Research on Face Recognition Technology Based on Real-World Application Scenarios

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Abstract: Face recognition technology is widely used in various fields has received extensive attention from researchers. This study classifies and summarizes different face recognition methods based on real life. In more detail, this paper is categorized into: masked face recognition and non-masked face recognition according to their application significance. First, each type of face recognition method is summarized and retrospectively compared based on the time series of development. Second, different face recognition methods are implemented based on the same de-emphasized dataset, and the recognition accuracy and execution time of each method are derived. The advantages and disadvantages of different methods are analysed and compared with the basic criteria of these two data metrics. And the experimental data results are visualized for more detailed analysis. The experimental results show that face recognition performance can be improved by introducing deep learning techniques. Therefore, the future direction of face recognition research should be to explore how to integrate different types of face recognition methods to achieve maximum efficiency. This study summarizes the face recognition methods from practical application scenarios, which has certain reference value for enterprises and related technicians.

1 INTRODUCTION

Face recognition technology is a means of identity verification through the extraction of facial features, and in recent years has become an area of significant research in various fields including artificial intelligence, computer vision, and psychology (Su, 2016). Other biometric features of the human body, such as iris and fingerprints, have been widely used for authentication and identification over the past decade (Su, 2016). As a physiological feature, the human face has similar special properties as iris and fingerprints. The face has uniqueness, consistency and a high degree of non-replicability (Zhi-heng, 2018). Those properties provide stable conditions for identification. The application scope of face recognition technology continues to expand, encompassing various domains such as criminal investigation, intelligent transportation systems, access control in physical environments, and internet services. Unlike traditional disciplines, face recognition requires a multidisciplinary approach, integrating concepts from computer vision, psychology, and related fields. This underscores the importance of a comprehensive understanding of diverse knowledge domains in the study of face recognition technology.

Initially, during the nascent stages of face recognition research, scholars delved into the structural delineations of facial contours, primarily exploring the silhouette curve of the face (Amarapur, 2006). This foundational exploration set the stage for subsequent advancements. Subsequently, the field witnessed a surge in development as elastic graph matching algorithms emerged as a pivotal technique for face recognition (Bolme, 2003). Concurrently, a gamut of 2D face recognition techniques burgeoned, ranging from linear subspace discriminant analysis to statistical epistemic models and statistical model recognition methods (Liao, 2003). However, recent years have ushered in a shift in focus towards real-world applications of face recognition, prompting researchers to confront the challenges posed by practical scenarios. Based on real-life application scenarios, face recognition technology has evolved from initially only recognizing unobstructed faces to

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later recognizing faces with obstructions such as sunglasses and masks. Initially, Amarapur and Patil proposed a relatively simple conventional accessible face identification method on the basis of facial geometric features, but the accuracy of this method is relatively low. Subsequently, Mu and Yan proposed a face recognition method based on algebraic features, which is relatively more tolerant to changes in light and facial expressions (Yanmei, 2016). After that Liao and Gu proposed a subspace-based face recognition method SESRC&LDF, which further improves the accuracy of unobstructed face recognition (Malassiotis, 2005). After that, several scientists proposed a face recognition method which is based on bimodal fusion, which is a state of the art occlusion-free face verification method (Guan, 2010). In recent years, due to the prevalence of new coronaviruses, people wear masks more frequently in their daily life. As a result, there is an increasing demand for the mask-based face identification technology by the society, which promotes the enhancement of the mask-based face recognition technology. Guan et al. have proposed a new exterior-based face verification method, tensor subspace regression (TSR) (Li, 2013). Li et al. have proposed a structural coding-based method to further improve the precision rate of masked face identification (Kunming, 2005). As the technology developed further, the "shallow" feature extraction based method proposed by Li et al. improved the speed of masked face recognition (Prasad, 2020). The deep learning based face recognition method proposed by Prasad et al. is among the most widely used face verification methods (Adjabi, 2020).

