A survey on face detection and recognition

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Abstract

Face detection and recognition techniques are significant branch in computer vision field that have been developing for a long history. Even to these days, the approaches mentioned above are playing an important role in our daily life involving service, public security, government affairs etc. Over the past few decades, researchers proposed a large number of approaches to make face relevant technology perform better, whether faster, more accurate or more robust. This paper attempt to give a glance at the face detection and recognition approaches proposed over the past few decades along the discussion order about detection and recognition, and especially discuss the traditional statistical methods including PCA, ICA, SVM, LBP, HOG etc. and novel Neural Network methods especially CNN and some network models based on it respectively. Feature extracting and representation are vital steps and works in the traditional approaches, whereas the Neural Network methods do not extract features explicitly in most cases rather execute that in the hidden layers of networks. After discussing available techniques, this paper would slightly discuss some future researches directed as the challenges existing still nowadays.

Keywords— Face Detection, Face Recognition, CNN

1 Introduction

Face recognition technology has become an inseparable part of our daily life, and its applications have penetrated in to various areas such as service, public security, government affairs, and transport as well as in retail services. Typically, it broadly follows these following processes to design a face recognition system: Face Detection, Features Extraction, and Classification whose goal is to carry out the downstream tasks, verification or identification to realize recognition.[1] With the wide use of deep learning approaches the past few decades, the Feature Extraction step are often not executed explicitly, and the procedure for a face recognition system could be simplified as mainly two steps: Face Detection and Face Recognition.

Researches on face detection and face recognition are long-standing tasks in the computer vision field. On the long history of research, the problem of machine recognition for human faces has been continuing attracting researchers from disciplines involving image processing, pattern recognition, neural networks, computer vision, computer graphics, psychology and so on. With a growing need for the face recognition application scenarios as well as the more and more demanding on its performance such as security and accuracy, there is still a long way to trudge on researches on the techniques.

This paper attempt to give a glance at the approaches proposed for face recognition over the past few decades by classifying them according to the core methods used, that is mainly conventional machine learning methods especially statistical approaches including PCA, KPCA, ICA, SVM etc. or the Neural Network approaches, which is the core implement of popular deep learning methods. In the traditional approaches, operators used to extract features, either global features or local features matter, whereas in the Neural Network approaches, features are not extracted explicitly, and the main tasks are designing suitable structures of networks to implement face recognition. Besides, for the factor that many Neural Network models consume expensive computation costs and time costs, the methods towards fastness and lightness

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are given more attention in this paper, such as cascade classifier, MobileFaceNet, BlazeFace, LFFD and etc.

2 Face Detection Techniques

Generally, the locations and sizes of any face must be obtained before applying face recognition to a general image. In Ming-Hsuan Yang's work(2002)[2], the definition of face detection was described as that: Given an arbitrary image, the goal of face detection is to determine whether or not there are any faces in the image and, if present, return the image location and extent of each face. Over the past few decades, a wide variety of face detection algorithm that can achieve the goal fast have been developed.

2.1 Taxonomy of Earlier Approaches

In the work of Yang, Kriegman, and Ahuja(2002)[2] and Zhao, Chellappa etal(2003)[3], there was a taxonomy, which was based on a comprehensive survey of those approaches proposed, according to which, the face detection techniques can be classified as feature-based , template-based and appearance-based technique.

2.1.1 Feature-based Techniques

The critical procedure of feature-based face detection techniques is to localize the distinctive image features, which take the mouth, nose, eyes for instance. After that, to verify whether these features are in a plausible geometrical arrangement is necessary.[4]

In feature-based methods researchers have been trying to find features that are invariant of faces for detection. With the assumption that humans can detect faces and objects in different poses and lighting conditions effortlessly, there must be invariant properties or features existing. A classic procedure of a wide range of proposed methods is to first detect facial features and then to infer the presence of a face. To extract these facial features such as skin-color, eyebrows, eyes, nose, mouth and hairline, edge detectors are commonly used. Then a statistical model is built to describe their relationships and to verify the existence of a face. These methods, however, have one problem that the image features can be severely corrupted due to illumination, noise, and occlusion. So that feature boundaries can be weakened, whereas shadows would cause some strong edges which together render perceptual grouping algorithms useless.

