous scale invariant feature transform (SIFT) [67] and the histogram of the oriented gradient (HOG) [68] have been applied to the feature extraction of face recognition [69] [70] [71] [72].

2) Nonnegative Matrix Factorization (NMF)

The nonnegative matrix factorization algorithm (NMF) was proposed by Lee and Seung in 1999 [73]. NMF realizes the application of matrix decomposition in digital image processing and realizes the feature decomposition in face recognition.

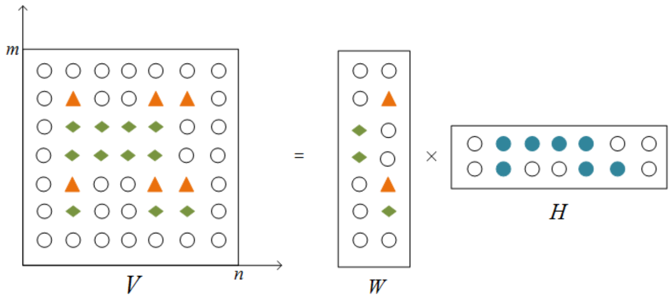

FIGURE 12: The nonnegative matrix factorization algorithm (NMF). Among them, V is the original matrix, W is the base matrix, and H is the feature matrix.

As is shown in Fig. 12, the idea of NMF is to divide a matrix into two matrix products. One matrix is the base matrix, and the other matrix represents the characteristic matrix. From the dimension reduction point of view, these two matrices are determined by NMF itself at the same time, so the feature matrix is not the projection of the original matrix on the base matrix, and NMF realizes nonlinear dimensionality reduction.

At present, NMF has been successfully applied in the image for face recognition [74] [75] [76] [77] [78] [79]. Using some new functional representations, the application of face recognition technology has been improved.

C. USE NEW DATA SOURCES

1) Adversarial sample attack

Traditional face recognition methods can be easily trained and learned in small-scale data, such as PCA and LDA. But for massive data, the training process of these methods is difficult. Adversarial samples can obtain data sources for face recognition. The so-called adversarial sample is to slightly modify the input data so that the face recognition algorithm gives wrong classification results to the input [80]. In many cases, these changes are so subtle that human observers will not even notice them, but the classifier will make mistakes. Moreover, the attacker can attack the machine learning system and disturb the result without knowing the basic model of face recognition. As is shown in Fig. 13, taking the classic bi-classification problem as an example, the machine learning model learns a segmentation plane by training on the samples in face recognition.

At present, generative adversarial networks (GAN) are one of the effective ways to resist attacks. Generative adversarial network was proposed by Ian Goodfellow in 2014 [81]. It was applied to deep learning neural network. As is shown in Fig. 14, GAN is a generative model. It is most commonly used for

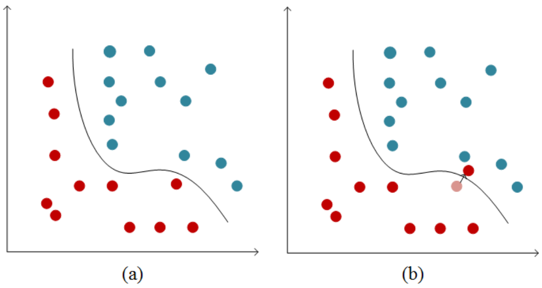

FIGURE 13: (Color online) Principle of the adversarial sample attack. The points on one side of the segmentation plane are recognized as Category 1, and the points on the other side are recognized as Category 2. When generating attack samples, we use some algorithm to calculate the change amount for the specified samples.

image generation on data generation. GAN is also a model of unsupervised learning, so it is widely used in unsupervised learning and semi-supervised learning [82] [83]. At present, an interesting application is to use GAN in image style migration, image noise reduction and repair, image super-resolution, which have better results in face recognition. Using new data sources, face recognition technology under real conditions has been continuously studied.

