Comprehensive Analysis of Face Recognition Technologies

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Abstract. This article provides a comprehensive review of face recognition research, focusing on advancements made over the past century. It presents a detailed examination of the core concepts, principles, steps, and classifications of face recognition technology. The review highlights the practical applications of face recognition in contemporary contexts and summarizes key datasets and preprocessing methods used in the field. The paper categorizes face recognition methods into three main types and places particular emphasis on hybrid methods. It explores the principles and research processes associated with these methods, offering an in-depth analysis of their results. Among the various techniques reviewed, deep learning methods emerge as the most promising for face recognition due to their superior performance. This review serves as a valuable resource for students and novice researchers by providing a clear overview of current research methodologies and tools. Additionally, it outlines potential research directions and contributes to the advancement of the field of computer vision.

1 Introduction

Computers have been changing people's lives since the last century. However, for a long time, the connection between computers and humans was not very close. It is only in the process of continuous development that computers have more and more interactions with humans. In recent years, as people's demand for intelligent life style increases, computer-related technologies have made a series of breakthroughs. Its progress in the field of biometric recognition deserves attention [1]. Because this technology applies traditional computer technology to the biological field, related research believes that this is the most promising choice for identifying individuals [2]. As a typical biometric recognition technology, face recognition technology has received more and more attention since its concept was proposed in the mid-20th century. Because it has the characteristics of non-intrusion and non-contact, and has the advantages of friendliness and convenience, it is also a very popular branch of technology that uses computer vision and recognition systems [3]. Face recognition has a wide range of applications. It is mainly used in the security field, but also in business and medicine.

The steps of face recognition are generally divided into three steps: face detection, feature extraction, feature matching and recognition [4]. The face recognition process does not

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require human operation. After collecting the image, it extracts the feature information of the face, processes it, and compares it with the face database, and finally confirms and recognizes the identity. Face recognition methods can be roughly divided into three categories based on the scope and method of feature extraction: Overall feature determination method: the entire face is recognized and input into the system as input data. For example, principal component analysis, feature face method, pattern matching, linear analysis method, independent component analysis, etc. Local feature method: focus on a certain organ of the face, extract their information for subsequent processing and recognition. For example, geometric feature matching method, feature template, etc. Hybrid method: effectively combine the above two methods. For example, neural network, support vector machine, hidden Markov model (HMM), etc. [5-7]. From the timeline of the development of this technology, in the middle of the last century, face recognition mainly used methods based on geometric feature matching, and later more linear recognition methods were added. Nowadays, face recognition technology increasingly uses more intelligent methods such as neural networks.

The purpose of this paper is to comprehensively study and summarize research on face recognition technology. It begins by exploring the role of computers in biometric recognition, outlining the fundamental concepts, procedural steps, and the general development trajectory of face recognition technology. The paper categorizes face recognition methods into three broad types: overall methods, local methods, and mixed methods. It examines these categories in detail, analysing their principles and outcomes based on extensive literature and experimental evidence. The paper then organizes and discusses these methods chronologically, comparing their experimental performances, advantages, and limitations. Additionally, it evaluates their potential for future development. In conclusion, the paper offers a summary of the discussed content and provides a forward-looking perspective on the field of face recognition. The significance of this study lies in its provision of a valuable reference for researchers exploring face recognition and in offering a comprehensive overview for relatively junior scholars keen on gaining an in-depth understanding of the field.

The article is structured as follows: Chapter 1 introduces relevant concepts and methods of face recognition. Chapter 2 provides a detailed exploration of face recognition steps, development processes, and various methods, including their principles and outcomes. Chapter 3 presents a comparative analysis and discussion of the methods described in Chapter 2. Finally, Chapter 4 offers a summary and outlook on the future of face recognition technology.

2 Methodology

2.1 Dataset description and preprocessing

A face recognition dataset is a database of many face images. There are many individual face images from multiple angles. It may also include various expressions, movements, postures, etc., which may reflect the age and gender of the individual. Some large face recognition datasets may contain tens of thousands or even millions of images. Two-dimensional datasets include Labelled Faces in the Wild (LFW) database, Microsoft Celebrity one Million (MS-Celeb-1M) dataset, Chinese Academy of Sciences Institute of Automation (CASIA)-Web Face dataset, masked face dataset, Celeb-500k dataset, Visual Geometry Group Face 2 (VGGFACE2) database, etc. Three-dimensional datasets include Face Warehouse, etc. Here thesis mainly introduce several two-dimensional datasets in detail. MS-Celeb-1M dataset: In 2016, Guo, Zhang and others from Microsoft Research conducted a benchmark test and proposed this huge dataset. This dataset contains facial information of about 1 million celebrities. There are about 10 million pictures in total. And each celebrity has his or her own corresponding entity key. The celebrity information and entity keys are all from Freebase. This is a knowledge graph containing many attributes [8]. The following Fig. 1 shows an example. To meet the needs of face recognition technology during the Corona Virus Disease (COVID)-19 epidemic, Wang, Huang and other researchers proposed three face datasets for dealing with situations where people are wearing masks [9], as shown in Fig. 2 and Fig. 3.