The primary objective of this study is to categorize face recognition methods into two distinct categories based on their practical usage scenarios: unobstructed face recognition and obstructed face recognition. Additionally, this study aims to summarize the key methods associated with each category, tracing their developmental history. In a more detailed analysis, first, unobstructed face recognition is categorized into traditional unobstructed face recognition and modern unobstructed face recognition based on its development history. Similarly, this study classifies covert face recognition into traditional concealed face recognition and modern concealed face recognition. Next, the core technologies contained in these four categories are analyzed and introduced respectively. Finally, this study discusses the advantages and disadvantages of the key technologies contained within face recognition as well as the prospects for future development. This study fills the gap of sorting out and learning about face recognition technologies from a practical point of view, and provides a reference for selecting appropriate face recognition systems for real-life individuals as well as enterprises.

This chapter begins with a background introduction and a review of previous work in related fields, along with a brief description of the research objectives and methodology of this paper. Secondly, chapter 2 introduces the core concepts as well as the principles of the approaches taken in each classification according to the categorization of occluded face recognition and unoccluded face recognition in the order of development. After that, the results of the study are analyzed and discussed in Chapter 3. Finally, a summary of the entire study is presented in Chapter 4.

2 METHODOLOGIES

2.1 Dataset Description and Preprocessing

The main datasets involved in this study include the Yale Face Database B, the Olivetti Research Laboratory (ORL) face dataset, the Augmented Reality (AR) face database, and the Multi Modal Verification for Teleservices and Security (XM2VTS) face database. The Yale Face Database B contains approximately 5,760 facial images of subjects in different lighting conditions and different postures. The ORL face dataset was created by Olivetti's lab in Cambridge, United Kingdom, and contains 400 facial images in Portable Gray Map (PGM) format taken by 40 different subjects at different times, under different lighting, different facial conditions, and different facial details. These images all have the same height and width. The AR face database contains more than 4000 face images from 126 different subjects, about 26 images per person, in 24-bit color at 576*768 pixels. The images in this database are frontal face images with variations in expression, lighting, and occlusion. The XM2VTS database is derived from the European Union's Ability and Competence Test System (ACTS) program, which handles access control and thus improves the efficiency of access through the use of multimodal recognition of faces. The database contains frontal face images of 295 subjects when they are speaking and when they are rotating their heads (Li, 2018).

2.2 Proposed Approach

Based on the practical application scenarios of face recognition techniques, this study divides them into two categories: unobstructed face recognition and obstructed face recognition. This study traces the representative methods in each category according to the time series and analyses them comparatively. Specifically, first, occlusion-free face recognition is divided into traditional occlusion-free face recognition methods and modern occlusion-free face recognition methods. According to the chronological order of its development, the geometric feature-based face recognition methods are searched first. Then, the methods based on algebraic features that appeared afterwards are searched. For modern occlusion-free face recognition methods, firstly, a face recognition method based on feature subspace is introduced. Secondly, a method based on bimodal fusion is proposed. Similarly, the occluded face recognition methods are classified into: traditional methods and modern methods. For the traditional occluded face recognition methods, firstly, a face recognition method based on subspace regression is analyzed. Secondly, the method based on structured error coding is analyzed. For modern occluded face recognition methods, firstly, the methods based on "shallow" robust feature extraction are reviewed. Secondly, deep learning-based methods are introduced. The specific flow is shown in Figure 1.

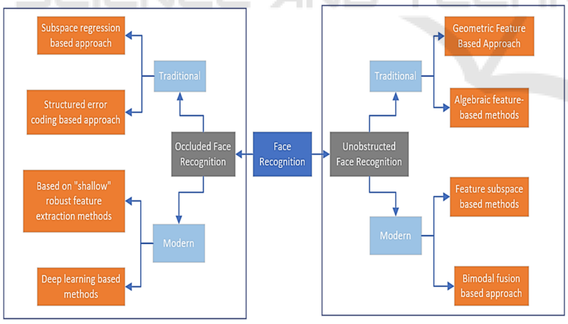

Figure 1: The pipeline of the model (Picture credit: Original).

2.2.1 Traditional Unobstructed Face Recognition Methods

Geometric feature-based methods are traditional in early face recognition, focusing on facial contours and organ shapes. However, due to facial non-rigidity, complex feature extraction necessitates additional algorithms. While widely used, limitations with non-rigid bodies must be considered for reliable recognition systems. Amarapur and Patil introduced a geometric model integrating features like ears and chin, enhancing accuracy. Their method includes image pre-processing, feature labeling, model construction, and validation, as shown in Figure 2. Algebraic feature-based methods offer robustness to lighting and expressions. Yanmei and Mu proposed a principal component analysis (PCA)-based method incorporating singular value decomposition (SVD) and Kullback-Leibler (KL) transform, reducing correlation between face images and improving accuracy.

