

3D Face Recognition system Based on Texture Gabor Features using PCA and Support Vector Machine as a Classifier

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ABSTRACT: Pioneer 2D face recognition based on intensity or color images encounters many challenges, like variation in illumination, expression, and pose variation. In fact, the human face generates not only 2D texture information but also 3D shape information. In this paper, the main objective is to analyze what contributions depth and intensity with texture information make to the solution of face recognition problem when expression and pose variations are taken into account, and a new proposed system is introduced for combining depth, texture and intensity information in order to improve face recognition performance. In the proposed approach, local features based on Gabor wavelets are extracted from depth, texture and intensity images, which are obtained from 3D data after fine alignment. Then a novel hierarchical selecting scheme embedded in symbolic principal component analysis (Symbolic PCA). Then a Support vector classifier is used for classification of the extracted features. All the Experiments are performed on the Bhosphorus 3D face database, which contain images of faces with various complex variations, including expressions, poses and long time lapses between two scans. The experimental result demonstrates the effectiveness in the performance of the proposed method.

KEYWORDS: 3D face recognition, Radon transform, Symbolic PCA, Gabor Filter, SVM

1. INTRODUCTION

Face recognition is one of the most active research areas in the study of pattern recognition and computer vision. Over the past several decades, much work is focused on two-dimensional images. Due to the complexity of the face recognition, it is still difficult to develop a robust automatic face recognition system. The difficulties mainly include the complex variations in many aspects, such as poses, expressions, illuminations, aging and subordinates, of these problems. The pose variations and illuminations commonly influence the accuracy of 2D face recognition. According to evaluations of commercially available and mature prototyped face recognition systems provided by face recognition vendor tests (FRVT), the recognition results under the unconstrained conditions are not satisfactory.

To develop a robust face recognition system, additional information needs to be considered. Two typical solutions are the use of infrared images and the use of 3D images. Infrared images are robust to changes in environmental lighting, but these are too sensitive to changes in environmental temperature. Thus, its use is still limited. Another solution is to utilize 3D information. With the development of 3D capturing equipments, it has become faster and easier to obtain 3D shape and 2D texture information to represent a real 3D face. Currently, many types of equipment based on active stereo vision are robust to illumination variations. Thus, the 3D shape obtained by such equipment represents the actual information irrespective of lighting. Moreover, the complete transformations between different 3D images can be computed in the image plane, which is very difficult in 2D face recognition. Recently, some research results have illustrated that 3D data have more advantages than traditional 2D data. Usage of 3D data is considered to be a promising way to improve the robustness and accuracy of recognition systems.

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Face recognition based on 3D information is not a new topic. Studies have been conducted since the end of the last century [1-7]. The representative methods use features extracted from the facial surface to characterize an individual. Lin *et al.*, [8] extracted semi local summation invariant features in a rectangular region surrounding the nose of a 3D facial depth map. Then the similarity between them was computed to determine whether they belonged to the same person. Al-osaimiet *al.*, [9] integrated local and global geometrical cues in a single compact representation for 3D face recognition. In another method, the human face is considered as a 3D surface, and the global difference between two surfaces provides the distinguishability between faces. Brumieret *al.*, [31] constructed some central and lateral profiles to represent an individual and proposed two methods of surface matching and central/lateral profiles to compare two instances. Medioniet *al.*, [32] built a complete and automatic system to perform face authentication by modeling 3D faces using stereo vision and analyzing the distance map between gallery and probe models. Lu *et al.*, [12] used the hybrid iterative closest point (ICP) algorithm to align the reference model with the scanned data and adopted registration errors to distinguish between different faces. Chang *et al.*, [8] divided the whole facial surface into sub regions. The rigid regions around the nose area were matched and combined to perform the recognition. Following the idea of dividing the sub-regions, Faltermoieret *al.*, [6] introduced a system for 3D face recognition based on the fusion of results from a group of regions that had been independently matched. Russ *et al.*, [7] presented an approach enabling a good alignment of 3D face point clouds while preserving face size information. All of these studies illustrated the feasibility of 3D face recognition. However, perhaps due to illumination of data, the above schemes only use the shape features of facial surfaces while ignoring the texture information. Wang *et al.*, [3] described facial feature points by using Gabor filter responses in a 2D domain and point signatures in a 3D domain. Chang *et al.*, [5] evaluated the recognition scheme with different combinations of 2D and 3D information, which showed that the combination of 2D and 3D information was most effective in characterizing an individual face. Cook *et al.*, [34] proposed a new method combining intensity and range images that was insensitive to expression variation based on log gabor templates. Maurer *et al.*, [33] analyzed the performance of the Geometrix Active ID Biometric Identity system, which fused shape and texture information.