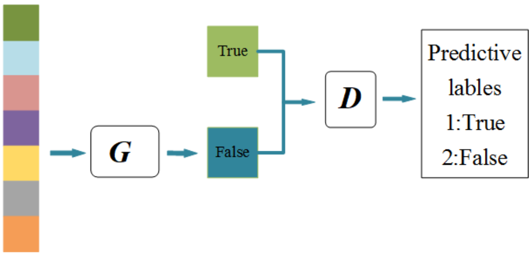

FIGURE 14: The model of GAN. The main functions of G and D are presented as follows. G is a generative network, which receives a random noise z and generates an image through this noise. D is a discrimination network, which judges whether a picture is "real". Its input parameter is x, which represents a picture, and the output $D(x)$ represents the probability that x is a real picture. If it is 1, it represents 100% of the real picture. If it is 0, which represents the impossible picture.

IV. COMMON EVALUATION CRITERIA OF FACE RECOGNITION

Accuracy (ACC), Receiver Operating Characteristic (ROC) curve and Area Under Curve (AUC) value are important indexes to evaluate the performance of the face recognition algorithm [84]. In face recognition tasks, ACC is a common index. Assuming that the testing set contains N images and the number of correctly recognized images is M. The definition of ACC is given as follows

$$ACC = M/N$$

The higher the ACC value is, the better the algorithm performance is. In the face recognition task, in order to determine whether two images (also known as sample pairs) come from the same person, ROC first calculates the distance measurement or the similarity between images, and then completes the recognition according to the threshold. The abscissa of ROC curve represents false positive rate (FPR), and the ordinate represents recall rate or true positive rate (TPR) [85]. The definitions of FPR and TPR are given as follows

$$TPR = TP/(TP + FN)$$
$$FPR = FP/(FP + TN)$$

TP refers to the positive sample pair correctly predicted by the model, FN refers to the positive sample pair wrongly predicted by the model, TN refers to the negative sample pair correctly predicted by the model, and FP refers to the negative sample pair wrongly predicted by the model. By changing different thresholds, different TPR values and FPR values can be obtained, and ROC curves can be generated (https://blog.csdn.net/). As is shown in Fig. 15, red curve and blue curve respectively represent the $TPR-FPR$ curve of two different classifiers, and the point on the curve corresponds to a threshold value, which is ROC curve. The closer the ROC curve is to the upper left corner, the better the performance of the algorithm is. In other words, it can achieve a high recall rate when the error recognition rate is very small. AUC value is a scalar to measure the merits of the model, which refers to the area below the ROC curve. Obviously, the larger the AUC value is, the better the performance of the algorithm is (https://blog.csdn.net/).

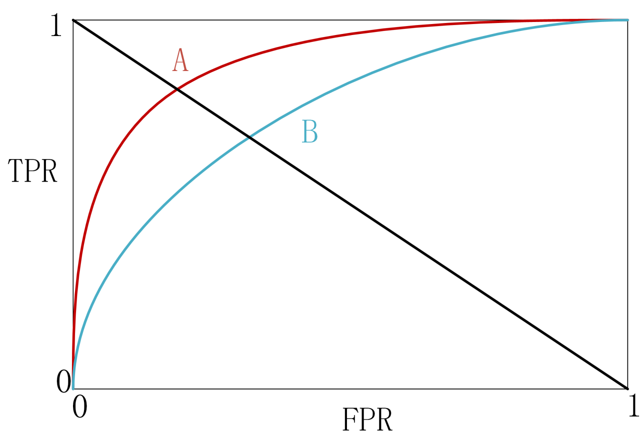

FIGURE 15: $TPR - FPR$ curve of two different classifiers

V. IMAGE EVALUATION SETS AND DATABASES OF FACE RECOGNITION

LFW is a public benchmark for face recognition, also known as pair matching. In Table 2, we get the performance of some famous algorithms on LWF website (http://vis-www.cs.umass.edu/lfw/).

