RADON Transform and PCA based 3D Face Recognition using KNN and SVM

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ABSTRACT
Reliable person recognition is integral to the proper functioning of our society.Many researches in face recognition have been dealing with the challenge of the great variability in head pose, lighting intensity and direction, facial expression, and aging. The last few years more and more 2D face recognition algorithms are improved and tested on less than perfect images. However, 3D models hold more information of the face, like surface information, that can be used for face recognition or subject discrimination. A 3D face image is represented by 3D meshes or range images which contain depth information. Range images have several advantages over 2D intensity images and 3D meshes. Range images are robust to the change of color and illumination, which are the causes for limited success in face recognition using 2D intensity images. In the literature, there are several methods for face recognition using range images, which are focused on the data acquisition and preprocessing stage only. In this paper, we have proposed a new method based on Radon transform and PCA for face recognition using 3D range images. The experimentation has been done using Texas 3D face database. The experimental results show that the proposed algorithm performs satisfactorily with an average accuracy of 96.00% and is efficient in terms of accuracy and detection time.

Keywords
3D face recognition, range images, Radon transform, principal component analysis, KNN, SVM.

1. INTRODUCTION
Reliable person recognition is integral to the proper functioning of our society.The fundamental task in identity management is to establish the association between an individual and his personal identity. One must be able to determine aperson’s identity or verify the identity claim of an individual whenever required. This process is known as person recognition.Biometric recognition, orsimply biometrics, offers a natural and more reliablesolution to the problem of person recognition.Since the biometric identifiers are inherent to an individual, it is more difficult tomanipulate, share, or forget these traits.Hence, biometric traits constitute a strong and reasonably permanent link betweena person and his identity.

Any person who presents his biometric identifier to a biometric system for thepurpose of being recognized can be called auserof the system. Since biometricsystems require the user to be present at the time of authentication, they can alsodeter users from making false repudiation claims. Moreover, only biometrics canestablish whether a certain individual is already known to the identity managementsystem, although the individual might deny it. Due to the above reasons, biometric recognitionis being increasingly adopted in a number of government and civilian identity management applications either to replace or to complement existing knowledge-basedand token-based mechanisms.

A biometric system measures one or more physical or behavioral characteristicsincluding fingerprint, palmprint, face, iris, retina, ear, voice, signature,gait, hand vein, odor, or the DNAinformation of an individual to determine or verify his identity. These characteristics are referred to by different terms such astraits,indicators,identifiers,ormodalities.In any generic biometric system, mainly, there are two phases,namely, enrollment and recognition. During theenrollmentphase, the biometric data is acquired fromthe individual and stored in a database along with the person’s identity. Typically,the acquired biometric data is processed to extract salient and distinctive features. Inmany cases, only the extracted feature set getsstored, while the rawbiometric data isdiscarded.During therecognitionphase, the biometric data is re-acquired from theindividual and compared against the stored data to determine the user identity. Thus,a biometric system is essentially a pattern recognition (ora pattern matching) systemconsisting of four basic building blocks, namely, (a) sensor, (b) feature extractor, (c)database, and (d) matcher.

Human face images are useful not only for person recognition, but for also revealing otherattributes like gender, age, ethnicity, and emotional state of a person. Therefore, face is an importantbiometric identifier in the law enforcement and human-computer interaction (HCI) communities.Detecting faces in a given image and recognizing persons based on their face images are classicalobject recognition problems that have received extensive attention in thecomputer vision literature.While humans are perceived to be good at recognizing familiar faces, the exact cognitive processesinvolved in this activity are not well-understood. Therefore, training a machine to recognize facesas humans do is an arduous task. However, general methods used in object recognition such asappearance-based, model-based, and texture-based approaches are also applicable to the specific problem of face detection andrecognition.

Face recognition can be defined as the process of establishing a person’s identitybased on their facial characteristics. In its simplest form, the problem of face recognition involves comparing two face images and determining if they are of the sameperson. While humans seem to be adept in determining the similarity between two face images acquired under diverse conditions, the process of automated face recognition is beset with several challenges. Face images of a person may have variationsin age, pose, illumination, and facial expressions as well as exhibitchanges in appearance due to make-up, facial hair, or accessories (e.g., sunglasses).Training a machine to recognize face images exhibiting such unconstrained intrauser variations is a difficult task, especially since the exact cognitive and neural processes involved in humans for the taskof face recognition (and recollection) isstill not completely known. Moreover, there may be similarities between the faceimages of different persons, especially if they are genetically related (e.g., identical twins, father and son, etc.). Such inter-class similarities furthercompound the difficulty of recognizing people based on their faces. Despite thesechallenges, significant progress has been made in the field of automated face recognition over the past two decades. Techniques for automated face recognition havebeen developed for the purpose of person recognition from still 2-dimensional (2D) images, video (a sequence of 2D images), and 3D range (depth) images.The face modality has several advantages that make it preferable in man.

