Effective 3D Face Recognition Technique Based on Gabor and LTP Features

M. Chandrakala, S. Ravi

Abstract – Face recognition is one of the evergreen research areas, owing to the increased applicability of the face recognition system in several real-time applications. Previously, 2D face recognition systems are employed to serve the purpose however, these systems suffer from several external environmental conditions. This drawback is addressed by the 3D face recognition system, which can withstand the adverse external environmental conditions. However, the 3D face recognition systems are very limited in the existing literature. Taking this as a challenge, this work presents a 3D face recognition system that relies on gabor and Local Ternary Pattern (LTP) features. The significant features are selected by means of Information Gain Ratio (IGR) and the Extreme Learning Machine (ELM) classifier is trained to classify between the human faces. The performance of the proposed approach is satisfactory in terms of accuracy, sensitivity and specificity rates.

Keywords – Face recognition, LTP, gabor, classification.

1. INTRODUCTION

The present era is the era of digital data and all the data are maintained in voluminous servers. It is difficult to manage the huge volume of data on premises and hence, data outsourcing is the most popular solution to the data storage issue. The outsourced data are managed by the cloud server, which makes the process of data storage hassle-free. However, the main issue comes into picture and is the data security. Data security can be achieved by employing several cryptographic algorithms. However, cryptographic algorithms are difficult to process and require prior knowledge.

At this juncture, biometric based security solutions play a role in attaining better security without any special knowledge. The main advantages of biometric based solutions are effortless processing, efficiency, constancy, uniqueness and universality [1,2]. The biometrics are common for all the humans and are unique. Some of the sample biometrics are face, fingerprint, palm-print, iris, retina, voice and so on. All the biometrics require some effort to collect the biometric except face. Face images have become a popular biometric, as they can be captured by a distant camera. Additionally, the face images contain several important information such as eyes, nose, lips and so on [3-5]. Realizing this fact, there are several face recognition systems available in the existing literature. However, most of the existing face recognition Systems are two dimensional, which usually suffer from lighting and pose variations.

Taking this point into consideration, this article aims to present a three dimensional face recognition system based on gabor and Local Ternary Pattern (LTP) features. The 3D face recognition systems are very limited in the existing literature and in addition to this, the 3D face recognition systems are robust with better accuracy rates. The 3D face recognition system withstands pose and poor lighting conditions. However, the 3D face recognition system demands the user to remain still for certain seconds during the process of scanning. Yet, the performance of 3D face recognition systems is better than the 2D systems and thus, this work proposes a 3D face recognition system.

The work introduces a novel face recognition system for 3D face images. The images are pre-processed by means of radon transform and the gabor and LTP features are extracted from the regions around the key points. Gabor features are rich in texture. Besides this, it works better in space and frequency domains. However, gabor features do not focus on the complete frequency spectrum and the gabor features are constrained to some specific shape.

For this reason, this work utilized LTP features, which are insensitive to noise as well. The extracted features are then optimized by means of Information Gain Ratio (IGR). The outcome of this step is the removal of incapable features, which in turn increases the discriminative power of the feature set. Finally, Extreme Learning Machine (ELM) is employed as the classifier for recognizing the human faces.

- The combination of gabor and LTP features work well for 3D face images.
- The time consumption of this work is reasonable, as the potential features are alone taken into consideration.
- Incorporation of ELM results in faster face recognition process.

The remaining sections of the paper are organized as follows. The related review of literature with respect to 3D face recognition system is presented in section 2. The proposed approach is described in section 3 and the performance of the proposed approach is evaluated in section 4. Finally, section 5 concludes the paper with the summary and the possible future directions.

II. REVIEW OF LITERATURE

This section reviews the state-of-the-art existing literature with respect to three dimensional face recognition systems.

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In [6], the human faces are recognized by employing a unified 3D morphable model. This work forms 3D data out of 2D face images, which is achieved by computing the difference between the texture map of the input and the reference face images. The texture maps are trained by means of Principal Component Analysis (PCA).

The end-to-end face reconstruction model is presented with the help of Deep Neural Networks (DNN) in [7]. This approach presents an end to end face reconstruction with the help of a 2D image. The DNN architecture of this work contains two different components, which are multi-task loss function and a fusion Convolutional Neural Network (CNN) to improve the construction of facial images with different expressions. With respect to multi-task loss function, the 3D face recognition is classified into two kinds and they are neutral and expressive 3D face shape reconstruction. The fusion CNN combines the features from different layers and transformed to predict the 3D face.