The face recognition based on combination of 3D shape information and 2D intensity/color information is a novel approach, which provides an opportunity to improve face recognition performance. In the present paper, the objective is to investigate how depth and intensity information contributes to face recognition when expression and pose variations are taken into account. Further, a robust and accurate face system is designed by selecting and fusing the most effective depth and intensity features. All the processes included in the training and test phases of the proposed approach are fully automated.

II. BOSPHORUS 3D FACE DATABASE

The Bosphorus 3D face database consists of 105 subjects in various poses, expressions and occlusion conditions. The 18 subjects have beard/moustache and the 15 subjects have hair. The majority of the subjects are aged between 25 and 35. There are 60 men and 45 women in total, and most of the subjects are Caucasian. Two types of expressions have been considered in the Bosphorus database. In the first set, the expressions are based on action units. In the second set, facial expressions corresponding to certain emotional expressions are collected. These are: happiness, surprise, fear, sadness, anger and disgust.

The facial data are acquired using Inspeck Mega Capturor II 3D, which is a commercial structured-light based 3D digitizer device. The sensor resolution in x, y & z (depth) dimensions are 0.3mm, 0.3mm and 0.4mm respectively, and colour texture images are high resolution (1600x1200 pixels). It is able to capture a face in less than a second. Subjects were made to sit at a distance of about 1.5 meters away from the 3D digitizer. A 1000W halogen lamp was used in a dark room to obtain homogeneous lighting. However, due to the strong lighting of this lamp and the device's projector, usually specular reflections occur on the face. This does not only affect the texture image of the face but can also cause noise in the 3D data. To prevent it, a special powder which does not change the skin colour is applied to the subject's face. Moreover, during acquisition, each subject wore a band to keep his/her hair above the forehead to prevent hair occlusion, and also to simplify the face segmentation task. The proprietary software of the scanner is used for acquisition and 3D model reconstruction [26].

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III. PROPOSED METHODOLOGY

The proposed methodology employs the following: (i) Radon transform, (ii) Gabor wavelets, (iii) Symbolic PCA (Principal Component Analysis), and (iv) Support Vector Machine as a classifier which are explained in the following sections.

3.1. Radon Transform

The Radon Transform (RT) is a fundamental tool in many areas. 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 \mathbb{R}^3 into the set of its plane integrals in \mathbb{R}^3 . Given a 3D function $f(\vec{x}) \equiv f(x,y,z)$ 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

$$\begin{aligned} \mathfrak{R}f(\vec{\alpha}, s) &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(\vec{x}) \delta(\vec{x}^T \vec{\alpha} - s) d\vec{x} \\ &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x,y,z) \delta(x \sin \theta \cos \phi + y \sin \theta \sin \phi + z \cos \theta - s) dx dy dz \end{aligned}$$

Where $\vec{x} = [x, y, z]^T$, $\vec{\alpha} = [\sin \theta \cos \phi, \sin \theta \sin \phi, \cos \theta]^T$, and δ 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 $(\vec{\alpha}, s)$. The 3D continuous Radon Transform satisfies the 3D Fourier slice theorem.

3.2. 2D Gabor Filter

The 2D Gabor filters of depth and intensity images of faces are used to characterize an individuals' face. The Gabor wavelets represent the properties of spatial localization, orientation selectivity, spatial frequency selectivity and quadrature phase relationships, and these have been experimentally verified to be a good approximation to the response of cortical neurons. The Gabor wavelet based representation of faces has been successfully tested in 2D face recognition. Such representation of an image describes the facial characteristics of both the spatial frequency and spatial relations. The 2D Gabor wavelets are defined as follows:

$$\psi(z) = \frac{k_{\mu,v}^2}{\sigma^2} \exp\left(-\frac{k_{\mu,v}^2 z^2}{2\sigma^2}\right) \left[\exp(ik_{\mu,v} z) - \exp\left(-\frac{\sigma^2}{2}\right) \right] \quad (1)$$