2.1.2 Template-based Techniques

Template-based approaches, however, is not suitable as a fast face detection method. These techniques require good initialization near real face.

2.1.3 Appearance-based Techniques

Appearance-based, also known as image-based approaches scan over small overlapping rectangular patches of the images searching for likely face candidates, which is similar to the kernels applied in Convolutional Neural Network(CNN), a extremely popular technique in computer vision, especially images processing field. In appearance-based methods template are learned from examples in images. Generally speaking, appearance-based methods rely on techniques from statistical analysis and machine learning to find the relevant characteristics of face and non-face images. Meanwhile, dimensionality reduction is usually carried out for the sake of computation efficiency and detection efficacy. This kind of approaches, however, are inefficient and time-consuming sometimes. To resolve this problem, a cascade method, which is a detector of more selective was used[5]. Besides, most appearance-based approaches rely heavily on training classifiers using sets of labeled faces and non-face patches.

2.2 Recent Development Review

Nowadays, the method that apply rectangular boxes for the face is extremely popular, and the first approach was proposed by Viola and Jones in 2004[6], with their work *Robust real-time face detection*, where the Haar like feature was used. This method, however, has some drawbacks, that is its feature size is extremely large. Take a 24×24 image for example, the number of Harr like feature reaches up to 160,000, which inevitably causes a great deal of calculations. Beside, it did not deal with the wild faces and frontal faces either. Through the submitted project source code, it is slightly obvious that the algorithm would fail to detect or trace a face once given a skewing head or side face.

To overcome these drawbacks, researchers have been attempting apply many other methods and feature descriptors such as SIFT, HOG, ACF and SURF to improve the face detector. In 2009, D.E.King and

Dlib-ml[7] designed a well known method named Dlib in their work *Dlib-ml: A machine learning toolkit*, in which they use support vector machine as the classifier so that improved the robustness of the algorithm. And in 2016, S.Liao, and A.K.Jain etc[8] introduced a new feature descriptor named Normal Pixel Difference(NPD) in their work *A Fast and Accurate Unconstrained Face Detector*, whose main function is to differentiate the intensity of two pixels.

Since deep learning methods obtain more and more attention and application, as well as some of the most explored work, it has been playing a vital role in face detection. Except many ConvNet and 3D mean face model framework, further improvements using CNN cascade and region proposal network(RPN) have been attempted as well. In 2018, X.Sun, and P.Wu[9] designed a faster R-CNN and ResNet in their work *Face detection using deep learning: An improved faster RCNN approach*, which bring significant boosts in performance on face detection. As is known to all that the models constructed by deep neural networks are generally huge with a large number of parameters, So that they always consume expensive computation costs and time costs. In many scenarios, however, the face detectors are always deployed on edge devices, such as mobile phones, IP cameras and IoT (Internet of Things) sensors, which have limited memory storage and low computing power. Such that proposing an approach that perform well on edge devices is necessary. In 2019, Yonghao He etc.[10] realized that with their work *LFFD: A Light and Fast Face Detector for Edge Devices*, which implemented a considerably balancing both accuracy and running efficiency. Later, they improved the methods and proposed the update algorithm called LFD, which is said that perform better than LFFD. The same year in 2019, researchers from google proposed another Light neural face detector called BlazeFace which is designed for mobile GPUs in their work *BlazeFace: Sub-millisecond Neural Face Detection on Mobile GPUs*[11]. The BlazeFace model architecture is built around four important design considerations containing Enlarging the receptive field sizes, Feature extractor, Anchor scheme and Post-processing. For the first part, they found that increasing the kernel size of the depth wise part is relatively cheap. So that they employed 5×5 kernels in the model architecture bottlenecks, trading the kernel size increase for the decrease in the total amount of such bottlenecks required to reach a particular receptive field size. As for Feature extractor, BlazeFace mainly focus on extracting features for the front-facing camera model. The extractor takes an RGB input of 128×128 pixels and consists of a 2D convolution followed by 5 single BlazeBlocks and 6 double BlazeBlocks.