In [8], a 3D face recognition system based on volumetric representation of range image is presented. This work involves three important steps and they are significant point detection, triangle formation and 3D volume computation. The initial step detects the significant facial landmarks and the second phase detects the triangular regions with the help of any three detected landmarks. The 3D volumes of the triangular regions are then computed with the help of plane fitting over the input range images. Finally, the classification is carried out by k-Nearest Neighbour (k-NN) and Support Vector Machine (SVM).

A bayesian convolutional network based face recognition system is proposed for a robust surveillance system in [9]. This work presents a model based on Deep Convolutional Neural Networks (DCNN) that employ softmax to measure the model confidence of a class with respect to the input face image. This work reduces the false positive rates by utilizing model uncertainty.

In [10], a registration free approach is proposed to recognize human faces based on 3D keypoint descriptors. This work presents a face matching approach for 3D keypoint descriptors. Initially, two different principal curvature based 3D keypoint detectors are presented, such that the locations of a face with maximal local curvatures are found out. This step is followed by forming a robust 3D local coordinate system for every keypoint, in order to extract pose invariant features. At last, a multitasking sparse representation based matching algorithm is presented.

A curvelet based multimodal approach is presented for 3D face recognition in [11]. This work detects the keypoints on the textured 3D face surfaces. The local surface descriptors are formed with respect to the detected keypoints and the curvelet components of varying orientation are integrated together. This integration results in the extraction of rotation invariant features. This work extracts both the texture and the 3D local features.

In [12], an expression robust 3D face recognition system is proposed by considering nasal patches and curves. This work detects the tip of the nose initially and the face is cropped and the nasal region is cropped. This algorithm detects seven keypoints on the nasal region with the help of a nasal landmarking algorithm. Finally, the feature extraction algorithm based on gabor wavelet is applied and the feature descriptors are provided. This step is followed by the application of genetic algorithm for selecting the features, such that the stable patches and curves are extracted.

A 3D face recognition system is proposed on the basis of covariance based descriptors in [13]. The covariance based descriptors are based on fusion and the features are encoded and represented in standard format. The covariance descriptors are symmetric positive definite matrices and geodesic distance is utilized for recognizing the faces. In [14], the local feature methods for recognizing the 3D faces are surveyed. This work explains the available 3D face databases and the 3D local descriptors such as key-points, curves and surface based methods are reviewed.

A 3D face recognition system based on emotions is presented on the basis of robust regional bounding spherical descriptor in [15]. The 3D face and emotion analysis is done by utilizing regional bounding spherical descriptor. The region segmentation is carried out with the help of shape index and spherical band. The regional descriptors are figured out by performing projection operation over regional bounding spheres. The weighted regional descriptor is based on the local and global regression.

In [16], a 3D face recognition system is proposed with the help of weighted extreme sparse classifier and Local Derivative Pattern (LDP). The LDP captures the detailed information on the basis of local derivative variation in multiple directions. The LDP is computed in three different directions such as x, y, z and different scales. The shape information are collected from the local surface, rather than the depth. The detailed features are extracted by means of n^{th} order LDP and finally Extreme Learning Machine (ELM) is utilized to select significant features.

In [17], an attempt to recognize human faces based on caricature is proposed. This work forms the 3D face structure with the help of 2D image and compares it with the reference model by representing the facial features. The 3D caricature image is formed by utilizing the laplacian mesh deformation algorithm. Some of the fundamental and advanced concepts of 3D face recognition systems are discussed in [18]. This work mainly focuses on the security applications which stimulated the growth of biometrics. In [19], a 3D face recognition approach based on DCNN is proposed. Initially, the images are pre-processed and the redundant information are eliminated. The features are extracted from both the 2D and the depth images, followed by the process of fusion. This work utilizes softmax classifier for identifying faces.

In [20], a robust 3D face recognition system based on Scale Invariant Feature Transform (SIFT) and Complete Local Binary Pattern (CLBP) is proposed. The significant features are selected by means of Information Gain Ratio (IGR) and the SVM is employed as the classifier to distinguish between the human faces. In [21],

a time conserving 3D face recognition system is proposed, which relies on the Speeded Up Robust Features (SURF) and Local Derivative Pattern (LDP) is presented.

