A Survey on Face Recognition Based on Deep Neural Networks

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ABSTRACT:
Face recognition is one of the most important and challenging issues in computer vision and image processing. About half a century ago, since the first face recognition system was introduced, facial recognition has become one of the most important issues in industry and academia. In recent years, with the developing of computers throughput and developments of a new generation of hierarchical learning algorithms called deep learning, much attention has been devoted to solving learning problems by deep learning algorithms. Deep neural networks perform feature learning instead of feature extraction which by this strategy they are much useful for image processing and computer vision problems. Deep neural network through feature learning perform data representation well and have gained many successes in learning and complex problems, many studies have been done on the application of deep neural networks to face recognition and many successes has been achieved. In this study we examine the neural network based methods used for face recognition such as multilayer perceptrons, restricted Boltzmann machine and auto encoders. Most of our study devoted to convolutional neural network as one of the most successful deep learning algorithms. At the end we have examined the results of the encountered methods on ORL, AR, YALE, FERET datasets and show deep neural network has gained high recognition rate in comparing with benchmark methods.

KEYWORDS: face recognition, artificial neural networks, Convolutional neural networks, Autoencoders, Restricted Boltzmann Machine

1. INTRODUCTION

Accuracy of a face recognition system and image classification algorithm is highly dependent on quality of extracted features. Deep neural network provide well feature learning instead of hand crafted feature extractions. Deep neural networks is a set of learning algorithms which provides feature learning well through non-linear transformations between layers of a neural network. In recent year deep neural network have attracted much attention for solving learning problems such as image classification, natural language processing and pattern recognition.

Dimensionality reduction and learning algorithms are mostly used methods for face recognition. Principal component analysis (PCA), independent component analysis (ICA) and linear discriminant analysis (LDA) as dimensionality reduction methods have been applied for facial recognition. In these methods pixels of images are represented in low dimensionality of feature with maintaining maximum of variance.

Unsupervised learning methods such as Restricted Boltzmann machines (RBM) and autoencoders have also succeeded in learning features and dimensionality reduction. Unsupervised neural networks perform non-linear dimensionality reduction which they are much more accurate than statistical methods and they improve accuracy of computer vision tasks. Generative restricted Boltzmann machine learn distribution of data and perform dimensionality reduction to represent data. Also they improve accuracy of deep neural networks and discriminative stacked autoencoders by pre training for weight initialization.

Convolutional neural network (CNN) have achieved high performance in computer vision in recent years. Many studies have been done on deep neural networks (DNN) for face recognition in recent years. Various and very deep architecture of CNN have been proposed in these years for computer vision tasks. Recurrent neural networks (RNN) are powerful tools for sequence modeling which they are applied with combination of learning methods for facial recognition.

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The purpose of this research is to investigate the researches and consequences of DNN and unsupervised neural networks for face recognition. In the next following section we first investigate multi-layer perceptron (MLP) and deep neural networks for face recognition in section 2. In section 3 we study unsupervised neural networks applied for face recognition. Then in section 4 we examine hybrid approaches for facial recognition. In section 5 the results of discussed methods on popular face recognition datasets is presented. Conclusion of the study is presented in section 6.

2. FACE RECOGNITION USING MULTILAYER PERCEPTRONS

Rowley et al [1] proposed the first advanced neural approach which reported performance statistics on a large and complex dataset. Their system incorporates face knowledge in the neural network architecture, with specialized window sizes designed to best capture facial information. Images are pre-processed before being classified by the network, the output is post-processed to remove overlapping detections, resulting in one detection per face, and a reduction in false positives. Multiple networks were trained independently and their outputs combined using various arbitration methods to further improve performance.

Bhattacharjee et al [2] presented a novel method for human face recognition that is based on fuzzy neural network has been presented. Here, Gabor wavelet transformation is used for extraction of features from face images as it deals with images in spatial as well as in frequency domain to capture different local orientations and scales efficiently. In face recognition problem, MLP has already been adopted owing to its efficiency, but it does not capture overlapping and nonlinear manifolds of faces which exhibit different variations in illumination, expression, pose, etc. A fuzzy MLP on the other hand performs better than an MLP because fuzzy MLP can identify decision surfaces in case of nonlinear overlapping classes, whereas an MLP is restricted to crisp boundaries only.

A constructive training algorithm for MLP applied to facial expression recognition applications [3]. The developed algorithm is composed by a single hidden-layer using a given number of neurons and a small number of training patterns. The proposed MLP constructive training algorithm seeks to find synthesis parameters as the number of patterns corresponding for subsets of each class to be presented initially in the training step, the initial number of hidden neurons and the number of iterations during the training step as well as the MSE predefined value.