Where $z = (x, y)$, and μ and v define the orientation and scale of the Gabor wavelets, respectively. The wave vector

$$k_{\mu,v} \text{ is defined as follows: } k_{\mu,v} = k_v e^{i\Phi_\mu}$$

Where $k_v = k_{\max} / f^v$ and $\Phi_\mu = \pi\mu / 8$. The constant k_{\max} is the maximum frequency and f is the spacing factor between kernels in the frequency domain. The Gabor kernels in the above equation are self-similar, since they can be generated from the mother wavelet by scaling and rotation via the wave vector $k_{\mu,v}$. More scales or rotations can increase the dependencies of neighbor samples.

In the proposed method, Gabor kernels with five different scales $v \in \{0, \dots, 4\}$ and eight orientations $\mu \in \{0, \dots, 7\}$ are used, with the parameters $\sigma = 2\pi \cdot k_{\max}^{-1} / 2$ and $f = \sqrt{2}$. The number of scales and orientations are selected to

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represent the facial characteristics in terms of spatial locality and orientation selectivity. The Gabor representation of an image, called the Gabor image, is the convolution of the image with Gabor kernels as defined by Eq(1). For each image pixel, it has two Gabor parts: the real part and imaginary part, which are transformed into two kinds of features: Gabor magnitude features and Gabor phase features. Herein, it is proposed to use the Gabor magnitude features to represent the facial features, since the Gabor transformation strongly responds to edges [19-21].

The depth Gabor images are smoother in comparison with the intensity Gabor images due to the fact that the value of the pixels in the depth image changes less than does the value in the intensity images. The smoother depth Gabor image can reduce the influence of noise, but it cannot describe the facial features in detail. This is why the face recognition is performed by combining depth and intensity information [14-16].

3.3. Principal Component Analysis (PCA)

Consider the 3D face images $\Gamma_1, \Gamma_2, \dots, \Gamma_n$, each of size $N \times M$, from a 3D face image database. Let $\Omega = \{\Gamma_1, \Gamma_2, \dots, \Gamma_n\}$ be the collection of n face images of the database, which are first order objects. Each object $\Gamma_l \in \Omega, l = 1, 2, \dots, n$ is described by a feature vector $(\bar{x}_1, \dots, \bar{x}_p)$, of length $p = NM$, where each component $\bar{x}_j, j = 1, 2, \dots, p$ is a single valued variable representing the values of the 3D face image Γ_l . An image set is a collection of 3D face images of m different subjects; each subject has same number of images but with different facial expressions and illuminations. There are m number of second order objects (face classes) denoted by c_1, c_2, \dots, c_m , each consisting of different individual images $\Gamma_l \in \Omega$. Let $E = \{c_1, c_2, \dots, c_m\}$ and $c_i \subseteq \Omega, i = 1, 2, \dots, m$. The feature vector of each face class $c_i \in E$ is described by a vector of p interval variables Y_1, Y_2, \dots, Y_p and is of length $p = NM$. The interval variable Y_j of face class c_i is declared by $Y_j(c_i) = [\underline{x}_{ij}, \bar{x}_{ij}]$ where \underline{x}_{ij} and \bar{x}_{ij} are minimum and maximum intensity values, respectively, among j^{th} values of all the images of face class c_i . This interval incorporates information of the variability of j^{th} feature inside the i^{th} face class. Let $X(c_i) = (Y_1(c_i), \dots, Y_p(c_i))$. The vector $X(c_i)$ of symbolic variables is recorded for each $c_i \in E$, and can be described by a symbolic data vector which is called as symbolic face :

$X(c_i) = (a_{i1}, a_{i2}, \dots, a_{ip})$, where $a_{ij} = Y_j(c_i), j = 1, 2, \dots, p$ (17-18). Let the m symbolic faces be represented $m \times p$ by a matrix ;

$$X = \begin{pmatrix} a_{11} & \dots & a_{1p} \\ \vdots & \ddots & \vdots \\ a_{m1} & \dots & a_{mp} \end{pmatrix} = (a_{ij})_{m \times p}$$

The symbolic PCA takes as input the matrix X containing symbolic faces pertaining to the given set Ω of images [27].