The features are reduced by means of Local Fisher Discriminant Analysis (LFDA) and the SVM is employed to classify between the faces.

Inspired by these existing works, the proposed approach intends to present a 3D face recognition system based on gabor and LTP features. The proposed approach is elaborated in the following section along with the work overview.

III. PROPOSED GABOR AND LTP BASED 3D FACE RECOGNITION SYSTEM

This section outlines the overview of the proposed face recognition system and the proposed approach is described in detail.

A. Overview of Proposed Work

The aim of this work is to present a face recognition approach for 3D images. The main reason for handling 3D images is that the 3D image processing leads to increased accuracy rates, when compared to the 2D images. In addition to this, the 3D images can deal with lighting and pose variations and on the other hand, 2D images are affected by these adverse conditions. Yet, the acquisition of 3D images is little bit tedious in contrast to the 2D image acquisition. This work proposes a 3D face recognition system, which relies on four important phases such as pre-processing, feature extraction, feature selection and classification. The overview of the proposed approach is depicted in figure 1.

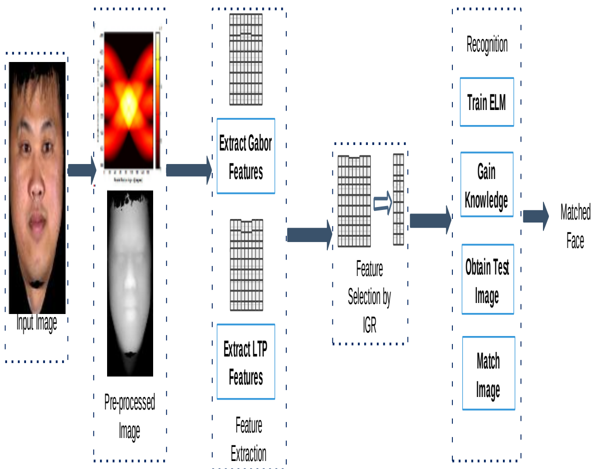

Fig.1. Overall flow of the proposed approach

The 3D images are pre-processed by the radon transform and the features are extracted by means of gabor and LTP feature descriptors. Both these feature descriptors are well-known for their texture pattern analysis. The gabor filter works better in both spatial and frequency domains, yet the gabor features are limited with respect to the shape. On the other hand, LTP features are insensitive to noise and the features represent the image well.

Both the gabor and LTP features are not processed as such and the significant features are selected by means of IGR. This idea results in reducing the processing time and memory consumption as well. Finally, the ELM classifier is trained with the reduced feature set and the face images are distinguished by the ELM classifier. The following section elaborates the proposed 3D face recognition system.

B. Proposed Gabor and LTP based Face Recognition

As stated earlier, the roots of the proposed 3D face recognition system rely on four significant phases and they are pre-processing, feature extraction, feature selection and classification. The pre-processing step prepares the face images to get processed with the forthcoming phases and is the base of all the image processing activities.

Feature extraction is the heart of any classification based system, as these features are the means through which the classifier is trained. Hence the better the feature set, the better is the classification performance. Feature selection is meant for picking the most powerful features from the feature set. Instead of processing the complete feature set, the feature selection step helps in minimizing the memory and time consumption. Finally, the classification is carried out and the performance of the approach is analysed.

a. Image Pre-processing

The images handled by the proposed approach are pre-processed by the radon transform, as performed in [20]. The Radon transform is applied over the input images in the orientations between 0 and 180 degrees with respect to h, which are degrees from 1 to 3. The radon transformed image is laid over the input image for obtaining an image with better quality. By this way, the input images are pre-processed and the high quality images are obtained. These enhanced images are treated by the following steps, which are feature extraction, feature selection and classification.

b. Gabor and LTP Feature Extraction

The proposed face recognition approach relies on two different feature extraction techniques, which are gabor and LTP. The gabor filters are effective texture descriptor of an image. Gabor filter is very popular for extracting the features of an image, especially texture features. Gabor filters are known for joint ambiguity reduction issue both in space and frequency domain. Besides this, they are used as tuned and scaled edge detector. It minimizes the joint uncertainty with respect to space and frequency.