Fig. 1. MS-Celeb-1M dataset sample (Picture credit: Original).

Fig. 2. Masked face dataset sample 1 (Picture credit: Original).

Fig. 3. Masked face dataset sample 2 (Picture credit: Original).

Image preprocessing is an almost necessary step in face recognition algorithms. Researchers use it to normalize and optimize images to make them more suitable for feature extraction and matching. The goal of these operations is to eliminate or reduce changes caused by lighting, expression, posture and other environmental factors. Most studies are motivated by this. Gross et al. proposed a new preprocessing method for illumination compensation [10]. First, the illumination field is estimated, which does not require a training step. After the illumination field is estimated, it is compensated. This can restore the reflectivity of the image scene and greatly reduce the impact of illumination changes on the image. This method uses a response model of local contrast changes to enhance contrast. This method is particularly suitable when the lighting conditions vary greatly. Pierce, Austin et al. evaluated several preprocessing methods based on eigenface technology [11]. These include linear and nonlinear brightness adjustment, geometric normalization, image filtering algorithms and other technologies. These operations can ensure accurate results when performing eigenface face recognition.

2.2 Proposed approach

The primary aim of this review is to study and summarize research results on face recognition, covering aspects such as face recognition datasets, preprocessing techniques, methods, and experimental results comparison. The introduction provides an overview of the application of computers in biometric recognition, summarizing the fundamental concepts, steps, classifications, applications, and general development history of face recognition. This section serves as a comprehensive introduction to the field. In the methodology section, the review first addresses face datasets established by researchers over the years, with a particular focus on three key datasets: MS-Celeb-1M, the Masked Face dataset, and Celeb-500k. It then introduces various preprocessing methods essential for face recognition. The article proceeds to review the three main categories of face recognition methods identified earlier: overall, local, and mixed methods. Emphasis is placed on hybrid methods and models. Three typical hybrid face recognition methods are discussed in detail: the Markov Random Field method, the multimodal 2D-3D hybrid method, and deep learning methods. The principles and processes of these methods are thoroughly examined, with a detailed exploration of deep learning techniques due to their diverse and complex nature. The results and discussion section compares and analyses the methods mentioned, assessing their experimental performance. This section also delves into the advantages and disadvantages of these methods, providing insights into their future development prospects. Finally, the review summarizes the key findings and presents an outlook for the future of face recognition technology. The overall structure and flow of the article are illustrated in Fig. 4.

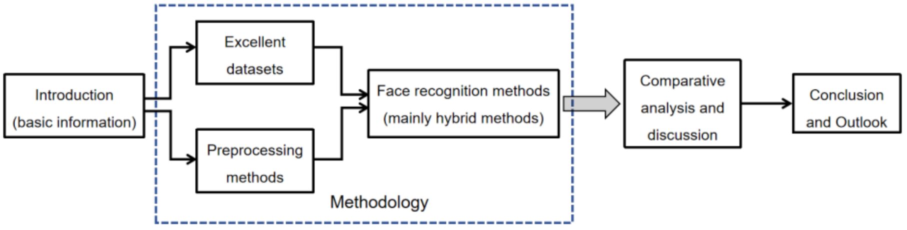

Fig. 4. Article flow (Picture credit: Original).

2.2.1 Introduction to the basics of hybrid methods

Thesis divide face recognition methods into three categories according to the scope of feature extraction. The overall feature method treats the entire face as data. Most overall methods pixelate the face image. Then convert it into a matrix and extract its feature vector for subsequent processing. And project it into a smaller subspace or plane. The local feature method focuses on discovering the uniqueness of some organs or regions of the face. This method is very sensitive to expressions, geometric features, occlusion, etc. The hybrid method combines the above two methods. The hybrid method uses overall features and local features for judgment. It uses global information and local information at the same time. This improves the accuracy and robustness of the face recognition system. Because it can more easily improve the performance of face recognition algorithms, hybrid methods also include many types, such as Markov models, multi-scale feature fusion, support vector machines, multimodal 2D-3D hybrid automatic methods, deep artificial neural networks, etc. The following will mainly review several of the many hybrid methods.