Table 1: Different Techniques for face Detection

Method Category	Presentative Work
Feature based	
Active Shape Model	Snakes Deformable Template PDM
Low Level Analysis	Skin Color Motion Gray Scale Edge
Feature Analysis	Viola-Jones Gabor Feature Constellation
Image Based	
Linear Subspace	Neural Networks Eigen faces
Statistical Approach	PCA SVM

Thanks to Ashu Kumar etc[12], who reviewed and summarized the main methods used for face detection in their work *Face detection techniques: a review*, and the mainstream approaches are listed in table1: Different Techniques for face Detection.

3 Face Recognition Techniques

On above of the discussion on face detection, the issue about finding faces in a image and extracting features of faces has been done. Based on these works, it comes the issue that how to recognize faces. The earliest work on face recognition can be traced back at least to 1950s in psychology and to the 1960s in the engineering literature. Even to this day, many face recognition techniques have been proposed with the fast-growing of this subject area and the tasking research topic in the field. W.ZHAO[3] *Face Recognition: A Literature Survey*

Table 2: Categorization of Still Recognition Techniques

Approach	Representative work
Holistic methods	
PCA	
Eigenfaces	Direct application of PCA [Craw and Cameron 1996; Kirby and Sirovich 1990; Turk and Pentland 1991]
Probabilistic eigenfaces	Two-class problem with prob. measure [Moghaddam and Pentland 1997]
Fisherfaces/subspace LDA	FLD on eigenspace [Belhumeur et al. 1997; Swets and Weng 1996b; Zhao et al. 1998]
SVM	Two-class problem based on SVM [Phillips 1998]
Evolution pursuit	Enhanced GA learning [Liu and Wechsler 2000a]
Feature lines	Point-to-line distance based [Li and Lu 1999]
ICA	ICA-based feature analysis [Bartlett et al. 1998]
Other Representations	
LDA/FLD	LDA/FLD on raw image [Etemad and Chellappa 1997]
PDBNN	Probabilistic decision based NN [Lin et al. 1997]
Feature-based methods	
Pure geometry methods	Earlier methods [Kanade 1973; Kelly 1970]; recent methods [Cox et al. 1996; Manjunath et al. 1992]
Dynamic link architecture	Graph matching methods [Okada et al. 1998; Wiskott et al.1997]
Hidden Markov model	HMM methods [Nefian and Hayes 1998; Samaria 1994; Samaria and Young 1994]
Convolution Neural Network	SOM learning based CNN methods [Lawrence et al. 1997]
Hybrid methods	
Modular eigenfaces	Eigenfaces and eigenmodules [Pentland et al. 1994]
Hybrid LFA	Local feature method [Penev and Atick 1996]
Shape-normalized	Flexible appearance models [Lanitis et al. 1995]
Component-based	Face region and components [Huang et al. 2003]

3.1 Global Features based

The methods where global features are used apply statistical features to represent. In these methods, the images are considered as a while so that they are called global feature, whereas many methods used to extract them are traditional machine learning methods as well, such as principal component analysis(PCA), kernel PCA(KPCA), 2D-Image PCA(2D-PCA) and Fisher-Linear Discriminate Analysis(LDA) etc.

