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Automatic Face Recognition in Digital World

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Abstract—*Digital images have become prevalent, through the spread of surveillance cameras, smart phones, and digital cameras. Economical data storage has led to enormous online databases of facial images of identified individuals, such as licensed drivers, passport holders, employee IDs and convicted criminals. Individuals have embraced online photo sharing and photo tagging on platforms, such as Facebook, Instagram, Picasa and Flickr. Face recognition is a biometric identification by scanning an individual's facial attributes and matching it against a digital library of known facial images or a video frame from a video source. In recent years, reliable automated face recognition has become a realistic target of biometric researchers. This paper addresses the current state-of-the-art strengths and weaknesses of the face (2D), general face (3D), and hybrid (2D+3D) face recognition methods. Some of the popular face recognition methods among them, including Eigenfaces, Fisherfaces, Local Binary Pattern (LBP) are critically evaluated. Furthermore, the obtained results of these methods are compared against our novel Augmented Local Binary Pattern (A-LBP) face recognition method. The experimental results of these methods are also verified by plotting the Receiver Operating Characteristic (ROC) curve on the face databases, such as AT & T-ORL, Indian Face Database (IFD), Extended Yale B, Yale A, Labeled Faces in the Wild (LFW) and Own database. A-LBP face recognition method performs better than Eigenfaces, Fisherfaces and LBP methods, especially for those facial databases having variations, such as mild pose and ambient illumination.*

1. INTRODUCTION

Face recognition system (FRS) is a technique that enables cameras to identify people automatically. Due to the necessity of correct and effective FRS, it leads towards the activeness of biometric research in the race of the digital world. The real-life face recognition applications, include civil application, access control, border controls, criminal investigations, identity checks in the field, Internet communication, computer entertainment, etc. Automated face recognition can be deployed live to trace for a watch-list of a suspicious person, or afterthe fact using surveillance footage of a crime to investigate from the suspects facial databases.

Facebook's tag suggestions, an automated system that identifies friend's faces each time you upload a photo, which automatically clusters pictures of the same person. It can be accurately recognize a person's gender. This capability is employed by electronic billboards that display different messages depending on whether a man or woman is looking at them, as well as by services that deliver dynamically updated reports on meeting-spot demographics [2]. Name Tag, a face recognition app that lets users match a face to their digital identity. It can also make a pretty good guess as to someone's age category [3]. Intel and Kraft employed this capability last year in developing vending machines that dispense free pudding samples only to adults [4]. Moreover, the Chinese manufacturing subcontractor Pegatron employed it to screen job applicants, spotting those who are under age [2]. Some of the digital footprints of individual recognition are shown in Fig. 1.

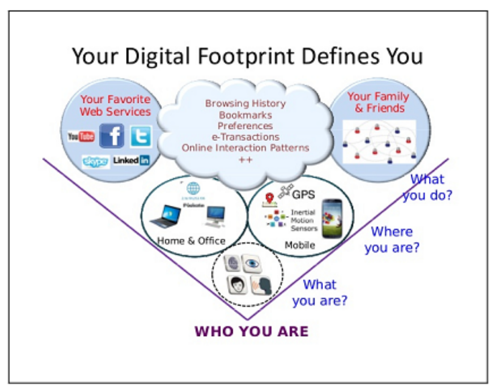


Fig. 1: Examples of digital footprints of individual recognition [1].

A mega project namely, unique identification (UID) programme of the government of India aims to provide a biometric-based unique number to every Indian for their identity proofing. Biometric identification seems to have become the government's new go-to solution for all kinds of problems. Biometrics prove to be an obvious choice in individual identification schemes. It is easier to identify different individuals with their faces and the automatic face recognition is playing a leading role in this direction. But, the unhitching optimism in the use of biometric technology and the collection of biometric data on a massive scale masks several concerns regarding compromises of individual privacy, such as Big Data and privacy issues, Biometric ID and theft of private data, and Biometric data and potential misuse [5].