2.2.2 Markov random field

Wang, Pavlov, et al. proposed a hybrid face recognition method based on Markov random field (MRF) at the International Committee for Prostitutes' Rights (ICPR) conference in 2004 [12]. This method combines the advantages of holistic recognition and feature matching. The Markov random field model contains two levels of nodes, namely observable nodes and hidden nodes. The observable nodes represent image blocks, while the hidden nodes represent the numbers of image blocks. First, the training images and the tested images of the face set must be pre-processed: they are divided into small blocks of the same size and the numbers of the training images are recorded [13]. Then the compatibility function is learned based on the training data. After the MRF model is learned for the training data, the Back Propagation (BP) algorithm and majority voting mechanism are used to finally determine the numbers of the test image blocks. The researchers also tested the effect of this method in multiple data sets to ensure its feasibility.

2.2.3 Multimodal 2D-3D hybrid method

Ajmal and others proposed a stable face recognition algorithm that combines 2D and 3D mixed data in 2007. This method also combines feature extraction and holistic matching techniques [14,15]. Feature extraction technology is mainly used to quickly screen candidate faces and improve efficiency. The holistic matching technology is used for accurate matching and verification. It also uses two different types of facial data: a 2D type that represents Gray or colour images and a 3D type that represents range images. The special feature of this method is that it can still stably recognize faces when the expression changes. The process implemented by the researchers for this method is as follows: First, the facial posture is corrected using techniques such as hotelling. The overall 3D descriptor of the face is calculated, which will be used in subsequent feature matching and face screening. Then, a high-efficiency rejection classifier is designed in combination with SIFR feature symbols. The iterative closest point algorithm is also innovated. Finally, regional matching is performed and the results of each region are fused to determine the identity of the test face.

2.2.4 Deep learning methods

Deep learning, a subset of machine learning also known as deep artificial neural networks, simulates the structure and function of the human brain using artificial neural networks. This approach enables the construction of models and data processing in a manner analogous to the human brain [11]. Deep learning involves complex neural networks that process data through multiple layers, making it a powerful tool for a variety of applications. In recent years, deep learning has emerged as a superior method compared to traditional techniques, leading to significant advancements in technology, particularly in pattern recognition tasks such as speech detection and computer vision [16]. Deep learning methods can be categorized into three types based on their usage: unsupervised generative, supervised discriminative, and hybrid. Unsupervised generative methods include autoencoders and recurrent neural networks, while supervised discriminative methods primarily involve convolutional neural networks (CNNs). Hybrid methods combine elements from both unsupervised and supervised approaches, often utilizing deep neural networks.

Among these categories, convolutional neural networks are particularly well-suited for complex tasks such as face recognition due to their ability to automatically extract hierarchical features from images. Consequently, this review focuses on various methods and models based on CNNs. One of the pioneering studies in deep learning for face recognition is DeepFace, which achieved high accuracy on the LFW dataset. Developed by Taigman et al., DeepFace is a multi-stage method based on the AlexNet architecture and is recognized as a major advancement in applying deep learning to face recognition. Deep face model effectively extracts facial feature representation [17]. Building on this work, researchers further explored and optimized the approach, leading to the development of the DeepID series of methods. In the realm of face recognition, neural networks are often used in combination with other techniques. For instance, Benradi et al. introduced an algorithm that integrates feature extraction technology with CNNs [18]. Their approach involves first extracting key features from images using feature extraction techniques and then classifying these features with a CNN. They enhanced the CNN architecture by experimenting with various activation functions (SoftMax and Sigmoid) and optimization algorithms (such as adaptive moment estimation (Adam), Root Mean Square Propagation (RMSprop), and Stochastic Gradient Descent (SGD)) to improve model accuracy. Similarly, Kang Sik Yoon et al. combined hidden Markov models with neural networks for frontal face recognition [19]. Their method demonstrated a higher recognition rate compared to some traditional techniques after extensive testing.

Overall, deep learning methods, particularly those involving convolutional neural networks, have significantly advanced the field of face recognition, demonstrating their effectiveness in handling complex recognition tasks and setting new benchmarks for accuracy and performance.

3 Result and Discussion

3.1 Results of experiments

The research will show some experimental results of hybrid models. For the experimental detection of Markov random field model, the researchers chose to use three relatively well-known face databases - Yale database, Online Reinforcement Learning (ORL) database and Face Recognition Technology (FERET) database for experiments. These databases contain different numbers of subjects and images without exception, which can effectively verify the performance of MRF method under various conditions. They also used Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA) and nearest neighbour (NN) methods for comparison. The final experimental results show the recognition accuracy under different databases and different numbers of training samples. Overall, the MRF method shows high accuracy in all experiments, especially when there are more training samples, which is significantly better than PCA and LDA methods. For example, in the Yale database, when k=10, the recognition accuracy of the MRF method reaches 99.33%; in the FERET database, when k=5, the recognition accuracy reaches 99.71%. The data obtained from the experiments on the three databases are shown in Table 1, Table 2, and Table 3.

