Face Recognition Methodologies for Biometric Authentication: A Survey

Karis Kim

Kennesaw State University

College of Computing and Software Engineering

Department of Information Technology

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Abstract

Biometric authentication is widely adopted as more reliable and secure than traditional authentication methods like passwords and PIN. However, after identity theft, you can change your passwords and have new cards issued in a couple of weeks, but who can change or get a new set of fingerprints to replace the stolen ones? Biometrics like fingerprints have been used for a long time as a means of identification without massive security threats, but the stakes change when biometrics is used as a means of authentication. Biometric data will be converted into a string of numbers and transmitted through a computer network. Hackers can steal that data from a computer network or database, regardless of whether the string of numbers is from a password or from a digital voice print. Biometrics can be categorized into physiological biometrics and behavioral biometrics. Examples of physiological biometrics are: fingerprint (touch and touchless), hand, hand veins, eye, ear, face, DNA, heart EEG, heat, butt, body odor, and even brainwaves. Examples of behavioral biometrics are: eye movement, voice, gait, mouse, key strokes, gesture, and handwriting to name a few. Of these numerous types, facial recognition methodologies used in biometric authentication will be introduced here along with current research trends for facial authentication.

Keywords: Face Recognition, Face Recognition Methodologies, Biometrics, Biometric Authentication

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I. Introduction

Facial recognition as biometric authentication may seem like a product of state of the art technological advances. Particularly, in the case of three-dimensional (3D) face recognition, a common perception would be that 3D face recognition methodologies would be distinctly innovative and new. However, facial recognition technology has been in use for decades in various contexts, most notably in law enforcement as forensic metrics for identification, and many two-dimensional (2D) face recognition methods are repurposed, transformed, and augmented to accommodate 3D face recognition. For that reason, it would be remiss to introduce 3D face recognition without engaging 2D face recognition methods. The scope of this paper will be to highlight a number of representative methods, rather than to provide an in-depth exhaustive overview of all existing face recognition technologies. In the following Face Recognition Methodologies section, well-known 2D face recognition methods will be introduced, followed by 3D face recognition methods in the subsequent section. Then, in the Comparison section, a general comparison of the methods will be charted, followed by a brief discussion of future research challenges deduced from an integrated overview of all the methodologies presented here.

II. Face Recognition Methodologies

A. Principal Component Analysis (PCA)

Principal Component Analysis for facial recognition is categorized as an appearance-based method also commonly referred to as the Eigenface. PCA approaches a facial image as a 2D statistical recognition problem, and looks at the “dimensional subspaces whose basis vectors correspond to the maximum variance direction in the original image space” (Bhatia, et al., 2017). PCA method compresses large dimensionality of information space down to smaller principal components of the feature space, in a process called Eigenspace projection. The result of the computation yields a set of Eigenfaces, which can describe features of the face by coefficients (Kim, n.d.). A subject's face is recognized by comparing the characteristic features or "the projection coefficients" (Joshi and Gupta, 2016) of a face to the original images in the subspace. PCA is a well-established method that dates back to the early 1990s and can be regarded as the foundation for many face recognition methodologies.

B. Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis is also categorized as an appearance-based method, but is considered to be an improvement to the PCA method. LDA reduces the number of features where each new dimension is a linear combination of pixel values called Fisherfaces, obtained through Fisher's linear discriminant. The reason why LDA is regarded as a better alternative to PCA, even though both are holistic template matching based methods is because LDA expressly facilitates classification, "finding a base of vectors providing the best discrimination among the classes" (Abate, et al., 2007), whereas PCA takes the entire input data for object reconstruction. However, the performance of classification is possible only with a wide training set, and so LDA is subject to what is known as the "small sample size" (SSS) problem (Lu, et al., 2003). Subsequent research to resolve this problem has produced many variations of LDA, beginning with a combination of PCA-LDA, RLDA, ELDA, FLDA, DLDA, and 2D-LDA to list a few (Joshi and Gupta, 2016; Abate, et al., 2007).

C. Fisherface Method

The Fisherface method is categorized as a holistic appearance feature based method that uses a class specific linear method "for dimensionality reduction and simple classifiers in the reduced feature space" (Suhag and Mishra, 2011). Even though Fisherface is limited by the fact that multiple images for training is required for each face, it can form “well-separated classes in a low-dimensional subspace” under high illumination and facial expression variations; so, it is considered to be a successful approach (Suhag and Mishra, 2011).

D. Dynamic Link Architecture (DLA)

In the Dynamic Link Architecture algorithm, a face graph is created in which an image of a face is represented by a rectangular graph and Gabor wavelets are used to extract a set of local features at each node of the graph. Then face recognition is achieved through a graph matching procedure (Joshi and Gupta, 2016; Bennamoun, et al., 2015). DLA translational invariance is robust against distortions, but is process intensive and affected by orientation (Jasiwal, et al., 2011). DLA led to the development of the Elastic Bunch Graph Matching algorithm for face recognition.