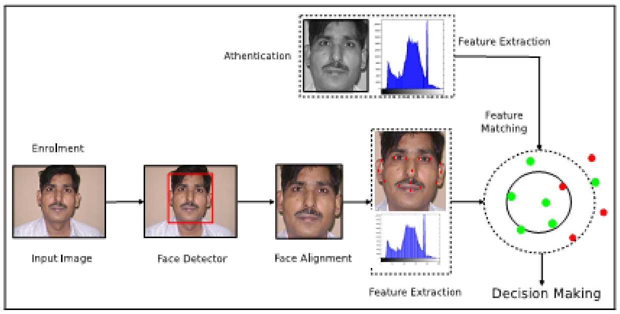


Fig. 2: Schematic of a typical automatic face recognition process [6].

Face recognition has made substantial progress in face modeling and analysis techniques in recent years, but this problem is still unsolved or partially solved. Some of its limitations are due to an insufficiently efficient database of facial images. And some of its limitations are a result of algorithms not yet able to compensate fully for things like pose variations, facial expressions, illumination, or subjects who are wearing hats or sunglasses or sport new face hair or makeup. Systems have developed for face detection and tracking, but reliable face recognition still offers a great challenge to computer vision and pattern recognition researches. There are several reasons for recent increased interest in face recognition, including rising private and public concern for strong security, the need for identity verification and recognition in the digital world, and the need for facial analysis and modeling techniques in multimedia data management and computer entertainment.

Furthermore, recent advances in automated facial analysis, pattern recognition, and machine learning have made it possible to devise automatic face recognition systems to address these applications. The different stages employed in a typical face recognition system are shown in Fig. 2. In addition, the automated facial analysis will find many applications, such as entertainment, home automation, medical or educational.

In summary, the contribution of the paper is to address the aspect of automatic face recognition in the digital world. The face recognition methods perform well in the favorable environments and require less computational effort in comparison to the general face recognition methods. The recognition accuracy achieved by most of the facial images are not as such that fulfill the stringent security requirement. Furthermore, human recognizes individuals using their faces with confidence but the performance reported by a facial images requires human intervention for final judgment. The face recognition using the general face image method recognizes individual using the general face model that synthesizes facial features. The general face images require more computational efforts. This paper outline the current state-of-the-art of the facerecognition methods using face (2D), general face (3D) andhybrid face (2D+3D) images and critically evaluate them. Therest of the paper is organized as follows. In Section 2, areview of face recognition methods is presented. The issuesof automated face recognition method are presented in Section 3. Our contributions are presented in Section 4, and Finally,conclusions are summarized in Section 5.

2. FACE RECOGNITION: A REVIEW

Automatic recognition of people from their facial geometryis a challenging problem because of the diversity in facesits variations. The facial geometry holds enough information to discriminate people from others. The morphologicalappearance of a person is subject to constant change andit differs in a significant manner during the various stagesof life. The discriminatory features of facial geometry arecommonly studied under the individuality of the faces thatrefers the characteristics that set one person apart from others.The conditions of being individual, or different from othersestablish the individuality of a person. The converging factorsthat increase the quantum of individuality are demographicinformation and facial marks. The demographic informationincludes race and skin color while face marks include scars,moles and freckles. These are soft biometric factors thatcan play an important role in improving face matching andretrieval [7].

From the past decades, considerable work has been done forface recognition methods and the issues related to automaticface recognition [8]–[15]. Typically, the best known facerecognition methods can be categorized as follows: (i) Facerecognition methods, (ii) General face recognition methods,and (iii) Hybrid face recognition methods.

2.1 Face Recognition Methods (Before1990's)

One of the earliest face recognition method was presentedby Bledsoe in 1966 [16]. Bledsoe outlined the challenges offacial recognition, such as changes in pose, illumination, facialexpressions and aging. He found very low correlation betweentwo images of the same person with two different poses.The first automated face recognition system was developedby T. Kanade in 1973 [17]. Since then there has been astagnant period in automatic face recognition. The work ofKirby and Sirovich [18], and Turk and Pentland on Eigenfaces[8] reinvigorated facial recognition research. The next milestone in facial recognition research achieved when the faceswere analyzed using linear discriminant analysis (LDA) andclassification was performed on Fisherfaces [9]. The multiclassLDA methods were also developed for managing more thantwo classes [19]. Belhumeur *et al.*

presented a comparativestudy on Eigenfaces and Fisherfaces [9]. They achieved therecognition accuracy of 99.6% using Fisherface method whenexperimented on Yale database [20]. The main weakness ofFisherface method is its linearity behavior. The independentcomponent analysis (ICA) is another method that has beenexplored for feature extraction as well as image discriminationfor facial recognition.