Principal component analysis L.Sirovich and M. Kirby[13] introduces a methods in their work *Low-dimensional procedure for the characterization of human faces* in 1987 called *KL transform*. To execute it, a transformation from 2D-face images matrixes to 1D vector which represents one column vector in the data matrix is first step. A co-variance matrix is computed after converting every face image into data matrix. To present a face, the approach applied a Eigen Pictures. After obtain a set of cropped face images, called face ensemble with KL transformer, PCA was applied to them.

Then M.Turk and A.Pentland[14] extended the work above in their work *Eigenfaces for recognition* in 1991, where they developed a fast, simple and accurate computational model, Eigen faces, in which the Information Theory based approach was emphasized, and PCA was used to transform face images from image space to face space.

Kernel principal component analysis Resemble the kernel methods in support vector machine, the approach called kernel principal component analysis map the input images to a feature space via some non-linear mapping function, and then apply PCA in the feature space to execute dimensionality reduction. In order to realize face recognition, the SVM mentioned above was applied as a classifier in transformed domain.

Independent component analysis(ICA) In PCA method, the pairwise relationships between pixels of the image database was exploited, while in Independent Component Analysis (ICA), high-order relationships among pixels are adopted to present some important information. In the work of Bartlett Marian Stewart etc.[15], *Face recognition by independent component analysis*, they developed Two different architectures, the first one considers images as random variables and their pixels as output and the second one is inverse. To summarize, a matrix was structured to present the face databases where each row is a different person. For the first approach, face images are considered as random variables and their pixels as trials, then calculate the degree of independence of two images. If two images are independent, then while moving across the pixels, it would not be possible to predict the value of a pixel on the basis of the value of same pixel in another image. While in the second approach, independence of two pixels is computed. That is, while moving across an image, it is not possible to predict the value of a pixel based on some other pixel in the same image.

3.2 Local Features based

The local feature based methods divide the face image into several blocks and each block is considered separately for extracting the features. Some researchers found that, some facial feature such as eyes, would contribute more for face recognition. So that local feature based method always perform well unexpectedly. In this method, some blocks will be ignored that does not play major role in discriminating features. For this reason, the accuracy of these methods are good comparatively global feature based methods. It is still an open issue to find a suitable descriptor for local facial regions. Beside, any such descriptor should ideally be easy to compute and have high inter class and low intra class variance.

Local binary patterns(LBP) For the factor that face is also composed of micro-patterns, local binary pattern is encouraged to be applied on face recognition. In the work of Timo Ahonen etc.[16], *Face Recognition with Local Binary Patterns*, they assigned a binary label to every pixel in the image with LBP, where applying a threshold on 8-neighborhood of the pixel, just as shown in the following figure, then a histogram of the labels is generated that acts as a texture descriptor.

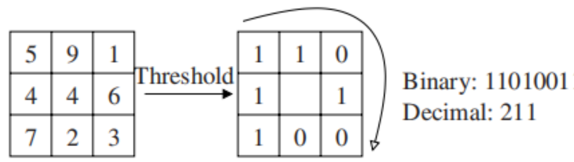

Figure 1: Basic LBP Operator.

Histogram of oriented gradients HOG is a well known feature descriptor. Initially, the image is divided into small connected regions, called cells, and for each cell, a histogram of edge orientations is computed. The histogram counts are normalized to represent the final HOG descriptor.[1]

Elastic bunch graph matching L.Wiskott etc.[17] proposed the Elastic bunch graph matching method through their work *Face recognition by elastic bunch graph matching* in 1999. In their methods, by choosing a set of fiducial points on the face to construct a graph, which was used to present an individual face. Then take each fiducial point as a node to generate a fully connected graph. The edge represents the distance between two corresponding joining fiducial points. A stack-like structure is obtained by combining a set of such graphs called a face bunch graph.

3.3 Neural Networks and Deep Learning

With the rapid growth of techniques about images, storage, computing power etc, it is inevitable to discuss the Neural Network and Deep Learning methods.