Ortega et al [4] presented a multiple scale neural architecture for face recognition. The architecture is composed of several stages: face detection, Difference of Gaussians, Gabor filter bank, Principal Component Analysis, and two-stage MLPs. The architecture was evaluated using two well-known face databases. A detailed study of all the parameters that influence the architecture performance was carried out. The architecture achieved a correct detection rate of 84% with face images changing in pose and gesture.VSS systems suffer from illumination changes such as sunglasses and scarf, connected face and multiple face sizes. In a new study [5] a novel algorithm known as Hierarchical-Skin-Ada-Boost-Neural-Network (H-SKANN) is introduced to overcome these problems. On top of this, face skin merging (FSM) is also introduced to connect blobs of skin regions to form a face. Experiments conducted on six single-face databases (AR [28], FERET [30], IMM [40], Georgia [41], Caltech[42], and Talking-PIE[43]) and one multi-face benchmark database (ChokePoint [44]) demonstrated that 98.07% and 95.48% of averaged accuracy have been achieved for single- and multi-face detection, respectively, using the proposed method

2.1. Deeper Neural Networks

Deep learning techniques have established themselves as a dominant technique in machine learning. Deep neural networks (DNNs) have been top performers on a wide variety of tasks, including image classification, speech recognition and face recognition. In particular, CNN have recently achieved promising results in face recognition.

2.2. Applications of CNN for Face Recognition

Jalali et al [15] proposed a sensitive convolutional neural network which incorporates sensitivity term in the cost function of CNN to emphasize on the slight variations and high frequency components in highly blurred input image samples. The proposed cost function in CNN has a sensitivity part in which the conventional error is divided by the derivative of the activation function, and subsequently the total error is minimized by the gradient descent method during the learning process. Due to the proposed sensitivity term, the data samples at the decision boundaries appear more on the middle band or the high gradient part of the activation function. This highlights the slight changes in the highly blurred input images enabling better feature extraction resulting in better generalization and improved classification performance in the highly blurred images.

Nwosu and his team [10] proposed the design of a Facial Expression Recognition (FER) system based on deep convolutional neural network by using facial parts. The proposed method consists of two channels CNN. The first channel is used for extracted eyes and the second one is used for mouth. Then classification is done on information from both channels. Experiments are carried out on the Japanese Female Facial Expression

(JAFFE [45]) and the Extended Cohn-Kanada (CK+ [46]) datasets to determine the recognition accuracy for the proposed FER system. The results achieved shows that the system provides improved classification accuracy when compared to other methods.

In recent years, deep learning has become a hot research area. The research on facial recognition is progressing rapidly, however, facial expression recognition faces many difficulties due to poor robustness and real-time performance. Li [11] designed a discriminative learning convolution neural network. The network combines the central loss function and the verification-recognition model, which make the model have better characteristics of the generalization and discrimination ability, and also reduce the misclassification in facial expression recognition. Experiments show that the accuracy of the designed facial expression recognition network has been effectively improved.

As for that there is only one training sample in single sample per person (SSPP) face recognition (FR), deep learning (DL) method is very difficult to be used. To overcome this problem, Zeng et al [12] proposed a series of methods to make it possible to be used in SSPP FR. Firstly, an expanding sample method is proposed to increase training sample. Secondly, a learned CNN model which is trained with amounts of face images and can represent face very well is brought in. Then, these expanding samples are used to fine-tune the CNN model. Thirdly, the fine-tuned CNN model is used to perform experiment. Experiments demonstrate that a better performance is obtained by using the fine-tuned CNN model.

Among various face recognition methods, Mubin Ara and his team used deep learning based face recognition method. This method uses CNN to generate a low dimensional representation called embeddings. Then those embeddings are used to classify the person's facial image. By this system different types of applications like student attendance-system, building security etc. can be developed [18].

RNN are powerful tools for sequence modeling such as face recognition in real time videos. Hasani and Mahbor proposed a 3D Convolutional Neural Network method for facial expression recognition in videos. The proposed method is consists of deep neural network called 3D Inception-ResNet followed by an LSTM unit that together extracts the spatial relations within facial images in videos [14].

Jalali et al [11] presented appropriate back propagation learning algorithm for the convolutional neural networks. They evaluated the performance improvement by the proposed method on a face recognition task and proved that it outperformed the state of art face recognition methods.