Local feature analysis (LFA) is another method used toconstruct a family of locally correlated features in eigenspace[21]. It produces a minimally correlated and topographicallyindexed subset of features that define the subspace of interest.The strength of LFA method is to utilize specific facial featuresinstead of the entire representation of the face for recognition.The method selects specific areas of the face such as the eyesor mouth, to define features and used for recognition. Thefeatures used in the LFA are less sensitive to illuminationchanges and are easier for estimating rotations. Ahonen *et al.*have proposed a method of facial image representation basedon local binary pattern (LBP) [22].

Wiskott *et al.* proposed the elastic bunch graph method(EBGM) where a set of jets corresponding to different facefeatures were derived from face images [10]. The successof the EBGM method may be due to its alikeness to thehuman visual system. The method performs well for frontalor nearly frontal face images, but their performance decreaseswith variations in illumination and pose. They reported therecognition accuracy of 80-82% on FERET database.

2.2. General Face Recognition Methods (after 1990's)

The processing steps of a general face recognition methodinclude general face construction, feature localization, featureextraction and matching. The general face is reconstructed bycombining the shading information with prior knowledge of asingle reference model to novel face. The general face modelcontains sufficient information about the face geometry. Ina general facial geometry, facial features are represented byboth local and global curvatures [23], Elastic Bunch GraphMatching (EBGM) [10] and general facial morphable models[12].

Chang *et al.* have proposed a multi-region based general face recognition method [24]. In this method, multipleoverlapping subregions around the nose are independentlymatched using ICP and the results of multiple general facematches fused. The recognition rate of 92% was claimed onFRGC 2.0 [25] database. The method selects landmark points,automatically and resulted an improved performance in thecase of facial expression changes. Blanz *et al.* have proposeda method based on a general facial morphable model thatencodes shape and texture in terms of model parameters [15].For face recognition, they used shape and texture parametersthat are separated from imaging parameters, such as poseand illumination conditions. They reported the recognitionaccuracy of 97.4%. Cootes *et al.* have experimented the synthetic images that are generated using a parametric appearancemodel [13]. They have shown an efficient direct optimizationapproach that matches the shape and texture simultaneously.

Numerous biometric researchers have described differentmethods for matching deformable models of shape and appearance to novel images. Naster *et al.* have proposed amodel of shape and intensity changes using a general facialdeformable model of the intensity landscape [14]. They haveused a closet point surface matching method for performingthe fitting of face or general face images. The proposed modelsof appearance can match any class of deformable objects. In[26], Passalis et al. have experimented an approach on thegeneral face using deformable models. An average generalface is computed on a statistical basis for a gallery databasethat results the recognition accuracy of 90% on FRGC 2.0database.

Chang et al. have presented a method that independentlymatches multiple regions around the nose and combines individual matching results to make the final decision. Bronstein*et al.* proposed a method based on the isometric model offace surfaces that infer an expression invariant face surfacerepresentation for general face recognition. Bronstein *et al.*haveexperimented an approach to general face recognitionthat is useful for deformation related to face changes [27].The objective is to change the general face to an Eigenformwhich is invariant to the type of shape deformation. Theyhave reported the recognition rates of 100% on the databasecontaining 220 images of 30 persons. Li *et al.* have proposed adiscriminative model that addresses face matching in the presence of age changes. In this model, each face is represented bydesigning a densely sampled local feature description schemesuch as scale invariant feature transformation and multi-scaleLBP [11]. They have claimed the recognition rates of 83.9%on MORPH database [28].