Table 1. Recognition accuracy in the Yale database [17].

k	Neural Network	Principal Component Analysis	Linear Discriminant Analysis	Markov Random Field
1	68.31	60.04	N∝A	81.60
3	83.48	79.03	98.20	95.17
5	83.51	81.13	99.69	96.11
7	82.63	81.90	99.97	98.67
10	83.07	81.73	100	99.33

Table 2. Recognition accuracy in the ORL database [17].

k	Neural Network	Principal Component Analysis	Linear Discriminant Analysis	Markov Random Field
1	69.07	56.43	N/A	51.06
3	88.09	79.66	81.74	79.21
5	94.64	88.31	88.87	86.95
7	96.80	92.58	91.62	92.17
9	97.90	95.20	93.75	96.75

Table 3. Recognition accuracy in the FERET database [17].

k	Neural Network	Principal Component Analysis	Linear Discriminant Analysis	Markov Random Field
1	39.49	30.19	N∝A	64.57
3	69.61	58.21	70.10	90.86
5	89.23	79.20	88.37	99.71

When testing the multimodal 2D-3D hybrid method, its researchers compared the three methods: 2D, 3D, and 2D-3D hybrid. They calculated the error rate and recognition rate. They compared and analysed the different results of the three methods in three different factors. In the case of changing lighting conditions, changing expressions, and changing occlusion, the hybrid method outperformed the single 2D or 3D method.

Based on the convolutional neural network in deep learning, many professionals have proposed various methods. Their methods are based on different architectures. At the same time, they have also done various tests to determine which method has a higher accuracy in face recognition.

Table 4. Results of methods based on convolutional neural networks [4].

	Authors	structure	Layers	Exact degree (%) ± SE
1	Taigman et al.	9-layer CNN	3	97.35 ± 0.25
2	Schroff et al.	GoogleNet	1	99.63 ± 0.09
3	Sun et al.	VGG	25	99.53 ± 0.10
4	Wen et al.	LeNet	1	99.28
5	Ranjan et al.	Residual Network-101	1	99.78

Combining feature extraction technology with CNN improves accuracy, as shown in the Table 4. The researchers tested it on both the ORL database and the Sheffield database. They found that the hybrid method was more accurate on both. The experimental results on the Sheffield database are quite outstanding, and the accuracy of the combination of the two reaches 98.5%. Generally speaking, this value changes less in the later stages of training and gradually stabilizes. Whether using only the convolutional neural network method or only the traditional method, their overall performance is generally lower than that of the hybrid model.

3.2 Discussion

Many methods of face recognition have been proposed and tested. Hybrid methods are superior to other methods in many cases. The hybrid method is used in the face recognition system to enhance the recognition accuracy and robustness, while reducing the false recognition rate. In particular, they show unique advantages when dealing with complex scenarios and diverse needs. However, hybrid methods also face many challenges. Because hybrid methods usually combine multiple algorithms and techniques, this will increase the complexity of the system. How to reduce computational complexity and computational cost while maintaining high accuracy is a major challenge facing hybrid methods. For example, face recognition now recognizes two-dimensional and three-dimensional face images. If they are replaced with object images or images of different categories, there will be some difficulties. However, relevant research can determine that in the future, although hybrid methods face many limitations, such methods will still be the development trend of face recognition technology. Among them, deep learning is the method that researchers are most optimistic about. It has many advantages such as automated feature extraction, high accuracy, and strong adaptability. In many aspects, deep learning series methods are considered to have more room for development than traditional methods. There are also two potential aspects, namely three-dimensional face recognition and multimodal face recognition. In today's 21st century, three-dimensional face recognition for face recognition has been widely studied by the scientific community to overcome the problem of feature loss in two-dimensional face recognition due to the three-dimensional structure.

4 Conclusion

Face recognition remains a prominent and significant research topic within the field of computer science, holding substantial implications for the advancement of computer vision in the 21st century. This paper has reviewed and synthesized the existing literature on face recognition, providing a comprehensive overview of the field. The review began by explaining the fundamental concepts, classifications, and applications of face recognition, drawing from previous research. It then summarized common face recognition datasets and preprocessing techniques. The focus of the paper was on various face recognition methods, with particular attention given to hybrid approaches. Detailed analyses of the principles, processes, and experimental results of these methods were provided. The results show that hybrid methods, especially those combined with deep learning techniques, outperform other methods in terms of effectiveness. This highlights the potential of deep learning methods in face recognition tasks. Consequently, future research directions will likely continue to explore and refine deep learning methods, particularly within the realm of CNNs. Future work will delve into other architectures within CNNs and investigate alternative approaches to face recognition that do not rely on convolutional networks. These areas present promising opportunities for advancing the field and enhancing face recognition systems.

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