This work acquires the depth and intensity images of the 3D data. The gabor filter is generated based on the below given formula. A 2D gabor function $g(x,y)$ is applied on both the depth and intensity images and are given by

$$g(x,y) = \frac{1}{2\pi\sigma_x\sigma_y}\exp\left[-\frac{1}{2}\left[\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right]+2\pi jWx\right] \qquad (1)$$

W is the modulation frequency. The two dimensional fourier transform is defined by

$$G(u,v) = \exp\left[-\frac{1}{2}\left[\frac{(u-w)^2}{\sigma_u^2}+\frac{v^2}{\sigma_v^2}\right]\right] \qquad (2)$$

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σ_u is $(2\pi\sigma_x)^{-1}$ and σ_v is $(2\pi\sigma_y)^{-1}$. Consider $g(x,y)$ is the mother wavelet and multiple filters can be created with different rotations by (3).

$$g_{mn}(x,y) = a^{-m} g(x', y') \quad (3)$$

Where $x' = a^{-m}(x\cos\theta + y\sin\theta)$,

$y' = a^{-m}(-x\sin\theta + y\cos\theta); a > 1$,

$\theta = n\pi/N; n = 0,1,2, .. N-1 ; m = 0,1,2, .. M-1$

where n and m are the orientation and scale of the gabor wavelet. In this work, we consider 3×3, 5×5, 7×7, 9×9 as different sizes of Gabor, theta values we consider are 15, 45, 75, 135 and 180 degrees.

Finally, each and every image pixel contains two parts and they are real and imaginary. The real part signifies the magnitude and the imaginary part indicates the phase features. The depth images are smoother than the intensity images and hence, the effect of noise can be controlled by depth images. However, the depth images cannot represent the features well, such that both the intensity and depth images are clubbed together. The LTP features are extracted as follows.

The LTP features are extracted from three multi-resolutional images by means of two dimensional circular symmetric Gaussian filter bank.

$$G(a,b,\mu) = \frac{1}{2\pi\mu^2} e^{-(a^2+b^2)/2\mu^2} \quad (3)$$

The Gaussian images are computed by

$$GI(\mu) = G(a,b,\mu) * I(a,b) \quad (4)$$

In the above equations, μ represents the scales and * is the convolutional operator. Three different multiresolutional images are formed in 3D grid and the eight neighbours of a centre pixel are computed with respect to the five different directions D. The feature vector is then formed by concatenating all the histograms together.

c. Feature Selection by IGR

The extracted gabor and LTP features are made crisper by employing IGR as in [20]. The objective of feature selection is to improvise the performance of the recognition system. The classifier is trained with the optimal features, which speeds up the learning speed of the classifier. As soon as the feature vector is formed, the ELM classifier is trained with the feature set as presented below.

d. ELM Classification

ELM is utilized to classify between the faces, as ELM is one of the fast learning and reliable classifiers [22]. In the training phase, the ELM is trained with the knowledge acquired from the feature extraction phase by means of feature vectors.

Consider X as the training samples indicated as (a_i, b_i); here $a_i = [a_{i1}, a_{i2}, \dots a_{is}]^q \in Im^s$; where n is the dimension of the training representatives. $b_i = [b_{i1}, b_{i2}, \dots b_{it}]^q \in Im^t$ indicates the i^{th} class label of dimension t. A Single hidden Layer Feed-Forward Neural Network (SLFN) is formed by an activation function $act(x)$ and R neurons, which is represented by

$$\sum_{i=1}^{R} \beta_i act(wt_i . a_j + e_i) = b_i; i = 1,2, \dots, n \quad (5)$$

In equation (5), wt_i is the weight of the feature vector, e_i is the bias of the i^{th} hidden neuron. Let Hd_l be the ELM's hidden layer output matrix in which the i^{th} column of Hd_l represents that the i^{th} hidden neurons output vector by taking the inputs $a_{i1}, a_{i2}, \dots, a_{in}$ into account.