The traditional methods for face recognition, like discussed above, involve pre-processing, local descriptor extraction, and feature transformation steps. Even though these steps have been improved separately, not much increase in the accuracy for face recognition has been reported. Also, most of the methods for unconstrained face recognition tackle with only one challenge among pose, expression or illumination. Hence, traditional methods are not much capable of extracting stable features for recognition that are invariant to real world situations. On the other hand, deep learning methods use a stack of layers to learn different representations at multiple levels, and these features extracted from these layers show robustness towards variation in illumination, expression and pose. Until now, these methods are developed mainly using neural network models by developing methods for staking one useful representation over other. The features extracted from the multiple stacked layers of a deep neural network show robustness towards any kind of variation in general.

In 2014, Y Taigman[18] et al proposed the initial deep learning face recognition methods *Deepface* in their work *Deepface: Closing the gap to human-level performance in face verification*. Deepface uses nine-layered convolutional neural network (CNN) in which last two layers are fully connected layer. The output of the fully connected layer is passed to a K-way softmax function, where K is the number of classes. The output of the softmax layer gives the probability distribution for various classes.

In 2015, Florian Schroff[19] et al designed another method based on learning an euclidean embedding for every image using CNN, called FaceNet in their work *FaceNet: A unified embedding for face recognition and clustering*. The network is trained such that the L_2 distance of the similar face representations are less as compared to the representation of faces of different persons. It introduces online triplet mining method that utilizes triplets of roughly aligned matched and non-matched face images.

In 2017, in the work of Zhong, Yuanyi[20] et al, *Toward End-to-End Face Recognition Through Alignment Learning*, they have proposed an end-to-end framework through alignment learning in which neither prior knowledge on facial landmarks nor artificially defined geometric transformations are required. Only human identity clues are used for driving the automatic learning of appropriate geometric transformations for the face recognition task.

In 2018, X Wu[20] et al introduced variation of maxout activation, called max-feature-map (MFM), into each convolutional layer of CNN, and three networks are carefully designed to obtain better performance, meanwhile, reducing the number of parameters and computational costs. So that a Light CNN framework to learn a compact embedding on the large-scale face data with massive noisy labels debuted.

With more and more popularity of deep learning technology, a large number of novel structures and algorithms have sprung up towards specific areas or branches, and it is a tough task to summarize all of the models and works in this field. As is mentioned before, the popular methods that perform well are experimented and proposed by combining the basic Neural Network modules. Besides, methods that are fast and light are techniques worth exploring, which are suitable to deploy on some edge devices so that to produce more industrial and practical value. The well-known methods mentioned above have been listed in the table 3.

Table 3: Methods of Face Recognition

Techniques Category	Approaches
Face Detection	
	Robust real-time gace detection. Viola&Jones.2004 Dlib-ml.D.E.King.2009 NPD.A.K.Jain.2016 faster RCNN.X.Sun.2018 LFFD.Yonghao He.2019 BlazeFace.Valentin Bazarevsky. 2019
Face Recognition	
Statistical Methods	PCA KPCA ICA SVM LBP HOG Elastic bunch graph matching
Neural Network and DL	Deepface.Y Taigman.2014 FaceNet.Florian Schroff.2015 End-to-end face recognition. Zhong.2017 MFM.X WU.2018 PIEs.Chih-Hui Ho.2019 Magface.Q Meng.2021
Reinforcement Learning	ARFace.Liping Zhang.2022

3.4 Other Approaches

Beside methods involving traditional Machine learning, novel Neural Network and Deep learning methods, reinforcement learning methods gradually come into view. In 2022, Liping Zhang[21] et al combined the deep CNN and reinforcement learning methods and proposed an attention-aware face recognition method called ARFace which is composed of an Attention-Net and a Feature-Net in their work *ARFace: Attention-Aware and Regularization for Face Recognition With Reinforcement Learning*.

