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A Survey of Face Recognition and Its Techniques

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Abstract: Face verification is a relatively easy task with the help of discriminative features from deep neural networks. However, it is still a challenge to recognize faces on millions of identities while keeping high performance and efficiency. This paper presents a review on various facial recognition techniques which exists in today's world and summarizing the differences between them. Searching for robust descriptors has been an important research in computer vision. We are presenting here the list of facial descriptors such as Eigen faces, Fisher faces, Gradient faces, Local Binary Patterns (LBP), Binary Gradient Patterns (BGP) and their corresponding accuracies on different facial databases.

Keywords: Face recognition**,** Eigen faces**,** Fisher faces, Gradient faces and Histogram of gradient faces.

I. Introduction

Face recognition is a process of identifying a person's face in a digital image or a video. It mainly works on the principle of object recognition, i.e.., where a system can recognize and discriminate between different objects, it has been trained to recognize. It uses computer vision and machine learning to its maximum advantage. It is one of the most active topics in Image processing and Object recognition. Object recognition is a sub discipline of pattern recognition. Face recognition has many applications out of which commonly used are video surveillance, to match the faces in the footage to the existing facial database. It also used as biometric passwords in smart phones as fingerprint passwords used. Recently, it is used in social networking sites to tag the pictures of people automatically. There are a lot of challenges in facial recognition such as illumination, Variations in facial expression, angle between face and camera, wearing glasses, changing facial hair and hairstyles, Noise and Occlusion.

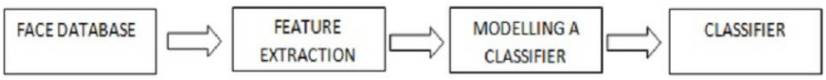

Figure1. Training a face recognition classifier.

To recognize a face, we need to train a system to extract feature of human faces from a facial database and draw conclusions from that database. From these conclusions, one need to model the classifier which discriminate the facial features to other features.

Figure2. A typical face recognition system.

After training the model, if we pass an input frame then the face is detected by cropping the other portion of photo than that of the face. Then the face is registered and the features of the particular face are extracted and it is matched against the faces in the face database. If the features of the registered face are matched with any of the faces in the database, then we can assure that both faces be owned by the same person. This is how facial recognition process works.

Except for powerful network structure, another kind of approaches to improve the performance of face recognition is metric learning. Using auxiliary loss to supervise the training of networks is a simply way in metric learning, such as contrastive loss [25], triplet loss [23], center loss [33], contrastive-center loss [22] and Norm Face [32]. These approaches are proposed for the purpose of more discriminative features by enforcing better intra-class compactness and inter-class reparability. The contrastive loss [25] and triplet loss [23] do really improve the performance of networks but they all need carefully selected pairs or triplets. And the selection of pairs and triplets has influences on the training results of deep neural networks. The center loss does not consider the inter-class reparability, but contrastive-center loss does. The Norm Face [32] considers feature normalization and optimizes cosine similarity directly instead of inner-product.

However, it is still a challenge to do face recognition in the wild, mainly because of the large variance of faces. In case of identifying one face in more than one million faces, conventional approach just compares the cosine similarity simply, which may decrease the performance and not that efficient.

1.1.1. Similarity search

Nowadays, there are large amounts of images and videos, especially from the Internet. How to get the images or videos we are interested in are important. However, interpretation and searching of images and videos are not that easy and require accurate and efficient algorithms. A variety of machine learning and deep learning algorithms are being used to help the interpretation and searching of these complexes, real-world entities. In this context, searching by numerical similarity rather via structured relations is more suitable [16, 7]. Using the similarity could find the most similar content to a picture, or find the vectors that are most similar. State of the art similarity search methods like NNDescent [4] have a large memory overhead on top of the dataset itself and cannot readily scale to billion-sized databases, such as MS-Celeb-1M[9, 8].