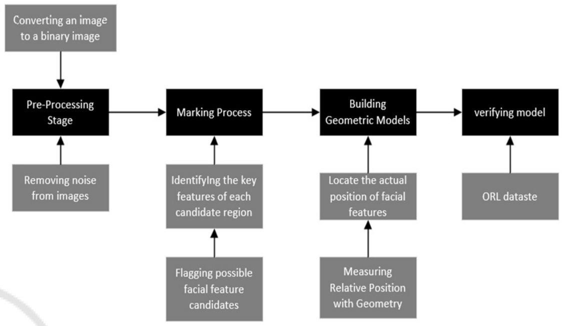

Figure 2: Amarapur and patil experimental procedure for geometric feature based face modeling (Picture credit: Original).

2.2.2 Modern Methods of Unobstructed Face Recognition

For methods based on feature subspaces, the feature subspace approach involves transforming a 2D face image into another space, aiding in distinguishing face features from non-face features. Common algorithms for this technique include Principal Element Analysis, Factor Decomposition, Fisher Criterion Method, and Wavelet Transform. Liao and Gu presented face recognition methods based on subspace extended sparse representation and discriminative feature learning - subspace extended sparse representation classifier (SESRC) and discriminative figure learning (DFL). In SESRC & DFL, each test image is treated as having either a small or significant pose change based on its symmetry. Test images with small pose changes are recognized using the SESRC, while those with significant changes are processed using the DFL method proposed in the paper. Empirical results on face databases like Yale and AR demonstrate that SESRC & DFL achieve the highest recognition rate, surpassing several state-of-the-art algorithms such as Perceptron Learning Algorithm (PLA) and Random Forest (FR). For methods based on bimodal fusion, a bimodal fusion-based approach simultaneously utilizes information from both 2D and 3D modalities and synthesizes them at three levels: signal, feature, and decision-making, in order to obtain better face recognition results than single modalities. Malassiotis et al. proposed a normalization method that is efficient and does not require expansion of the training set.

2.2.3 Traditional Occluded Face Recognition Methods

For methods based on subspace regression, the subspace regression method evaluates whether face samples can be accurately regressed into their corresponding subspace, considering the high correlation and occlusion effects in face images (Zhang, 2020). Guan et al. introduced Tensor Subspace Regression (TSR), building upon the traditional Tensor Subspace Analysis (TSA) algorithm. TSR, like TSA, represents face images in tensor space but transforms the face subspace learning into a regression framework, addressing the time-consuming aspect of TSA. Guan et al. validated TSR on popular face databases AR, ORL, and Yale face B, demonstrating its high performance in face classification and clustering tasks. For methods based on structured error coding, errors induced by physical occlusion have a specific spatial structure, e.g., sunglasses occlusion, scarf occlusion, etc., which are different from those induced by Gaussian noise. Li et al. proposed a morphogram model to describe the morphological structure of errors based on the feature of the shape of the occluder in facial recognition. Experimental validation on the XM2VTS face database shows that this method is more stable in dealing with the occlusion problem in facial recognition compared to other related methods.

2.2.4 Modern Methods of Face Recognition with Occlusion

For methods based on "shallow" robust feature extraction, it relies on manually designed methods closely tied to face recognition but may lack robustness against mixed light and physical occlusions. Li et al. introduced a method based on the Weber operator algorithm, combining directional difference mode and localized directional difference excitation accumulation mode to enhance recognition speed and reduce space consumption. This approach incorporates chunk-based linear discriminant dimensionality reduction, achieving a reported recognition rate of up to 98% on the ORL face database (Prasad, 2020). For deep learning-based approach, successful face recognition in occluded face images relies on understanding higher-order attributes. Deep learning addresses these challenges through multi-layer nonlinear mapping and backpropagation-based feedback learning, surpassing traditional classifiers in handling transformation issues, as depicted in Figure 3. Deep networks offer stable and powerful distributed representations, enabling the design of effective network structures for face recognition tasks. Prasad et al. evaluated the accuracy of deep learning-based face recognition under diverse conditions, including occlusion, varying head postures, and lighting variations. Their experiments with lightweight Convolutional Neural Networks (CNNs) and Visual Geometry Group (VGG) models demonstrated robustness to misalignment and localization errors in intraocular distance.