Singh & Om [16] proposed to apply CNN to IIT (BHU) newborn [47] database. The database has its own advantages where the quality of images is high and segregation has been done for various expressions of newborn. The CNN applied in this paper is more advantageous when compared to regular MLP. Along with this the results taken from application of proposed technique have been compared to state-of-the-art technique applied on the same database and it shows improved results. It has been found CNN improves PCA by 22.09%, LDA by 12.98%, ICA by 11.35%, LBP by 17.08% and SURF by 10.8% for Neutral-Neutral faces. Along with this results have also been gathered to understand which CNN architecture is most suitable for the database.

Rasti et al [17] proposed a new system which super resolves the image using deep learning convolutional network followed by the Hidden Markov Model and Singular Value Decomposition based face recognition. The proposed system has been tested on many well-known face databases such as FERET [30], HeadPose [48], and Essex University [49] databases as well as our recently introduced iCV Face Recognition database (iCV-F). The experimental results show that the recognition rate is improving considerably after apply the super resolution.

An adaptive convolutional neural network (ACNN) is proposed, which can determine the structure of CNN without performance comparison [14]. The experiment results of face recognition on ORL [27] face database show that there is a better tradeoff between the consumption of training time and the recognition rate in ACNN.

Grundstrom et al [19] have investigated face verification based on deep representations from CNNs to find an accurate and compact face descriptor trained only on a restricted amount of face image data. Transfer learning by fine-tuning CNNs pre-trained on large-scale object recognition has been shown to be a suitable approach to counter a limited amount of target domain data. Using model compression they reduced the model complexity without significant loss in accuracy and made the feature extraction more feasible for real-time use and deployment on embedded systems and mobile devices.

3. UNSUPERVISED APPROACHES FOR FACE RECOGNITION

In this section we present researches and applications of restricted Boltzmann machines and autoencoders as unsupervised neural networks for face recognition.

Kang et al [6] proposed a method which convert non frontal faces into frontal face images by using a deep neural network. The advantage of the proposed in comparing with previous studies is it only relies on a face detector rather than depending on complex appearance models. The experimental results using the Georgia tech face database demonstrate the advantages of the proposed method.

Tan & Eswaran [7] presented presents techniques for image reconstruction and recognition using autoencoders. Experiments are conducted to compare the performances of three types of autoencoder neural networks based on their efficiency of reconstruction and recognition. Reconstruction error and recognition rate are determined in all the three cases using the same architecture configuration and training algorithm.
Autoencoders are capable of producing low-dimensional representations with enough discriminative ability such that the face recognition accuracy achieved by simple, lightweight classifiers surpasses even that achieved by more complex models. Nousi & Tefas [8] proposed a method of training Auto encoders (AEs) where the low-dimensional representation is learned in a way such that the various classes are more easily discriminated.

Elaiwat et al [9] proposed a novel RBM-based model to learn effectively the relationships (or transformations) between image pairs associated with different facial expressions. The proposed model has the ability to disentangle these transformations (e.g. pose variations and facial expressions) by encoding them into two different hidden sets, namely facial-expression morphlets, and non-facial-expression morphlets. The first hidden set is used to encode facial-expression morphlets through a factored four-way sub-model conditional to label units. The second hidden set is used to encode non-facial-expression morphlets through a factored three-way sub-model. With such a strategy, the proposed model can learn transformations between image pairs while disentangling facial-expression transformations from non-facial-expression transformations.

4. HYBRID METHODS

Recurrent neural networks are powerful methods for sequence models. A new study by Jain et al [20] proposed a Hybrid Convolution-Recurrent Neural Network method for facial expression recognition in Images. The proposed method use CNN to learn features of images which CNN layers followed by RNN to classify facial expressions. The proposed model is applicable in real time applications.

A novel deep learning method for face sketch synthesis is presented by Jiao and his team [21]. They have designed a lightweight neural network which contains two convolutional layers, a pooling layer and a multilayer perceptron convolutional layer to learn a mapping from face photos to sketches. In the proposed method unlike CNN methods it only computes convolutions and pooling operations. Experiments demonstrate that the proposed method is more robust to illumination and expression variations.

Khalajzadeh et al [22] presented a hybrid system by combination of a CNN and a logistic regression classifier (LRC). A CNN is used to detect and recognize faces images and then by a LRC learned features by CNN is classified. A CNN is trained to detect and recognize face images, and a LRC is used to classify the features learned by the convolutional network. The experiments completed on Yale [29] face database shows improved classification rates in smaller amount of time.