$$Hd_l = \begin{bmatrix} act(wt_1 . a_1 + e_i) & \dots & act(wt_v . a_1 + e_G) \\ \vdots & \vdots & \vdots \\ act(wt_1 . a_n + e_i) & \dots & act(wt_v . a_n + e_G) \end{bmatrix} \quad (6)$$

$$\beta = \begin{bmatrix} \beta_1^q \\ \vdots \\ \beta_G^q \end{bmatrix} \quad (7)$$

$$B = \begin{bmatrix} b_1^T \\ \vdots \\ b_n^T \end{bmatrix} \quad (8)$$

The matrix form is denoted by

$$Hd_l \beta = B \quad (9)$$

The output samples are computed by norm least-square solution and the equation is presented as follows.

$$\beta = Hd_l^{\dagger} B \quad (10)$$

In the above equation, $Hd_l^{\dagger}$ is the HL's Moore-Penrose generalized inverse. The ELM is trained by processing eqn.10. In the testing phase, the output matrices are computed and combined together for detecting the greatest value in the row. The output matrix is computed as follows.

$$b_{testing}(z) = Hd_{l_{testing}}(z) \times \beta_z$$

(11)

In this work, value of z is set to 12 and is chosen by trial and error method. The performance of the proposed approach performs bad, when the value of z reaches above 12. By this way, the ELM is imparted knowledge to recognize the human faces and the performance of the proposed approach is analysed in the following section.

VI. RESULTS AND DISCUSSION

The performance of the proposed approach is evaluated over the Texas 3D face recognition dataset and CASIA-3D face dataset downloaded from [23].

The Texas 3D face recognition database is comprised by including 105 human faces, which includes the colour and range images. As the colour and range images are taken in parallel, the registration process is attained effectively.

CASIA 3D face database contains the 3D face images of 123 persons. The simulation of the proposed approach is carried out in MATLAB environment on a standalone machine with Intel i7 Processor and 8 GB RAM.

The performance of the proposed approach is evaluated by considering multiple scenarios such as by varying feature extraction techniques, classification

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techniques and the recent analogous techniques. The importance of feature reduction is also justified. The results of all the cases are analysed by the standard performance metrics such as classification accuracy, sensitivity, specificity and time consumption.

Classification accuracy is the metric that measures the correctness of the proposed approach. In this work, classification accuracy implies the correct recognition of a face with respect to the test face, from a database of numerous faces. For instance, a test face image is passed to the proposed face recognition system and the system is supposed to match the test face image with a number of faces, which are already stored in the database. Finally, SVM makes decision in the recognition of face. For any recognition system, classification accuracy is the most important metric, as the efficiency of the system is decided by accuracy rates. The accuracy rates are computed by

$$A_r = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \quad (12)$$

Sensitivity and specificity are other two important parameters, which is hard to achieve. The reason is that most of the recognition systems intend to increase the accuracy rates, which in turn increases the FP and FN rates. This is a serious issue, because FP rates indicate that the system claims the face to be a match for a wrong face.

Similarly, FN rates increase when the system declares a correct matching face as unmatched. The sensitivity and specificity rates are closely related to the FN and FP rates respectively. When the FN rates increase, the sensitivity rate of the system falls. Similarly, the specificity of the system increases, when the FP rates of the system is minimized. The sensitivity and specificity of the proposed approach are computed by

$$sn_r = \frac{TP}{TP+FN} \times 100 \quad (13)$$

$$sp_r = \frac{TN}{TN+FP} \times 100 \quad (14)$$

In the above equations, TP, TN, FP and FN are True Positive, True Negative, False Positive and False Negative rates respectively. The experimental results of the proposed approach under different scenarios are tested and the results are presented as follows.

A. Performance Analysis by Varying the Feature Extraction Techniques

This section intends to justify the power of the combination of LTP and gabor features. In order to justify the potential of the LTP and gabor features, both the feature extractors are utilized individually for checking the performance. The experimental results of this analysis are presented in table 1.

Table 1: Experimental results by varying the feature extractors

Techniques	Texas			CASIA		
	A_r (%)	sn_r (%)	sp_r (%)	A_r (%)	sn_r (%)	sp_r (%)
Gabor	73.4	70.34	69.8	79.54	76.8	72.6
LTP	86.9	81.9	79.7	89.7	83.4	81.6
Gabor+LTP	**98.9**	**97.4**	**95.8**	**98.4**	**95.8**	**93.9**

Initially, the gabor features alone are extracted from the face images and then the LTP features alone are extracted from the images. When the ELM is trained with the individual gabor or LTP features rather than the combination of them, the performance of ELM goes down. The experimental results show the capability of the combination gabor and LTP features. The following section analyses the performance of the proposed approach with and without feature selection technique.