E. Elastic Bunch Graph Matching (EBGM)

Improvements to the DLA precipitated the Elastic Bunch Graph Matching (EBGM) algorithm for face recognition. In EBGM, a face graph is constructed with nodes at facial landmarks like the corners of the eyes/mouth, the center of the eyes, and the noise tip. Afterwards, a face bunch graph is generated and a face graph of a probe image is compared to all model graphs, where the similarity between two faces is measured by the overall distance between the Gabor jets at the corresponding nodes of the two faces. EBGM is reported to have high accuracy with single frontal poses, but is subject to problems with cluttered backgrounds and occlusions (Wiskott, et al., n.d.).

F. Hidden Markov Model (HMM)

The Hidden Markov Model comes from the Markov model, which is a mathematical approach to solve probability of observations. The HMM statistical process finds the probability and the most likely transition trajectory of observation states that are not visible or “hidden” (Sharif, et al., 2017). HMM method was first applied in signal processing and speech recognition, but since the mid-1990s, it is being applied to face recognition with a number of derivations like 2D HMM, DCT-HMM, MC-HMM, SHMM, AHMM, EHMM, and Sub-Holistic HMM (Bicego, et al., 2003; Sharif, et al., 2017).

G. Other Notable Methods

As a result of robust research and development in face recognition over the past couple of decades, numerous face recognition methodologies are available. In addition to those introduced in the preceding sections, face recognition methodologies also include: Kernel Methods, Geometry-based method, Active Appearance Model (AAM), Active Shape Model (ASM), Independent Component Analysis (ICA), Support Vector Machine (SVM), Neural Network (NN), and Gabor Wavelet.

III. 3D Face Recognition

A. Stages of 3D Face Recognition

3D Face Recognition Technology (FRT) can be roughly divided into a few stages, with multiple methods and algorithms applicable at each stage, according to G¨okberk, et al. (2009). The first stage involves the acquisition of the face image. The second stage involves preprocessing and detection of the acquired face data. The third stage involves registration of the image. The fourth stage involves feature extraction and measurement. The fifth stage involves representations and matching, where the data is represented as code and algorithm(s) are applied, then finally matching the rendered face data. In the following sections, methodologies in each stage will be briefly introduced.

Stage 1: Acquisition of Facial Image

One cost-efficient method to capture facial image is known as stereo acquisition. This method reconstructs a 3D surface from images simultaneously captured with several 2D cameras. The benefit of stereo acquisition is that 2D and 3D methods can be applied in combination for higher accuracy. Another method is to project a structured light pattern with near-infrared light on the face with stereo acquisition, which increases cost but has a higher scan accuracy. A third method reflects laser beams on the surface of the subject and laser sensors indicate the distance to produce a range image, but the subject must be motionless for the capture duration.

Stage 2: Preprocessing, Detection

Whichever method is used to acquire the face image data, it will contain “noise” or spikes in local surfaces, and may also contain holes. Preprocessing removes noise, fills holes, and smooths the surface. The face data is then prepared with facial landmark detection for registration and feature extraction, using one of a number of landmark detection methods. In 3D face recognition, the most important facial landmark is the nose tip, whereas in 2D, important facial landmarks are the corners of eyes and mouth (Gökberk, et al., 2009,).

Stage 3: Registration

In the 3D face recognition process, registration may be the most expensive phase. Registration is guided by the landmark detection and influences the recognition. Registration can be divided into rigid and non-rigid. In rigid registration, the Iterative Closest Point (ICP) algorithm is normally applied. In non-rigid registration, deformable models are used to register faces to a 3D model and then use them to synthesize faces with a specific facial expression or a pose. A common model (the AFM, a.k.a. Average Face Model) is constructed and several exact anchor points from facial landmarks are mapped and the deformable face model simulates the bending of a thin metal plate fixed by anchor points (Gökberk, et al., 2009).

Stage 4: Feature Extraction, Measurement

Different techniques are applied based on the type of registration method used. According to G¨okberk, et al., most registration methods use a common model (the AFM) to enable dense correspondence between facial points. Common techniques for feature extraction include methods like PCA, LDA, and ICA (Independent Component Analysis), and other 2D facial feature extraction methods can also be applied. Curvature-based surface descriptors have been successfully employed in 3D surface representations, as well as combination of different representations and score fusion to combine shape and texture information, which include EHMM and 2D Gabor Wavelet among others.

Stage 5: Representation and Matching

Once features are extracted using one of many methods, the face data is represented using one of many algorithms. Then the 3D representation is matched to a set of models or one to one with a stored model.