It is proposed to use centers method, which essentially applies the conventional PCA method to the centers $x_{ij}^c \in \mathbb{R}$ of the interval $[\underline{x}_{ij}, \bar{x}_{ij}]$ that is

$$x_{ij}^c = \frac{\underline{x}_{ij} + \bar{x}_{ij}}{2}$$

Where $j = 1, \dots, p$ and $i = 1, \dots, m$. The $m \times p$ data matrix X^c , which contains the centers x_{ij}^c of the intervals α_{ij}^c for m symbolic faces, is given by:

$$X^c = \begin{pmatrix} x_{11}^c & \dots & x_{1p}^c \\ \vdots & \ddots & \vdots \\ x_{m1}^c & \dots & x_{mp}^c \end{pmatrix}$$

The mean vector Ψ of X^c is defined by $\Psi = [\psi_j]$. Where $\psi_j = \frac{1}{m} \sum_{i=1}^m x_{ij}^c, j = 1, 2, \dots, p$. Each row vector of X^c differs from the mean vector Ψ by the vector $\Phi_i = (x_{i1}^c, x_{i2}^c, \dots, x_{ip}^c) - \Psi$. We define the matrix Φ as $\Phi = [\Phi_1, \Phi_2, \dots, \Phi_m]$. The covariance matrix C is obtained as $C = \Phi^t \Phi$. Then, the eigenvalues are calculated and arranged in the order of decreasing

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magnitude: $\lambda_1 \geq \lambda_2 \geq \dots, \lambda_m \geq 0$. Further, and the corresponding orthonormalized eigenvectors $y_1, y_2, \dots, y_m \in \mathbb{R}^m$ of the covariance matrix Care obtained. The eigenvectors of the symbolic PCA can be obtained as $V_m = \Phi Y_m$, where $Y_m = (y_1, \dots, y_m)$ is the $m \times m$ matrix with column y_1, y_2, \dots, y_m and V_m is the $p \times m$ matrix with corresponding eigenvectors v_1, v_2, \dots, v_m and its columns. The subspace is extracted from the $p \times m$ dimensional space by selecting number of eigenvectors s , which contain maximum variance and are denoted by v_1, v_2, \dots, v_s corresponding to eigenvalues $\lambda_1 \geq \lambda_2 \geq \dots, \lambda_s$. The weights W_{ik} for i^{th} symbolic face, $I = 1, 2, \dots, m$, are computed as

$$W_{ik} = V_k^T (x_{ij}^c - \Psi) \quad (6)$$

Where $k = 1, 2, \dots, s$. The weights of i^{th} symbolic face form the feature vector $(w_{i1}, w_{i2}, \dots, w_{is})$ of the i^{th} symbolic face (28, 29). The weights of test image I^{test} are computed by projecting the test image into face subspace of s dimension as :

$$w_k^{\text{test}} = v_k^T (I^{\text{test}} - \Psi), \quad k = 1, 2, \dots, s. \quad (7)$$

3.4. SVM and Multi-class SVM classification

The basics of SVMs for binary classification are explained first. Then we discuss how this technique can be further extended to deal problems with general multi-class classification.

Binary Classification

SVMs belong to the class of maximum margin classifiers. They perform pattern recognition between two classes. They find a decision surface that has maximum distance with the closest points in the training set. These are termed as support vectors. We are taking a training set of points $x_i \in \mathbb{R}^n$, where each point x_i belongs to one of two classes identified by the label $y_i \in \{-1, 1\}$. we are assuming linearly separable data¹, the goal of maximum margin classification is to distinguish the two classes by a hyperplane such that the distance to the support vectors is maximized. The hyperplane is known as the optimal separating hyperplane (OSH). The OSH has the form[24]:

$$f(x) = \sum_{i=1}^l \alpha_i y_i x_i X + b \quad (8)$$

The coefficients α_i and b in Eq. (9) are the solutions of a quadratic programming problem. Classification of a new data point is performed by computing the sign of the right side of Eq. (8). In the following we will use[24]

$$d(x) = \frac{\sum_{i=1}^l \alpha_i y_i x_i X + b}{\|\sum_{i=1}^l \alpha_i y_i X_i\|} \quad (9)$$

to perform multi-class classification. The sign of d is the classification result for x . $|d|$ is the distance from to the hyperplane. The farther away a point is from the decision surface, i.e. as the larger $|d|$, the more consistent the classification result.