Therefore, using NN-Desent like methods to compute a k-NN graph is not practical. Rendering both exhaustive search and exact indexing for non-exhaustive search are impractical on billionsized databases. So, the approximate search or graph construction is fit for the task of efficient and accurate similarity search on billion-sized datasets. The methods based on product quantization(PQ) codes [14, 16, 2, 5] are shown to be more effective than binary codes [19], for the binary codes incur important overheads for non-exhaustive search [20]. However, most of the methods about PQ are difficult to implement efficiently on GPUs [16].

There are also many other implementations of similarity search on GPUs [16], but most of them are with binary codes [21], small datasets [31], or exhaustive search [3, 24, 30], which are not elegant. The most outstanding similarity search methods based on PQ are [34] and [16]. Using effective similarity search method will help the task of similarity search significantly.

1.1.2. Combining similarity search with face recognition

To boost the performance of face recognition, there are many strategies, such as using very large scale training data[23], metric learnings [25, 23, 33, 22, 32] and deeper and wider neural networks[10, 35]. However, these strategies are not that appropriate in the condition of face recognition 1:N when N is a too large number. In some cases, the base search datasets may contain some error-labeled face images or non-face images. Otherwise, the internal structure and contact of base search datasets is a good clustering reference, which is significant for face recognition in billion-sized datasets. In the condition of searching faces when base dataset is billion-sized, it is necessary to adopt some strategies to speed up the searching while keeping high accuracy. In face verification or face recognition, similarity score is mostly used to indicate the similarity of two faces.

To speed up the searching while keeping high accuracy in million-sized face recognition, such as MS-Celeb-1M [9, 8], we adopt similarity search strategies based on product Quantization [16], which are most efficient and accurate similarity search methods. What's more, these methods are implemented on GPUs, which will boost the search speed further.

1.2. Pre-processing on face images

There are many non-face images and error-labeled face images, as shown in Fig. 2 and Fig. 3, which will decrease the final accuracy. Therefore, image classification and clustering are used firstly in our proposed scheme to remove the error-labeled face images and non-face images in the large scale face datasets [9, 8]. Then, face re-detection and re-alignment is used to improve the accuracy of face recognition further.

1.2.1. Image classification and clustering

Firstly, we train an image classification model to class face and non-face. The dataset used is WIDER FACE [36]. After training the classification network, all the images in base and novel set in challenge 2 of MS-Celeb-1M [9, 8] are classified by the network and only the face images suitable for face recognition are kept. In the process of classification, face images not containing full faces are removed. Secondly, to remove those error-labeled face images, clustering is done for every image folders in the base set. Face images of different people are divided into corresponding folders, which are named by Freebase MID. One folder should contains images of one person. Clustering on every folder is proposed through features extracted from a deep neural network. The number of clustering center of every folder is set to 2, and the center has more points will be set as main center. The scheme of removing error-labeled face images is to compare the extracted features' distance between the image and main center. If the distance is larger than twice of the average distance of corresponding points, the image will be removed. After the clustering, most of the folders in the base set only contain single person's face images.

1.3. Discriminative face feature extractor

A deep neural network is used as feature extractor. And the input images are normalized by face detection and alignment through similarity transformation. Note that the model for extracting features is only trained on CASIAWebface[37], not trained on MS-Celeb-1M[9, 8].

1.3.1. Face detection and alignment

Face features can be extracted through a deep neural network. Before extracting features, face detection and alignment will be done here. MTCNN[38] algorithm is used for face detection and landmark detection.

1.3.2. Face recognition model

After preprocessing, face detection and alignment, we train a single deep neural network for feature extraction, called FRN(or FaceResNet), which is the same as NormFace[32]. The FRN is trained under the supervision of improved softmax loss used in NormFace[32] and contrastive-center loss[22] jointly to get more discriminative feature.