The face modality has several advantages that make it preferable in many biometric applications. Firstly, unlike fingerprints, face can be captured at a longer standoff distance using non-contact sensors. Hence, face is a suitable biometric identifierin surveillance applications. Secondly, the face conveys not only the identity, butalso the emotions of a person (e.g., happiness or anger) as well as biographic information (e.g., gender, ethnicity, and age). The automated recognition of faces and associated emotions is necessary for designing interactive human-computer interfaces.Thirdly, there are large legacy face databases (e.g., U.S. driver's license repositoriescovers over 95% of the adult population), which enable large scale analysis of theface modality in terms of individuality or scalability. Finally, compared to other biometric traits like fingerprint and iris, people are generally more willing to share theirface images in the public domain as evinced by the increasing interest in social media applications (e.g., Facebook) with functionalities like face tagging. Due to theabove reasons, face recognition has a wide range of applications in law enforcement,civilian identification, surveillance systems, and entertainment/amusement systems.

With recent advancements in image capturing techniques and electronic devices, various categories of face image data have been utilized and various computer based algorithms have been developed for each type of image data sets. Among various categories of face images, a 2D intensity image has been the most popular and common image data used for face recognition, since it is easy to acquire through digital cameras. However, 2D intensity image has the intrinsic problem that it is vulnerable to the variations in illumination and poses. Sometimes the change of light illumination or different poses gives more difference than the change of people, which degrades the recognition performance. Therefore, illumination-controlled human face images are required to avoid such an undesirable situation when 2D intensity images are used. To overcome the limitation of 2D intensity face images, 3D face images are being used, such as 3D point clouds, meshes and range images.Efforts in acquiring the face biometric in a 3D format have resulted in the development of 3D face capture systems.There are two types of 3D face capture systems: one is based on laser scanningand the other is based on stereographic reconstruction. It is generally regarded thatlaser scanners provide more accurate 3D face models, while stereographic camerasprovide near real-time capture capability with slight loss in accuracy.The image captured by a 3D sensor typically covers about 120^0 of the humanhead and this image is referred to as a 2.5D scan. If a full 3D model of the face isrequired, it can be constructed by combining approximately three to five 2.5D scanscaptured from multiple views. 3D face models are usually represented as a polygonal mesh structure (e.g., triangular or rectangular) for computational efficiency.

A 3D range image is simply an image with depth information. A 3D range image is an array of numbers where the numbers of that image quantify the distances from the focal plane of the sensor of the acquisition device to the surface of objects within the field of view along rays emanating from a regularly spaced grid. 3D Range image has some advantage over 2D intensity images. Range images are robust to the change of illumination and color because the value on each point represents the depth value which does not depend on illumination or color. Also, range images are simple representations of 3D information.

The majority of the 3D face recognition algorithm studies have focused on developing holistic statistical techniques based on the appearance of face range images or on techniques that employ 3D face surface matching. A survey of literature on the research work focusing on different potential problems and challenges in the 3D face recognition can be found in [1-5]. Chang et al. [7] describe a "multi-region" approach to 3D face recognition. It is a type of classifier ensemble approach in which multiple overlapping sub regions around the nose are independently matched using ICP and the results of the 3D matching are fused. Gupta et al. [8] presented a novel anthropometric 3D face recognition algorithm. This approach employs 3D Euclidean and Geodesic distances between 10 automatically located anthropometric facial fiducial points and a linear discriminant classifier with 96.8% recognition rate. Jahanbim et al. [9] presented an approach of verification system based on Gabor features extracted from range images. In this approach, multiple landmarks (fiducials) on face are automatically detected, and also the Gabor features on all fiducials are concatenated, to form a feature vector to collect all the face features. Hengliang Tang et al.,[10] presented a novel 3D face recognition algorithm based on sparse representation using BJUT-3D and FRGC v2 databases with recognition rate of 95.3%. In this paper, our objective is to propose a new face recognition method based on Radon transformation and PCA, which are applied on 3D facial range images. The two different classifiers, namely, KNN and SVM, are used for recognition and results are compared with that of minimum distance classifier method[16]. The experimentation is done using the Texas 3D face database[6].