TABLE 2: Face recognition on the dataset

Method	Face recognition (%)	Method	Face recognition (%)
Deep Face [86]	97.35	FaceNet [87]	99.63
DeepFR [88]	98.95	DeepID2+ [89]	99.47
Center Face [90]	99.28	Baidu [91]	99.13
SphereFace [92]	99.42	VGGFace [88]	99.13
Face++ [93]	99.50	FR+FCN [94]	96.45
DeepID [95]	97.45	GaussianFace [96]	98.52
DeepID2 [95]	99.15	DeepID3 [97]	99.53
YouTu Lab, Tencent [98]	99.80	PingAn AI Lab [98]	99.80
yunshitu [98]	99.87	Deepmark [98]	99.23
Camvi [98]	99.87	Innovative Technology [98]	99.88
Fisher vector faces [99]	93.03	CMD+SLBP [100]	92.58
Simile classifiers [101]	84.72	DFD [102]	84.02
LBP PLDA [103]	87.33	LBP multishot [104]	85.17

TABLE 3: Common face image databases

Database	Number of people	Number of samples	Image changes	Degree of difficulty
Yale A	15	165	Expression, simple illumination	Simple
AR	100	2600	Illumination, expression,shelter	General
Extended Yale B	38	2414	Different degrees of light	More difficult
Georgia Tech	50	750	Posture,expression	General
FERNT	1196	13539	Posture,age,expression, illumination,race	difficult
LFW	5749	13233	Posture,age,illumination, shelter,visual angle, scale	difficult
CAS-PEAL-R1	1040	9060	Posture,expression, decoration,age, background,distance	difficult

As is shown in Table 3, there are seven common face image databases, including Yale A, AR, Extended Yale B, Georgia Tech, FERET, LFW and CAS-PEAL-R1 [105] [106]. These databases have greatly promoted the progress of face recognition technology.

Yale A [107] is a simple database, which contains 165 images from 15 persons. The AR database [105] contains 2600 images of 120 persons. The image in the Extended Yale B database [108] contains 9 postures and 64 light changes. The database is divided into 5 subsets according to the angle between the light direction and the camera axis. Georgia Tech database [109], established by Georgia Institute of technology, contains 750 images from 50 persons. The FERNT database [85], published by the National Institute of standards and technology, contains 13539 images from 1565 individuals and six subsets. LFW is one of the most important face image evaluation sets in the field of face recognition. It was released by the Computer Vision Laboratory of the University of Massachusetts in 2007 [110]. LFW database [111] is a more complex and challenging face image database, and it is mainly used for face recognition in uncontrolled environment. LFWa [112] is an alignment version of LFW database, in which the images are aligned by commercial software. MegaFace is also one of the most authoritative and popular indicators to evaluate the performance of face recognition [113]. Even though the evaluation of MegaFace still does not calculate the time cost, compared with LFW data set, MegaFace is more difficult and closer to practical applications [114] [115]. The CAS-PEAL-R1 database [106] was established and released by the Chinese Academy of Sciences. In September 2018, Sogou image technology team won the first place in the competition with 99.939% recognition accuracy. In this MegaFace competition, the massive and high-quality face image resources accumulated by Sogou image search, and the powerful computing platform of Sogou also provides data guarantee and computing power guarantee for recognition effect [116] [117].

VI. CONCLUSIONS

With the development of science and technology, the face recognition technology has made great achievements, but there is still room for its improvement in practical application. In the future, there may be a special camera for face recognition, which can improve the image quality and solve the problems of image filtering, image reconstruction [118], [119], denoising [120]–[122] etc. We can also use 3D technology to supplement 2D images to solve some problems such as rotation and occlusion.

VII. FUTURE WORK

Face recognition technology has been widely used in security and financial fields because of its convenience. With the rapid development of science and technology, the application of faces will be more developed, and the application scenarios will be more diverse. However, face recognition will easily cause technical, legal, and ethical problems. Due to the automated features of face recognition technology, similar related information may be processed or decided through automation, lacking transparency and not easy to supervise, and even in the event of errors or discrimination. It is difficult to trace back. For example, the face recognition information is used to achieve non-recognition purposes such as judging an individual's sexual orientation, race, or religion. How to enhance the interpretability of algorithms to avoid discriminatory algorithms or incomplete information that will lead to decision errors? How to promote the development of new technologies related to face applications while ensuring public safety and personal rights? These problems remain to be discussed in depth.

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AUTHOR CONTRIBUTIONS

L. Li and X. Mu wrote the paper. S. Li and H. Peng modified the paper.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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