The complete construction can be comprehended to the nonlinear separating surfaces case[24]. Every point in the input space has been mapped to a point $z = \phi(x)$ of a advanced dimensional space which is known as the feature space. It is the feature space where the data are separated by a hyperplane. The main property in this structure is that the mapping $\phi(\cdot)$ is subject to the condition that the dot product of two points in the characteristic space $\phi(x) \cdot \phi(y)$ can be rewritten as a kernel function $K(x, y)$. The equation for decision surface is given as[24]:

$$f(x) = \sum_{i=1}^l y_i \alpha_i K(X, X_i) + b_i \quad (10)$$

There are two basic methods to solve class problems with SVMs. These are:

1). SVMs are trained in the one-vs-all approach. Every single SVM separates a single class from the remained classes [5, 17].

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(2). The machines are trained in the pairwise approach. Every single SVM separates a pair of classes. The pair-wise classifiers are arranged in trees where each SVM is represented by tree node. A bottom-up tree was proposed in [16] for recognition of 3-D objects .It was applied to face recognition in [7]. Recently, a top-down tree structure has been published in [15].

There is no notional analysis for the two strategies with respect to classification performance. With regards to the training effort, the one-vs-all approach is more preferred because only SVMs have to be trained as compared with SVMs in the second approach. The run-time complexity of both the methods is almost alike. Recently, experiments have been performed on person recognition to show similar classification performances for the two methods [13]. Since the number of classes in face recognition can be large enough, we have opted the one-vs-all method instead of pair-wise, because the number of SVMs used is linear with the number of classes.

3.5. Proposed Method

The proposed methodology comprises the following steps:

- (i) Radon transform is applied to the input depth and intensity images of a 3D face, which yields binary images that are used to crop the facial areas in the corresponding images.
- (ii) Gabor filter are applied to the cropped facial images, which yield Gabor magnitude features as facial feature vectors.
- (iii) PCA is applied to the facial Gabor features in order to achieve dimensionality reduction and obtain subsampled feature vectors
- (iv) Lastly, SVM multi class function as a classifier is used to perform face recognition based on subsampled feature vectors.

The Figure 1 shows the Block diagram of the proposed framework.

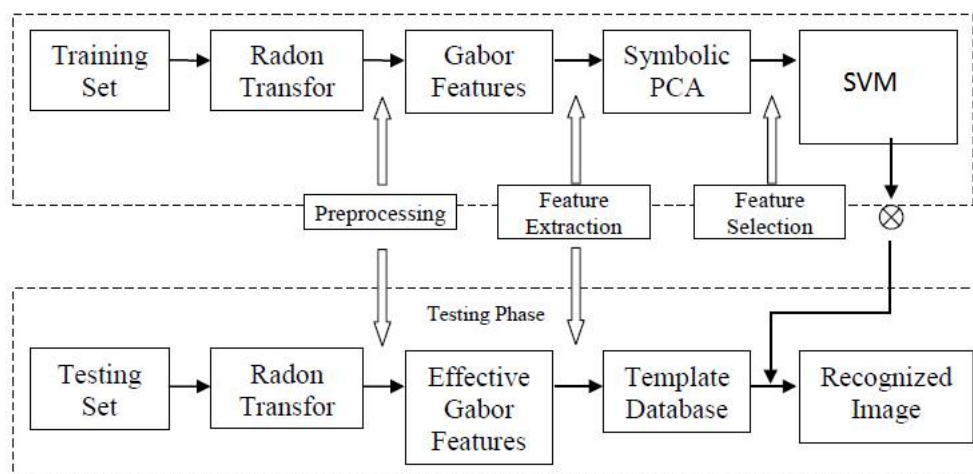


Fig 1: Block Diagram of the Proposed technique

The algorithms of the training phase and the testing phase of the proposed method are given below:

Algorithm 1: Training Phase

1. Input the depth, texture and intensity images of a face from the training set containing M depth images and M intensity images corresponding to M Faces.
2. Apply Radon transform, from 0^0 to 180^0 orientations (in steps of h), to the input images converting it into the corresponding binary images.