2. PROPOSED METOD

2.1 Radon Transform:

The Radon transform (RT) is a fundamental tool in many areas. The Radon Transform technique is named after the American mathematician "Johsnn Radon", which is the integral transform consisting of the integral of a function over straight lines. Johann Radon in 1917also provided a formula for the inverse transform. Radon transform further included formulas for the transform in three-dimensions, in which the integral is taken over planes. The radon transform techniquewas later generalized to higher-dimensional Euclidean spaces, and more broadly in the context of integral geometry. The complex analog of the Radon transform is known as the Penrose transform. The 3D Radon transform is defined using 1D projections of a 3D object *f* (*x, y, z*) where these projections are obtained by integrating *f* (*x, y, z*) on a plane, whose orientation can be described by a unit vector $\vec{\alpha}$. Geometrically, the continuous 3D Radon transform maps a function in $\mathbb{R}^3$ into the set of its plane integrals in $\mathbb{R}^3$. Given a 3D function $f(\vec{x}) \triangleq f(x, y, z)$ and a plane whose representation is given using the normal $\vec{\alpha}$ and the distance s of the plane from the origin, the 3D continuous Radon transform of f for this plane is defined by

$$\Re f(\vec{\alpha}, s) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(\vec{x})\delta(\vec{x}^T\vec{\alpha} - s)d\vec{x}$$

$$= \int_{-\infty}^{-\infty}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x, y, z)\delta(x\sin\theta\cos\phi + y\sin\theta\sin\phi + z\cos\theta - s)dxdydz$$

where $\vec{x} = [x, y, z]^T$,

$\vec{a} = [\sin\theta\cos\phi, \sin\theta\sin\phi, \cos\theta]^T$, and δ is Dirac's delta function defined by

$$\delta(x) = 0, x \neq 0, \int_{-\infty}^{\infty}\delta(x)dx = 1,$$

The Radon transform maps the spatial domain (x, y, z) to the domain $(\vec{\alpha}, s)$. Each point in the $(\vec{\alpha}, s)$ space corresponds to a plane in the spatial domain (x, y, z) [10-12].

2.2 Principal Component Analysis

The main objective of the Principal Component Analysis (PCA) is to reduce the dimensionality of a dataset contains a large number of inter related data variables, while retaining as much as possible of the variation present in the dataset. The Principal component analysis (PCA) is basically a statistical technique that uses orthogonal transformation to transform a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. In this technique, the number of principal components is less than or equal to the number of original variables present in the dataset. This transformation is defined in such a way that the first principal component of that data set has the largest possible variance, and each succeeding component in turn has the highest variance possible under the constraint that it be orthogonal to (i.e., uncorrelated with) the preceding components of the dataset. Principal components are guaranteed to be independent if the data set is jointly normally distributed. PCA is sensitive to the relative scaling of the original variables.

2.3 Proposed methodology

The Radon transform is applied to an input facial range image I_1 in steps of h from 0^o to 180^o orientations, where h may be 1^o, 2^o, 3^o or any convenient value. It yields a binary image I_2 with facial area being segmented. After superposing I_2 and I_1, the cropped facial range image I_3 is obtained. Next, the principal component analysis (PCA) technique is applied to the complete set of such cropped facial range images corresponding to the face images in the face database. It yields the set of eigenfaces, which are used for face recognition in a given test face range image. The Fig. 1 shows the intermediate results of the Radon transformation of an input face image. The algorithms of the training phase and the testing phase of the proposed method are given below:

Algorithm 1: Training Phase

1. Input the range image I_1 from the training set containing M images (Fig.1(a)).
2. Apply Radon transform, from 0^o to 180^o orientations (in steps of h), to the input range image I_1 yielding a binary image I_2 (Fig.1(c)).
3. Superpose the binary image I_2 obtained in the Step 2 on the input range image I_1 to obtain the cropped facial range image I_3 (Fig.1(d)).
4. Repeat the Steps 1 to 3 for all the M facial range images in the training set.
5. Apply PCA to the set of cropped facial range images obtained in the Step 4 and obtain M eigenfaces.
6. Compute the weights $w_1, w_2, ..., w_m$ for each training face image, where m < M is the dimension of feature subspace on which the training face image is projected.
7. Store the weights $w_1, w_2, ..., w_m$ for each training image as its facial features in the feature library of the face database.