B. Performance Analysis w.r.t Feature Selection Technique

The proposed approach utilizes IGR as the feature selection technique, which attempts to select the significant features from the voluminous feature sets. It is stated earlier that the inclusion of feature selection phase helps in minimizing the time consumption and the statement is proven with the following experimental results.

Table 2: Experimental results w.r.t feature selection technique

Techniques	Texas		CASIA	
	Avg.Time (s)	A_r (%)	Avg.Time (s)	A_r (%)
Proposed approach (without IGR)	11.84	97.7	10.98	97.3

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Proposed approach (with IGR)	**8.31**	**98.9**	**7.93**	**98.4**

The performance of the proposed approach is analysed with and without IGR. The time consumption of classification differs in addition to the accuracy rate. The change in accuracy rate is very mild, however the time consumption is prominent. The classifier is trained with all the features extracted from the faces and the accuracy rate achieved is 97.7%. On the other hand, when the features are selected prior to the process of classification, then the accuracy rate achieved is 98.9%. Though the difference is minimal, the time consumption is reduced when the classifier is trained with selected features. The following section intends to analyse the performance of the proposed approach in comparison with the existing approaches.

C. Performance Analysis against Existing Approaches

The experimental results attained by the proposed approach are compared with the existing face recognition approaches such as DCNN [19], Curvelet based [11], covariance based [13]. The experimental results are tabulated in table 3.

Table 3: Performance analysis against existing approaches

Techniques	Texas			CASIA		
	A_r (%)	sn_r (%)	sp_r (%)	A_r (%)	sn_r (%)	sp_r (%)
Curvelet based [11]	86.4	81.9	78.3	88.4	85.9	81.7
Covariance based [13]	89.3	87.21	84.6	91.7	88.4	87.1
DCNN [19]	96.4	94.7	91.9	95.8	92.6	90.7
Proposed CLBP+SIFT	**98.9**	**97.4**	**95.8**	**98.4**	**95.8**	**93.9**

The proposed approach shows better results when compared to the existing approaches. The reason behind the attainment of better results is that the utilization of effective feature set, employment of feature selection and ELM classification. On the other hand, the DCNN gives a tough competition to the proposed approach with better performance rates. Yet, the proposed approach shows better results than DCNN and the poor performer is the curvelet based approach. Hence, the performance of the proposed approach is satisfactory with reasonable performance rates.

V. CONCLUSION

This article presents a 3D face recognition approach by utilizing gabor and LTP features. The proposed approach is sub-divided into four main processes, which are pre-processing, feature extraction, feature selection and classification. The images are pre-processed with the help of radon transform, followed by which the gabor and LTP features are selected. As the feature set is massive, significant features are selected by means of IGR and the ELM classifier is trained with these features. The performance of the proposed approach is analysed in different scenarios with respect to accuracy, sensitivity and specificity rates. The proposed work shows better performance with better results, when compared to the existing approaches. In future, this work plans to enhance this approach by considering the facial emotions.