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3. Superpose the binary images obtained in the Step 2 on the corresponding input images to obtain the cropped facial images.
4. Repeat the Steps 1 to 3 for all the M facial images in the training set and build the set M_1 of cropped facial images
5. Apply Gabor wavelet filter on M_1 set to extract Gabor magnitude features.
6. Apply Symbolic PCA to subsample the Gabor feature set to reduce the dimensionality of the feature set. Let P be the reduced dimensionality of feature set.
7. Compute the weights w_1, w_2, \dots, w_p for each training image as its facial features and store these values in the Symbolic PCA feature library of the face database.
8. Training is done using the multi class SVM classifier with proper training data and its corresponding label.

Algorithm 2: Testing Phase

1. Input the depth and intensity images from the probe set containing P images.
2. Apply Radon transform, from 0° to 180° orientations (in steps of h), to the input images yielding the binary images.
3. Superimpose the binary images on the corresponding input depth and intensity images to obtain the cropped facial images.
4. Apply Gabor wavelet filter on cropped facial images to extract effective Gabor features
5. Compute the symbolic weights $w_i^{test}, i = 1, 2, \dots, p$, for the extracted Gabor magnitude features by projecting the test image on the Symbolic PCA feature subspace of dimension p .
6. Apply the svm prediction algorithm with one vs rest logic to identify the said sample belongs to which class.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

As in typical biometric systems, the proposed method includes two phases: the training phase and the testing phase as illustrated in the Figure 1. The proposed method is implemented using Intel Core 2 Quad processor @ 2.66 GHz machine and MATLAB 2013. The 1000 images of Bhosphorus 3D face database which is divided into two subsets, that is the training set, and testing set. The training set contains 700 images. The testing set contains 300 images which are randomly chosen from the set dataset.

The training process is performed once on a predefined training set to learn an effective classifier. It includes three important procedures: preprocessing, feature extraction and feature selection. By translating and rotating one input 3D image to align one reference 3D image, face poses and changed positions between the face and the equipment are normalized. This step is fully automatic. According to the aligned images, the normalized depth images and intensity images are obtained. Robust feature representation is very important to the whole system. It is expected that these features are invariant to rotation, scale and illumination. The proposed method uses raw depth and intensity features to describe the individual information using Gabor filters with multiple scales and multiple orientations. As it is commonly a problem, using multiple channels and multiple types of local features results in a much higher dimensional feature space. A large number of local features can be produced with varying parameters in the position, scale and orientation of the filters. Some of these features are effective and important for the classification task, whereas others may not be

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so. The sample training depth images which are used for the experimentation are shown in the Figure 2, and their corresponding texture images are shown in the Figure 3.

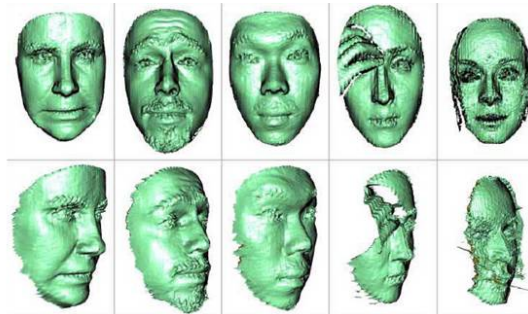


Figure 2: Sample Depth Images



Fig 3: Sample Texture Images

To demonstrate the performance of the proposed algorithm, comparison of experimental results that have been reported in recent literature, has been done. The Table 1 shows the performance comparison of the proposed method with other methods.

Table 1. The Performance Comparison of Proposed Method with other Methods

Method	Recognition Rate
Proposed Method	98.50%
H. usken et al.[19]	97.30%
Maurer et al.[20]	95.80%
Faltemier et al.[6]	94.90%
Kakadiaris et al.[13]	97.00%

IV. CONCLUSION

Intensity information is more pertinent than depth information in the context of expression variations; depth information is more pertinent than intensity information in the context of pose variations. Thus, their combination is helpful in improving recognition performance. In this paper, a new scheme is proposed to combine depth and intensity features in order to overcome problems due to expression and pose variations, and thus build a robust and automatic face recognition system. The Gabor features are used, in which the dimensionality of the Gabor features is extremely large, since multiple scales and orientations are adopted. To reduce the large dimensions of Gabor features, we propose a hierarchical selection scheme for selecting effective features by using PCA and with the use of the SVM multi class

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the classification is also done accurately and fast enough. The recognition accuracy can be further improved by considering a larger training set and a better classifier.

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