Vetter and Poggio proposed a general face morphablemodel, which is based on a vector space representation offaces [29]. The general face morphable model to imagescanbe used for recognition across different pose and texture offaces. They reported 95% recognition rates on CMU Multi-PIE [30] and FERET [31] database. Park and Jain haveproposed a method, namely structure from motion (SfM)that reconstructs the general face model for compensatinglow resolution, poor contrast and non frontal pose [32]. Afactorization based structure from motion method is used forgeneral facial reconstruction. The proposed synthetic modelhas been tested on a CMU face database and they claimedan improvement in matching to 30-70%. Furthermore, Shyamand Singh have presented the concept of new face recognitionmethod, called A-LBP which is a variant of LBP. This methodshows the significant improvement in recognition accuracyover LBP [6], [33]–[35].

2.3. Hybrid face Recognition Methods (2000' onwards)

The hybrid face recognition methods outperform both faceand general face methods alone. Hybrid face recognitioncombines the face information of face images and general facemodel to render a decision. Chang et al. have presented different approaches for combining face information that performsindividually the Eigenfaces on the intensity and range images[36]. They reported recognition performance of 99% forhybrid, 94% for general face, and 89% of face images. Godil *et al.* have experimented hybrid face recognition on the CAESARdatabase [37]. They use eigenfaces for matching both the faceand the general face, where general face represents a rangeimage. Numerous approaches to score level fusion of the twoor more results have been explored. They have reported therecognition rates of 82% on the range images.

Lu and Jain have experimented on hybrid system using iterative closest point and the face matching using LDA [38]. Theyhave reported 98% recognition rates on neutral expressionsand 91% on the larger set of neutral and smiling expressions.Wang *et al.* have experimented hybrid face recognition usingGabor filter responses in face and point signatures in generalface [39].

Mian *et al.* have proposed a novel holistic general facespherical face representation (SRF) method [40]. The SFR isused in conjunction with the scale invariant feature transform(SIFT) descriptor to form a rejection classifier. It eliminatesa large number of ineligible candidates faces from the galleryat an early stage. The SFR is a low-cost global general facedescriptor that achieves an improved performance of 95-99%for non-neutral and neutral face images, respectively.

3. ISSUESOF AUTOMATED FACE RECOGNITION

The effectiveness of a face recognition method depends onhow much it utilizes the knowledge of facial anatomy thatincludes face skeleton, muscles of the face and skin properties;image analysis techniques, photographic information, historyof facial identification and the computing resources. However,the idea of organizing the facial features into levels as soft biometrics for achieving better performance is also appealing. Forexample, the easily observable features like skin color, gender,and the general appearance of the face can be considered first.Then localized facial features are considered next and finallyfacial marks, skin discoloration, and moles are considered.

Primarily, the working of a face recognition system can beviewed as favorable and non-favorable conditions. In favorableconditions the frontal face detection from static images undernormal lighting and favorable conditions is a well solved problem. Methods such as the LDA, LFA, LBP, A-LBP, EBGMand their combinations perform well in favorable conditions.In non-favorable conditions the face detection from videoimages under variations of pose, expression, illumination, background, aging and the distance between the camera andsubject, is a partially solved problem. In order to mitigate theissued involved in non-favoring conditions, the face recognition methods mostly employ synthetic models such as generalface deformable model and active appearance model to detectdiscriminative facial features.

The lack of statistical analysis of the facial morphologyand geometry reduces the discriminatory information availableto an individual. Therefore the research must be focused onto compute the statistics of facial uniqueness that cover thehierarchical analysis of facial features as suggested by Klareand Jain [7]. Some biometric researchers suggest that theinformation of the ears is also a noticeable factor that maybe included with the face detection. Because, anatomy ofears is considered to be stable than other facial features, inparticular, the ears of two individuals cannot be the same[17]. Singh *et al.* have suggested that the fusion of the physiological signal such as electrocardiogram with an unobtrusivebiometrics faces improves the recognition accuracy of theresulting system [41], [42]. The ECG can supplement themissing information contents of the face biometrics and solvethe problem of spoofing attacks on the face recognition system[43], [44].

The general face recognition methods can achieve significantly higher accuracy than facial counterpart. The main challenge of general face recognition methods is the acquisitionof general face images. However, the methods like surfacematching of facial features are more robust against expressionchanges. Similarly, the general face deformation model reportsbetter results, but it suffers from computational problems andpoor generalization. The commercial solutions claim a goodrecognition accuracy, using general face models, but generalface recognition is still an active research field.