REFERENCES

1. Prabhakar, S., Pankanti, S., & Jain, A. K. (2003). Biometric recognition: Security and privacy concerns. IEEE security & privacy, (2), 33-42.
2. Buciu, I., & Gacsadi, A. (2016). Biometrics systems and technologies: a survey. International Journal of Computers Communications & Control, 11(3), 315-330.
3. Neves J, Narducci F, Barra S et al (2016) Biometric recognition in surveillance scenarios: a survey.
4. Artif Intell Rev 1–27. doi:10.1007/s10462-016-9474-x
5. Yin J, Zeng W, Wei L (2016) Optimal feature extraction methods for classification methods and their applications to biometric Recognition. Knowl Based Syst 99:112–122.
6. Blanco-Gonzalo R, Poh N, Wong R et al (2015) Time evolution of face recognition in accessible scenarios. Human-centric Comput Inf Sci 5(1):1–11
7. Guosheng Hu, Fei Yan, Chi-Ho Chan, Weihong Deng, William Christmas, Josef Kittler, Neil M. Robertson, "Face Recognition Using a Unified 3D Morphable Model", European Conference on Computer Vision, Lecture Notes in Computer Science, Vol.9912, 2016.
8. Pengfei Dou ; Shishir K. Shah ; Ioannis A. Kakadiaris, "End-to-End 3D Face Reconstruction with Deep Neural Networks", IEEE Conference on Computer Vision and Pattern Recognition, Honolulu, USA, 21-26 July, 2017.
9. Koushik Dutta, Debotosh Bhattacharjee, Mita Nasipuri, Anik Poddar, "3D Face Recognition Based on Volumetric Representation of Range Image", Advanced Computing and Systems for Security, Advances in Intelligent Systems and Computing, Vol.883, pp. 175-189, 2019.
10. Umara Zafar, Mubeen Ghafoor, Tehseen Zia, Ghufran Ahmed, Ahsan Latif, Kaleem Razzaq Malik, Abdullahi Mohamud Sharif, "Face recognition with Bayesian convolutional networks for robust surveillance systems", EURASIP Journal on Image and Video Processing, Vol.10, 2019.
11. Huibin Li, Di Huang, Jean-Marie Morvan, Yunhong Wang, Liming Chen, "Towards 3D Face Recognition in the Real: A Registration-Free Approach Using Fine-Grained Matching of 3D Keypoint Descriptors", International Journal of Computer Vision, Vol.113, No.2, pp.128-142, 2015.
12. S.Elaiwat, M.Bennamoun, F.Boussaid, A.El-Sallam, "A Curvelet-based approach for textured 3D face recognition", Pattern Recognition, Vol.48, No.4, pp. 1235-1246, 2015.
13. Mehryar Emambakhsh, Adrian Evans, "Nasal Patches and Curves for Expression-Robust 3D Face Recognition", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.39, No.5, pp. 995-1007, 2017.
14. Walid Hariri, Hedi Tabia, Nadir Farah, Abdallah Benouareth, David Declercq, "3D face recognition using covariance based descriptors", Pattern Recognition Letters, Vol.78, pp.1-7, 2016.
15. Sima Soltanpour, Boubakeu Boufama, Q.M.Jonathan Wu, "A survey of local feature methods for 3D face recognition", Pattern Recognition, Vol.72, No. 391-406, 2017.

16. Yue Ming, "Robust regional bounding spherical descriptor for 3D face recognition and emotion analysis", Image and Vision Computing, Vol.35, pp.14-22, 2015.
17. Sima Soltanpour ; Qing Ming Jonathan Wu, "Weighted Extreme Sparse Classifier and Local Derivative Pattern for 3D Face Recognition", IEEE Transactions on Image Processing, Early Access, 2019. DoI:10.1109/TIP.2019.2893524
18. João Neves ; Hugo Proença, "“A Leopard Cannot Change Its Spots”: Improving Face Recognition Using 3D-Based Caricatures", IEEE Transactions on Information Forensics and Security, Vol.14, No.1, pp.151-161, 2019.
19. Soodamani Ramalingam, Aruna Shenoy, Nguyen Trong Viet, "Fundamentals and Advances in 3D Face Recognition", Biometric-Based Physical and Cybersecurity Systems, pp.125-162, 2018.
20. Jianying Feng, Qian Guo, Yudong Guan, Mengdie Wu, Xingrui Zhang, Chunli Ti, "3D Face Recognition Method Based on Deep Convolutional Neural Network", Smart Innovations in Communication and Computational Sciences, pp.123-130, 2018.
21. Chandrakala M. and Ravi S., "Robust 3D Face Recognition System based on Feature Selection and SVM", Cluster Computing, Article in Press, 2018. DoI.
22. Chandrakala M. and Ravi S., "Time Conserving Face Recognition System for 3D Face Images Based on SURF and LDP", International Journal of Pure and Applied Mathematics, Vol.119, No.17, pp.1291-1305, 2018.
23. Guang-Bin Huang, Hongming Zhou, Xiaojian Ding, and Rui Zhang, Extreme Learning Machine for Regression and Multiclass Classification, IEEE Transactions on systems, Man and Cybernetics - Part B, Vol.42, No.2, pp.513-529, 2012.
24. http://www.face-rec.org/databases/

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