II. LITERATURE SURVEY

Face recognition has lot of applications in various disciplines such as Law enforcement, Entertainment, Smart cards, Information security etc. In law enforcement, it used to track suspects using CCTV control. In Entertainment, it is used for human-robot interaction. In Smart cards, it is used in the process voter registration and driving license. So, a key solution lies in facial representation but a great deal of effort is needed. Deep learning mechanisms helps in building well defined, discriminative facial descriptors, which still plays a dominant role in face recognition applications. Searching for robust descriptors has been an important research in computer vision. A list of past adopted approaches is being discussed here. Eigen faces and Fisher faces are facial descriptors where faces are represented by pixel intensities. They are proposed using linear PCA and have been enhanced by nonlinear PCA. But they are sensitive to Illumination, Variation, Noise and occlusion. Gradient face is a novel descriptor which uses IGO [image gradient orientation] instead of pixel intensities to achieve strong invariance to illumination. But they are sensitive to Local deformation, Rotation, Spatial scale, thus prone to facial expression and poses. Gabor wavelets descriptor extracts micro textual details, fusing these local features can provide global shape information, making it robust to local distortions.

Table1. Applications of Face Recognition.

Area	Application
Law enforcement	CCTV control, suspect tracking
Entertainment	Human-robot interaction
Smart cards	Voter registration, driver license
Information security	Smart phone login, Secure trading terminals

III. FACE RECOGNITION TECHNIQUES

A. Eigenfaces and Fisherfaces: The aim is to represent a face image as a linear combination of a set of eigenvectors, given training set of 'M' images and an unknown face, all of same size. These Eigen faces (eigenvectors) are in fact the principal components of the training set of face images generated after reducing the dimensionality of the training set. To reduce the dimensionality of the training dataset, it uses a method called PCA. PCA is proposed by Karl Pearson in 1901. It is mostly used tool in exploratory data analysis and for making predictive models(example: face recognition). PCA is used to reveal internal structure of data by explaining the variance in data. In Eigen faces, the principal component is referred to Eigen face, data point or variable is referred to image and dataset is referred to training set of images.

The only difference between Eigen faces and fisher faces is the process of reducing the dimensionality of training dataset. Eigen faces uses PCA, where fisher faces uses linear discriminant analysis. The linear discriminants obtained on a training datasetare called fisher faces. LDA is used to reduce a dimensionality of dataset with good class separability. Although these two algorithms used for facial recognition, they have their own limitations in illumination, variation, noise and occlusion.

Table2. Comparison of previous works on Eigen faces and Fisher faces.

S.no.	Author	Advantages	Limitations
1	Rajib saha et al.	Extracts useful features by reducing the dimensionality [8].	Prone to other facial poses [8].
2	Magali segal et al.	Best in handling variation in lighting and expressions [9].	Prone to variation in facial expression [9].
3	M. Turk et al.	Gives good results in orientation variation [10].	Prone to variation in sizes [10].
4	Marijea et al.	Provides better dimensionality reduction [11].	Prone to variation in illumination [11].
5	Pentland et al.	Gives modular Eigen faces [12].	Prone to variation in orientation [12].
6	Peter N. et al.	Insensitive to large variation in lighting direction and facial expression [22].	Prone to cluttered backgrounds [22].
7	Xiaofei He et al.	Preserves the local structure of the image space [23].	It does not deal with Biometric characteristics [23].
8	Alex et al.	Use in face recognition under variable pose [24].	Insensitive to substantial variations in light direction [24].
9	Ming –hsuan yung et al.	Use higher order statistical relationships among the pixels for facial recognition [25].	Insensitive to substantial variations in face pose [25].
10	Keun- Chang et al.	Reduced sensitivity to variations in illumination and viewing directions [26].	Prone to cluttered backgrounds [26].

B. Gradient faces and Histogram of gradient faces: To reduce the illumination problem in facial recognition systems, a new facial descriptor called gradient face is proposed. It uses image gradient orientation (IGO) instead of pixel intensities to achieve strong invariance to illumination. The directional change in the intensity or color of an image is called as image gradient, which is used to extract information from the image. This IGO used to detect edges of a particular image. This HOG descriptor is used to obtain facial features by the distribution of image gradients on the image. Here the image is divided into small connected regions called cells and a histogram of image gradients for pixels within the cell is calculated. Combining these cells of the particular image together forms a facial descriptor. To improve the accuracy, we can divide the larger portion of the image into blocks, in which in turn we can divide them into cells. This process is called 'Normalization', which results in better invariance in illumination and shadowing. These algorithms are sensitive to Local deformation, Rotation, Spatial scale, thus prone to facial expression and poses.