It has been reported that hybrid methods of face recognitionperforming better than face or general face alone. Somemethods notify that facial images cannot be directly applied togeneral face images. But efficient methods are still needed forhandling the changes between the gallery and probe images.The approaches that treats the face as a rigid shape doesnot work well with expression changes. It is suggested thatapproach would be to enroll a person in the gallery bydeliberate sampling a good set of different facial expressionand to match against probe using the well set of shapesrepresenting a person. We need an efficient method for generalface as well as hybrid face images for handling the subjectvariations.

In order to compute the facial similarities between faceimages acquired at different sources of frontal image and agedimages, the availability of a database that contains the imageswith substantial facial expression change, inter-class subjectvariation with demographic change and images with time delayis essentially needed.

4. OUR CONTRIBUTIONS

Here, we present our contribution to address some issuesof automated face recognition. The brief introduction of ournovel method that relies on the LBP, called Augmented LocalBinary Pattern. Earlier work on the LBP have not given muchattention on the use of non-uniform patterns. They are eithertreated as noise and discarded during texture representation, orused incombination with the uniform patterns. The proposedmethod targets the non-uniform patterns and extract the discriminatory information available to them so as to prove theirusefulness. They are used in combination to the neighboringuniform patterns and extract invaluable information regardinglocal descriptors.

The proposed method employs a grid-based regions. However, besides the directly putting all non-uniform patterns into59th bin, it replaces all non-uniform patterns with the mode ofneighboring uniform patterns. For this, we have taken a filterof size 3x3 that is moved on the entire LBP generated surfacetexture. In this filtering process, the central pixel's value isreplaced with the mode of a set in case of the non-uniformityof the central pixel. This set contains 8-closet neighbors ofcentralpixel, in which non-uniform neighbors are substitutedwith 255. Here 255 is the highest uniform value.

Table 1: Face Recognition Accuracies (%) of Eigenfaces, Fisherfaces, LBP and A-LBP Methods on Different Face Databases.

Databases	Face Recognition Techniques			
	Eigenfaces	Fisherfaces	LBP	A-LBP
AT & T-ORL	94.90	95.03	92.50	**95.00**
IFD	88.00	88.14	96.61	96.61
Ext. Yale B	56.65	60.53	74.11	**86.11**
Yale A	81.19	86.67	60.00	**67.86**
LFW	56.92	55.00	65.00	**67.37**
Own Database	87.50	87.50	85.00	85.00

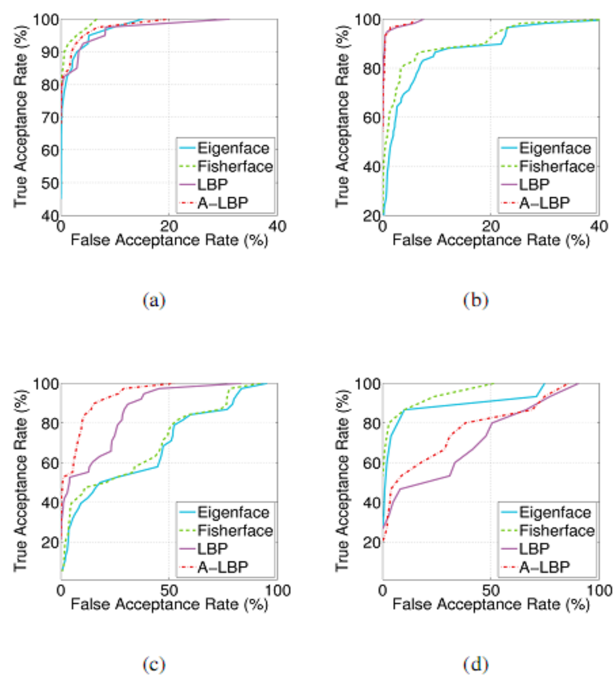
Our novel A-LBP along with other face recognition methods, such as Eigenfaces, Fisherfaces and LBP are tested on