Algorithm 2: Testing Phase

1. Input the test range image Z_1.
2. Apply Radon transform, from 0^o to 180^o orientations (in steps of h), to the input range image Z_1 yielding a binary image Z_2.
3. Superimpose the binary image Z_2 on Z_1 to obtain the cropped facial image Z_3.
4. Compute the weights $w_i^{test}, i = 1, 2, ..., m$, for the test image Z_1 by projecting the test image on the feature subspace of dimension m.
5. Compute the Euclidian distance D between the feature vector w_i^{test} and the feature vectors w_i stored in the feature library.

The face image in the face database corresponding to the minimum distance D computed in the Step 5 is the recognized face. Output the texture face image corresponding to the recognized facial range image.

3. EXPERIMENTAL RESULTS

For experimentation, we consider the Texas 3D face database [6]. The face images of the Texas 3D face database are the range images acquired using a MU-2 stereo imaging system. The database contains 1149 3D models of 118 adult human subjects. The number of images of each subject varies from 1 per subject to 89 per subject. The subjects age ranges from 22-75 years. The database includes images of both males and females, and also contains facial expressions like smiling or talking faces with open/closed mouths and/or closed eyes. The proposed method is implemented using Intel Core 2 Quad processor @ 2.66 GHz machine and MATLAB 7.9. In the training phase, 100 frontal face images with neutral expression of each subject are selected as training data set. In the testing phase, randomly chosen 200 face images of the Texas 3D face database with variations in facial expressions are used. The sample training images which are used for our experimentation are shown in the Fig.2, and their corresponding texture images are shown in the Fig.3. The eigenfaces and mean facial range image computed for PCA during the training phase are shown in the Figs.4 and 5, respectively.

The comparison of recognition rates obtained by the proposed (RT+PCA) approach and the PCA(alone) approach using different classifiers namely, minimum distance, KNN (with K=5) and SVM classifiers is presented in the Table 1. The projection orientation of Radon transform is in steps of 1^o, 2^o and 5^o. We observe that the proposed method, namely, RT (with steps of 1^o orientation) and PCA, yields better results as compared to the PCA(alone) method. We compare the rank-one recognition rates of the proposed method to the state-of-the-art 3D face recognition methods, namely, LDA [8] and sparse representation [10] in the Table 2. It is observed that the proposed method has lesser complexity and yet yields comparable recognition rate as other methods.

The Fig. 6 shows a Receiver operating curve (ROC) space, defined by FAR versus FRR as x and y axes respectively, which depicts relative trade-offs between true positive and false positive for the proposed method and shows the equal error rates (ERR) 23.997 for RT+PCA method and 25.281 for PCA (alone) .

4. CONCLUSION

Face as a biometric modality is widely acceptable for the general public, and face recognition technology is able to meet the accuracy demands of a wide range of applications. While the accuracy of algorithms have met requirements in controlled tests, 3D face recognition systems have yet to be tested under real application scenarios. For certain application scenarios such as airport screening andaccess control, systems are being tested in the field. The algorithms in these application scenarios will need to be improved to perform robustly under time changes and uncooperative users. In this paper, we proposed a novel method for 3D face recognition using Radon transform and PCA on range images of 3D faces. The proposed method provides a recognition accuracy of 96.00% for SVM classifier, which compares well with other state-of-the-art methods. The experimental results demonstrate the efficacy and the robustness of the method to illumination and pose variations. The recognition accuracy can be further improved by considering a larger training set of 3D faces.

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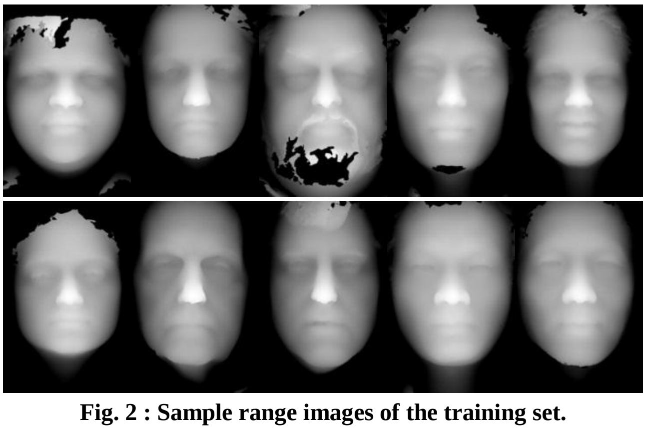

Fig. 2 : Sample range images of the training set.