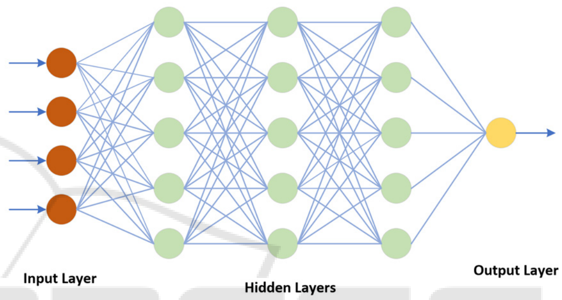

Figure 3: Artificial neural network (Picture credit: Original).

3 RESULTS AND DISCUSSION

In this section, firstly, representative algorithms for face recognition in two major categories, masked and unmasked, are analysed separately and their advantages and disadvantages are illustrated in tables. Secondly, the performance of different representative methods is compared with experimental data and the optimal method is evaluated. Finally, this study discusses future research directions in face recognition related areas.

As shown in Table 1, this study analyses the advantages and disadvantages of the different face identification methods mentioned above. The results of the analysis show that each method has certain advantages and disadvantages and there is no such thing as a perfect method that does not have disadvantage.

Table 1: Analysis of the pros and cons of face recognition methods.

Approaches		Advantages	Disadvantages
Unobstructed Face Recognition	Geometric Feature Based Approach	● Simple ● High efficient	● Limited by geometric features ● Easy to be interfered
	Algebraic feature-based methods	● High recognition accuracy	● High computational complexity
	Feature subspace-based methods	● Suitable for large-scale data	● Data loss ● Sensitive to data distribution
	Bimodal fusion based approach	● High accuracy and robustness ● High stability	● High complexity ● High complexity of algorithms
Occluded Face Recognition	Subspace regression-based approach	● High flexibility and adaptability ● High data utilisation	● Higher requirements for data ● Limited ability to generalise
	Structured error coding-based approach	● Highly expressive features ● High resistance	● Difficulty in tuning model parameters
	Based on "shallow" robust feature extraction methods	● Fast calculation speed	● Fast calculation speed ● Relatively low data requirements
	Deep learning-based methods	● High accuracy ● Simple system setup	● Higher data requirements ● Incomprehensible

As shown in Table 2, this study evaluates the experiments of different face recognition methods under different conditions. For face recognition without occlusion, the geometric feature approach shows high recognition accuracy (80.25%) and has a short implementation time (0.1212 seconds). Whereas, in the case of occlusion, the deep learning method performs the best in terms of accuracy (93.25%) but accordingly has a longer implementation time (2.4266 seconds).

Comparison of the experimental results with the addition of light and noise interference factors reveals that the recognition accuracy of most of the methods decreases slightly, but the deep learning method still maintains a high accuracy (83.75%). This indicates that the effects of light and noise interference are more significant for geometric and algebraic feature methods, but relatively small for deep learning methods. These results reflect the robustness and adaptability of different face recognition methods under different conditions.

As shown in Figure 4, this study compares the average recognition accuracy and execution time of different face recognition methods. As it can be seen from the figure, the deep learning method has the best performance in terms of average recognition accuracy, which reaches 95%, but accordingly, its average execution time is also longer, which is 2.4266 seconds. The "shallow" robust feature extraction-based method, on the other hand, although slightly lower than the other methods in terms of average recognition accuracy, has the shortest average execution time of 0.0512 seconds. This result can be attributed to the differences in feature extraction and model complexity between the different methods. Deep learning methods are able to achieve higher recognition accuracy through deep feature learning and model training, but also result in longer execution times. On the contrary, the "shallow" robust feature extraction-based methods have lower accuracy, but their simple feature extraction process leads to a significant reduction in execution time.

According to the current development trend, combining deep learning with other complementary methods will be a key direction for the future development of face recognition. For example, combining deep learning with techniques such as expression correction to design new model architectures is a promising direction for innovation.