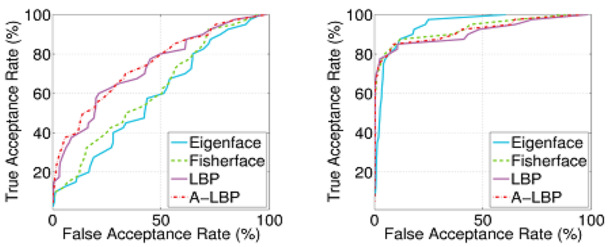
thepublicly available and our own created (characteristics of thedatabase is frontal and near to frontal) face databases, such asAT & T-ORL [45], Indian Face Database (IFD) [46], extendedYale B [47], Yale A [20], Labeled Faces in the Wild [48] andown database. These databases differ in the degree of variationin pose (p), illumination (i), expression (e) and eye glasses (eg)present in their facial images.

The performance of these face recognition methods as wellas our own A-LBP face recognition method (See Table I) isanalyzed using equal error rate, which is an error, where thelikelihood of acceptance assumed the same value to the likelihood of rejection of people who should be correctly verified.The performance of the proposed method is also confirmed bythe receiver operating characteristic (ROC) curves (See Figure3). The ROC curve is a measure of classification performancethat plots the true acceptance rate (TAR) against the falseacceptance rate (FAR).

The recognition accuracy of Eigenfaces, Fisherfaces, LBPand A-LBP is 94.90%, 95.03%, 92.50% and 95% at 5.1%,4.7%, 7.5% and 5% of the FAR respectively, on the AT &T-ORL database. A-LBP shows the significant improvementfrom LBP. The recognition accuracy of Eigenfaces, Fisherfaces, LBP and A-LBP is 88%, 88.14%, 96.61% and 96.61%at 12%, 11.86%, 3.39% and 3.39% of the FAR respectivelyon the IFD database. A-LBP does not make any change ascompared to LBP, because this database is highly affected bythe pose variations.

The recognition accuracy of Eigenfaces, Fisherfaces, LBPand A-LBP is 56.65%, 60.53%, 74.11% and 86.11% at43.35%, 39.47%, 25.89% and 13.89% of the FAR respectively,on the Ext. Yale B database. A-LBP shows the significantimprovement from all methods, because this database is highlyaffected by the variations of ambient illumination. The recognition accuracy of Eigenfaces, Fisherfaces, LBP and A-LBP is81.19%, 86.67%, 60% and 76.86% at 18.81%, 13.33%, 40%and 32.14% of the FAR respectively on the Yale A database.A-LBP shows the significant improvement from LBP methods.





(e) (f)

Fig. 3: ROC curves showing the performance of Eigenfaces, Fisherfaces,LBP and A-LBP face recognition methods on face databases: (a) AT & T-ORL, (b) Indian Face Database, (c) Extended Yale B, (d) Yale A, (e) LabeledFaces in the Wild, and (f) Own Datasets.

The recognition accuracy of Eigenfaces, Fisherfaces, LBPand A-LBP is 56.92%, 55%, 65% and 67.37% at 43.08%,45%, 35% and 32.63% of the FAR respectively on the LFWdatabase. A-LBP shows the significant improvement from allmethods. The recognition accuracy of Eigenfaces, Fisherfaces,LBP and A-LBP is 87.50%,87.50%, 85% and 85% at 12.50%,12.50%, 15% and 15% of the FAR respectively, on the owndatabase.

5. SUMMARY

Digital images have become prevalent, through the spreadof surveillance cameras, smart phones, and digital cameras.Economical data storage has led to enormous online databasesof facial images of identified individuals, such as licenseddrivers, passport holders, employee IDs and convicted criminals. Individuals have embraced online photo sharing andphoto tagging on platforms, such as Facebook, Instagram,Picasa and Flickr. We have experimented and compared theperformance of the Eigenfaces, Fisherfaces, LBP and A-LBP face recognition methods, after observing recognitionaccuracy results of the face recognition methods. It showsthat the results are also highly vulnerable by the nature of theface databases apart from having favorable and non-favorableconditions. Although, A-LBP face recognition method performs better than Eigenfaces, Fisherfaces and LBP methods,especially for those facial databases having variations, such asmild pose and ambient illumination.

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