Table3. Comparison of previous works on Gradient faces and Histogram of gradient faces.

S.no.	Author	Advantages	Limitations
1	M. Ishiwaka et al.	Classifies the given input into pedestrian Non -pedestrian [4].	Fails to differ between human like animals such as bear etc.., [4].
2	N. Dalal et al.	Provides better invariance to illumination and Shadowing [13].	Prone to cluttered backgrounds [13].
3	Chandrasekhar et al.	Provides robust object discrimination [14].	Prone to wide range of poses [14].
4	Stanley et al.	Improves accuracy of object detection by using Gestalt descriptors [15].	Prone to noisy databases [15].
5	O. Deniz et al.	Provides invariance to occlusions, pose and illumination changes [27].	Prone to variation in discrimination [27].
6	Qiang Zhu et al.	Provides features to achieve fast and accurate human detection system [28].	Sensitive to local deformation [28].
7	Tomoki et al.	Used to detect pedestrians from images [29].	Prone to differentiation between humans and animals [29].
8	F. Suard et al.	Used for pedestrian detection applied to infrared images [30]	Prone to spatial scale [30].
9	Xiaodong et al.	Used to recognize human actions from sequences of depth maps [31].	Prone to variations in facial occlusion [31].
10	Alexander et al.	Presents a novel local descriptor for video sequences [32].	Prone to cluttered backgrounds [32].

C. Local binary patterns:LBP is a visual descriptor which is described in 1994. It classifies the image or pixels of the images using the texture classification. It is proved that when we combine Local binary patterns with HOG, we can assure high accuracy in face recognition. In LBP, an image is divided into cells. For each pixel in a cell, compare the pixel value to its 8 neighboring pixels in clockwise or anti-clockwise. When the center pixel value is greater than the neighboring pixel, write the value as"0", otherwise write the value as"1". This pattern gives us a 8-digit binary number. Now, compute the histogram of these values and normalize it. Combining the all normalized values of all cells gives us the facial features of the image [7].

D. Binary gradient patterns:BGP uses features of both IGO domain and LBP [1], presents a new local facial descriptor**.** It measures relationships between local pixels in the image gradient domain and encodes the local structures into set of binary strings. Local features extracted by BGP shows stronger orientation power than LBP and Gabor descriptors. It increases discriminative powerby simplifying computational capacity [1].BGP is implemented in 3 steps. Computing image gradient from multiple directions is the first step. Encoding them into binary strings is the second step. Division of structural and non-structural patterns is the final step [1].

Table4. Comparison of previous works on Local Binary Patterns and Binary Gradient Patterns.

S.no.	Author	Advantages	Limitations
1	Md. Abdur et al.	Provides similarity measure between images [16].	Prone to facial occlusions [16].
2	Timo et al.	Provides robustness against face localization error [17].	Prone to pose and lighting variations [17].
3	Timo et al.	Provides very powerful tool for rotation invariant texture analysis [18].	Prone to expression and age variations [18].
4	Marko et al.	Very robust to occlusion and illumination changes [19].	Prone to extreme lighting [19].
5	Weilin et al.	Provides invariance against both illumination and local distortions. [1].	Yet to use in real-time applications [1].
6	Semin et al.	Provides robustness against rotation and has high accuracies for image based coin recognition [20].	Prone to variation in size of the objects [20].
7	Ning et al.	Provides feature possible for human detection [21].	Window size used here is fixed [21].
8	Guoying et al.	It provides local processing, robustness to monotonic gray-scale changes [33].	Limited by extra lighting [33].
9	Shengcai et al.	Provides Multi-scale Block Local Binary Pattern [34].	Prone to lighting variations [34].
10	Caifeng et al.	Used in real-world applications where only low-resolution video input is available [35].	Prone to local deformation [35].

IV. CONCLUSION

We have made an attempt to present the review of several papers on facial recognition. Present study reveals that the facial recognition algorithms such as Eigen faces, fisher faces are sensitive to variation, illumination, noise and occlusion. The binary gradient faces facial descriptor has significantly improvements over other algorithms such as discrimination, robustness and complexity. So, it has higher accuracy over other algorithms.

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