4 CONCLUSIONS

This study reviews and summarises previous face recognition methods based on realistic use scenarios of face recognition. The face recognition methods are categorised according to their real-world significance: face recognition with occlusion and face recognition without occlusion. Subsequently, this study reviews the development of methods in each category based on time series. Finally, this study compares and enumerates the advantages and disadvantages of different methods. Experimental data on recognition accuracy and execution time of each method is derived by conducting experiments on

Table 2: Performance of different face recognition methods based on the same dataset.

Approaches		Experimentation	
		Recognition Accuracy (%)	Implementation time (sec)
Unobstructed Face Recognition	Geometric Feature Based Approach	80.250000	0.1212
	Algebraic feature-based methods	75.000000	0.2025
	Feature subspace-based methods	85.200000	1.0215
	Bimodal fusion based approach	90.000000	1.5250
Occluded Face Recognition	Subspace regression-based approach	72.500000	1.6152
	Structured error coding-based approach	78.000000	0.5325
	Based on "shallow" robust feature extraction methods	70.250000	0.0512
	Deep learning-based methods	95.000000	2.4266
Adding interfering factors light and noise			
Unobstructed Face Recognition	Geometric Feature Based Approach	75.250000	0.1212
	Algebraic feature-based methods	70.000000	0.2025
	Feature subspace-based methods	82.250000	1.0215
	Bimodal fusion based approach	84.250000	1.5250
Occluded Face Recognition	Subspace regression-based approach	68.650000	1.6152
	Structured error coding-based approach	75.000000	0.5325
	Based on "shallow" robust feature extraction methods	65.250000	0.0512
	Deep learning-based methods	93.250000	2.4266

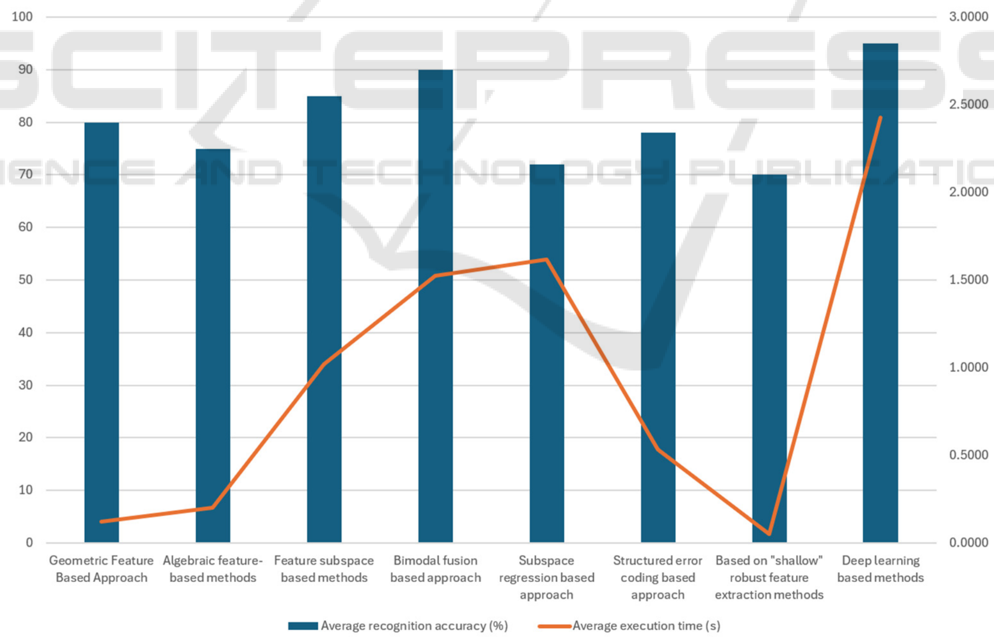

Figure 4: Performance of different face recognition methods (Picture credit: Original).

the same dataset, providing real-world data to support the advantages and disadvantages mentioned above. The experimental results show that there is no such thing as one perfect method and each method has certain advantages and disadvantages. So in recent years most programmers have been using a combination of several different face recognition methods to maximise efficiency. In the future, the integration of deep learning with other methods is going to be an essential direction in the evolution of face recognition, such as combining deep learning with face light calibration to design new models.

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