Fig. 3: The facial texture images corresponding to the training range images in the Fig.2

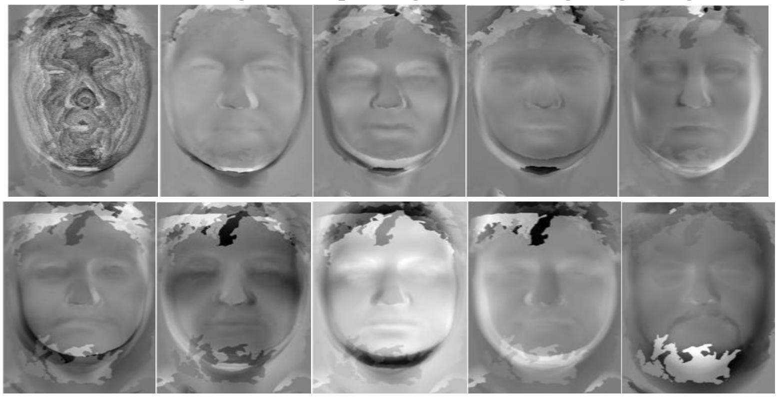

Fig. 4: The first ten eigenfaces obtained by using the proposed method in the training phase.

Fig. 5 : Mean facial range image computed in the Step 5 for PCA during the training phase.

Table 1. Comparison of face recognition rates obtained by using proposed method and PCA alone

Method	**Projection Orientation of RT in steps of**	**Recognition Accuracy**			**Average Recognition Time (in Sec.)**
		Minimum Distance Classifier [16]	KNN Classifier (K=5)	SVM Classifier	
Proposed (Radon Transform with PCA)	1^o	95.30%	95.90%	**96.00%**	14.8151
	2^o	95.26%	95.80%	95.90%	14.7627
	5^o	90.18%	90.70%	91.00%	14.7612
PCA	-	89.47%	89.90%	90.30%	14.1881

Table 2. Comparison of the proposed method with the state-of-the-art 3D face recognition algorithms.

Method	**Recognition Accuracy**	**Dataset used**	**Features Set and Classifiers**
Proposed method (RT+PCA)	96.00%	Texas 3D face database	RT+PCA; KNN and SVM
Gupta S. et. al., [8]	95.80%	Texas 3D face database	Anthropometric fiducial points; LDA
Hengliand Tang. et. al.,[10]	95.30%	BJUT-3D and FRGC v2	Sparce Representation; FLDA
P. S. Hiremath et. al., [16]	95.30%	Texas 3D face database	RT+PCA; Min. Distance Classifier

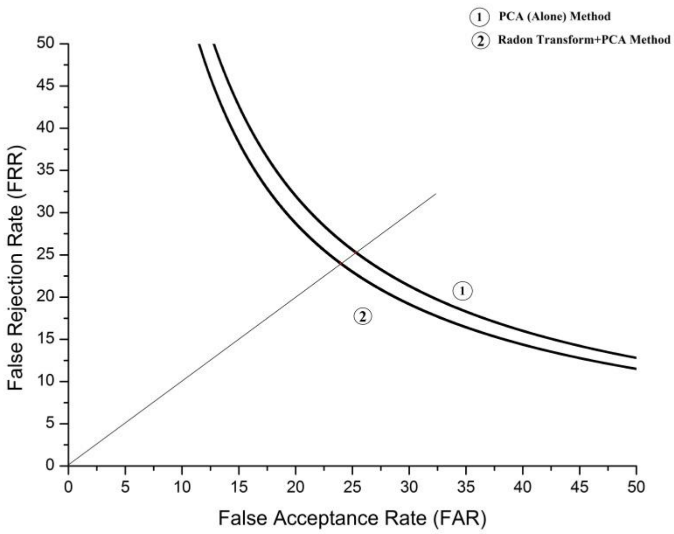

Fig.6. Receiver operating characteristic (ROC) curve for the proposed method PCA (alone) and RT+PCA method, using SVM classifier