The ARFace structure, furthermore, select patches in the input face images with the Attention-Net according to the facial landmarks which would be trained by reinforcement learning to maximize the recognition accuracy, then extract discriminative embedding features with the Feature-Net. To construct the Feature-Net, two basic Network structure, MobileFaceNet that consists of convolutions with 1×1 kernels and depthwise convolutions with 3×3 kernels. and ResNet, or specially ResNet50 are applied, which are both representative and widely used methods in face recognition tasks[21].

4 Future Researches

After a brief summary of the available technology, it is necessary to discuss the future research directions of the face recognition. There is no denying that there still exists a mass of challenges in the research on face detection and recognition, involving the facial occlusions caused by face masks, shades, scarf, hat etc., heterogeneous faces, aging, single sample of face, accuracy and security, etc. At the meantime new challenges will emerge as application scenarios change and research progresses. On above of these, the following directions might worth going on research.

Pre-processing approaches Most face recognition approaches concentrate more on the feature extraction and classification stages, and as result neglect specific pre-processing steps that can enhance face recognition systems. Take the face alignment technique as an example, it has comprehensive application in automatic face analysis. This approach, however, has shown to be challenging in unconstrained environments. Besides, face image enhancement is another pre-processing step that can help improve the performance of face recognition techniques. In the work *A new evaluation function for face image in unconstrained environments using metaheuristic algorithms* done by Oloyede MO etc[22]., they pointed out that a major setback with the process is the ability to extract effective features from the enhanced face images that can be effective for classification.

Face datasets The facial datasets are discussed describing the various issues that each contains. Access to the facial datasets is somewhat difficult as much processes is involved, thus making research in the area slow. Also, face datasets should be developed such that the collection of faces can include most of the facial constraints[23]. By doing this, a face recognition algorithm can be evaluated with just a single face dataset that depicts a typical real-life scenario. Lastly, it is seen from the results reported on the different face datasets that continuous research work on improving face recognition algorithms needs to be done.

Deep neural networks Deep neural networks have shown to be effective techniques for computer vision tasks and most recently for face recognition tasks. Notwithstanding, the attempts of previous authors to solve facial constraints during face recognition, there still exist the possibility of improving individual layers of the CNN that can make the network perform optimally. The pooling layer of the CNN architecture is an essential layer because it can reduce the size of the feature map that portrays the filtered image in the convolution layer. The pooling layer consists of both the max and average pooling, therefore, the performance of the CNN can largely depend on the type of pooling method used; which is also a function of the input image. Even though the max and average pooling method perform well on certain datasets, it is unsure which pooling method will outperform the other on different face recognition problems. Besides, other approaches can be introduced into the pooling layer on how to select features that can perform efficiently.

5 Conclusion

This paper gives a brief review and summary of face detection and recognition approaches along the branches of traditional statistical methods and novel neural network methods. The statistical methods, which are popular in earlier research paid more attention on extracting features, both global features and local features. And the recognition work will be executed based on the features. By contrast, the Neural Network methods execute the feature extracting with their hidden layers in most cases. Aiming at different type of features, the corresponding approaches perform well, that is methods based PCA' KPCA, ICA etc. for global features whereas LBP, HOG, Elastic bunch graph matching for local features.

There is no denying that techniques with Neural Network model have been providing a disruptive contribution to the research on face relevant techniques with the increasing popularity of deep learning technology. The deeper and deeper models, however, are computation consuming and time consuming, whereas the application scenarios about face recognition are executed by some called edge devices most of cases, like smartphones, IP cameras, IoT etc., and these devices can not support such large computation. For this pair of contradictions, fast and light models worth researching as well. Perhaps in the near future, deep learning techniques and reinforcement learning techniques that are supported by deep neural networks will bring us more surprises on face relevant researches.

In the end of this paper, some imagines about future research directions are given, which is about preprocessing approaches, face databases , and deep neural networks. In general, the new developments in face recognition must meet four objectives: always faster (immediate response seen from the user's point of view), accuracy close to 100%, optimal security, miniaturized, and portable equipment[24].

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