B. Advantages of 3D Face Recognition

Behrad summarizes the following as the main advantages of 3D face recognition:

- Face shape and features acquisition can be independent of lighting conditions
- Pose can be corrected and is invariant for feature extraction
- Skin color or cosmetic factors have less effect on face data

Unlike many 2D face recognition that are sensitive to illumination and pose, as most people have experienced with passport photo restrictions, 3D face recognition is more robust against pose and illumination. 3D face recognition is also expected to perform better with liveness detection, where in 2D face recognition, spoofing can easily be accomplished with a photograph of the subject. Also, unlike 2D, the size of the face image is not a major factor. Moreover, 3D face recognition has greater industry implementation potential, such as in video surveillance for border security or more recently with biometric authentications like iPhone. Another advantage of 3D face recognition is that 3D methods can be combined with many and various 2D methods to specifically address and mitigate known weaknesses. However, the acquisition of 3D face images and changes with aging and face expressions are some limitations of 3D face recognition (Behrad, 2016) that is fueling much research.

IV. Comparison

According to the resources referenced in this paper, representative strengths and weaknesses (pros and cons) for the face recognition methodologies previously listed will be charted below.

Table 1.

Comparison of Face Recognition Methodologies

METHOD	STRENGTH	WEAKNESS
PCA	Performs well on small number of images; Efficient in reducing useless data, dimensionality reduction	Takes the entire input data for object reconstruction
Eigenfaces	Efficient in processing time & storage	Sensitive to illumination & pose
LDA	Improved Eigenfaces with classification; Facial expressions handled better than Eigenfaces	Sensitive to pose & illumination
Fisherfaces	Insensitive to high illumination, facial expression variation	Small Sample Size(SSS) limitation;

METHOD	STRENGTH	WEAKNESS
		More storage & processing time than Eigenfaces
DLA	Large gallery of objects, robust against distortion, rotation	Process-intensive; Inability to handle large size and orientation changes
EBGM	High success w/single frontal pose; Change or missing a feature does not prevent recognition; Person recognized with up to 22 degree rotation	Sensitive to cluttered backgrounds, occlusions, illumination
HMM	Very effective in modelling faces; Better performance than Eigenfaces; Robust against scaling, facial expressions, hair, glasses	Sensitive to image noise, rotation, illumination; Higher computational cost

As shown in Table 1, every method has advantages and disadvantages, and even more strengths and weaknesses that may not have been included here. So, current researchers in facial recognition technology are offering numerous multi-modal methods that are combinations or hybrids of the methods listed here as well as many more that are outside the scope of this paper and not included.

V. Future Research Challenges

Future research challenges on face recognition as biometric authentication can be categorized into two broad concern areas: performance and security.

A. Performance

Overarching focus of face recognition, as with other types of biometrics, concerns accuracy; and performance is directly correlated to the level of accuracy. Current research and literature on 3D face recognition attempt to remedy the effects of aging, facial expression, illumination, pose and occlusion on the accuracy of facial recognition (Sharif, et al., 2017). While some researchers assert that 3D methodology significantly mitigates the adverse effects of facial expression, illumination, pose and occlusion over 2D face recognition methodologies, there is not yet irrefutable scholarly proof or even anecdotal consensus from users of facial biometric authentication that the level of inaccuracy is negligible. Even under the best-case scenario in which it can be safely presumed that a particular approach or algorithm to address one of these areas is successful, further research will be needed to comprehensively address all of the listed areas, as they all affect the accuracy, viability and reliability, i.e. the performance, of facial biometric authentication. As for the effects of aging or reconstructive plastic surgery on facial biometric authentication, 3D face recognition methodologies do not yet account well for mitigating that variable and researchers will need to wrestle with that challenge.

B. Security

Facial recognition technology has been in use for years in a variety of forensic applications such as law enforcement. 3D face recognition as a biometric authentication has been in development for at least a decade, but widespread consumer adoption as a means of biometric authentication is relatively recent, arguably due in large part to the introduction of Apple iPhone X Face ID in November 2017. Face recognition research is still heavily focused on overcoming the challenges with accuracy for performance as outlined in the preceding section, but security issues also demand more research and development to protect against the most obvious vulnerability of face recognition methodology as a biometric authentication; replay attacks. In the case of 2D face recognition, a quick internet search will easily yield cases of average users as well as hackers, who have been able to use a photograph as a means to spoof and hack facial biometric authentication. In the case of 3D face recognition, a simple internet search will also report accounts of a child who was able to beat the Apple iPhone X Face ID because of his resemblance to his mother’s face, as well as reports of using a 3D clay generation of a face to spoof facial biometric authentication. Research in 3D face recognition currently does involve improving live detection measures to counter the replay attacks, but the stakes are higher when face recognition is used as a biometric authentication.

VI. Conclusion

Due to the limitations and vulnerabilities with each of the face recognition methodologies, whether for 2D or 3D face recognition, the general agreement is that multi-modal authentication methods (i.e. a combination of two or more authentication methods) will be the most secure and prudent method at present.

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