A new method based on Local Gabor Binary Patterns and Convolutional Neural Network proposed in the study [23] firs local binary patterns extracts shape, texture and local neighbor relationship features then CNN is applied for face recognition. Experiments are implemented on the FG-NET [50] database and the results can outperform the state of the art ones.

Deng et al [24] propose a novel method that uses stacked denoising autoencoders (SdA) for feature extraction and random forests (RF) for object-background classification in a classical cascading framework. This architecture allows much simpler neural network structures, resulting in efficient training and detection.

To address the sequential changes of images including poses, Li et al [25] proposed a recurrent regression neural network (RRNN) framework to unify two classic tasks of cross-pose face recognition on still images and videos. To imitate the changes of images, they explicitly construct the potential dependencies of sequential images so as to regularizing the final learning model. By performing progressive transforms for sequentially adjacent images, RRNN can adaptively memorize and forget the information that benefits for the final classification. For face recognition of still images, given any one image with any one pose, it recurrently predicts the images with its sequential poses to expect to capture some useful information of other poses.

LSTMs are kind of recurrent neural network which they are suitable for sequence modeling. Zhao et al [26] proposed a robust LSTM (Long Short Term memory)-Autoencoders (RLA) model to effectively restore partially occluded faces even in the wild. LSTM encoder, reads facial patches of various scales sequentially to output a latent representation. Receiving the representation learned by the encoder, the LSTM decoder with a dual channel architecture reconstructs the overall face and detects occlusion simultaneously.

5. RESULTS AND DISCUSSION

In this section we examine results of studied methods applied for face recognition on some popular datasets. There are popular private and public datasets for face recognition problem. Features of mentioned datasets are shown in table 1.

Table 1. Features of face databases.

Database	RGB Color/grey	Images Size	#persons	Number of Images/ Person
ORL [27]	gray	92 ×112	40	10
AR database [28]	RGB	576×768	126 (70 M and 56 F)	26
Yale [29]	Gray	320×243	15 (14 M And 1 F)	11
FERET [30]	RGB	256×384	30,000	-

Accuracy of neural networks-based methods and hybrid approaches for face recognitions are shown in table 2. These results are grouped according to the used database.

Table 2. Summary of the results of the different face recognition approaches.

Database	Approach	Recognition rate (%)
ORL	- Hidden Markov model (HMMs) [31] - PCA + MLP [32] - SVM + PCA [33] - PCA [34] -CNN[11] -Denoising Autoencoder + Random Forest[24] -Local Gabor Binary Patterns + CNN[23] -CNN+ Simple Logistic Classifier [22] -Adaptive CNN[14]	87 75.2 97 80.5 98.5 97.6 99.4 99.2 98.8
AR database	- SVM + PCA [33] - SVM + ICA [33] -CNN[11]	92.67 94 99.6
Yale	- SVM + PCA [35] - PCA [36] -Local Gabor Binary Patterns + CNN [23] -Deep CNN[6]	99.39 88.1 99.8 99.5
FERET	- HMM-LBP [37] - PCA [38] -CNN+ Simple Logistic Classifier [22] -Local Gabor Binary Patterns + CNN[23] - 2D-PCA + SVM [39]	95 90 96.5 99.1 85.2

6. CONCLUSION

Face recognition is a hard task, through learning features of faces, the accuracy of face recognition system increase. In this study the results show feature learning by deep neural network and unsupervised neural network improve accuracy of face recognition in comparing with traditional methods.

In this paper, we first discussed about face recognition and it's applications. Subsequently, we presented neural network based approaches for face recognition. Then, we presented new studies about face recognition by using deep neural networks and at the end we summarized experimental finding on the popular datasets.

ABBREVIATIONS

PCA	Principal component analysis
ICA	independent component analysis
LDA	linear discriminant analysis
RBM	Restricted Boltzmann machines
CNN	Convolutional neural network
DNN	deep neural networks
RNN	Recurrent neural networks
MLP	multi-layer perceptron
H-SKANN	Hierarchical-Skin-Ada-Boost-Neural-Network
FSM	face skin merging
FER	Facial Expression Recognition
JAFFE	Japanese Female Facial Expression
SSPP	single sample per person
FR	face recognition
DL	deep learning
ACNN	adaptive convolutional neural network
AEs	Auto encoders
LRC	logistic regression classifier
SdA	stacked denoising autoencoders
RF	random forests
RRNN	recurrent regression neural network
LSTM	Long Short Term memory
RLA	Autoencoders

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