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Gabor-SVM Applied to 3D-2D Deformed Mesh Model

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Abstract*—We propose a robust method for 3D face recognition using 3D to 2D modeling and facial curvatures detection. The 3D-2D algorithm permits to transform 3D images into 3D triangular mesh, then the mesh model is deformed and fitted to the 2D space in order to obtain a 2D smoother mesh. Then, we apply Gabor wavelets to the deformed model in order to exploit surface curves in the detection of salient face features. The classification of the final Gabor facial model is performed using the support vector machines (SVM). To demonstrate the quality of our technique, we give some experiments using the 3D AJMAL faces database. The experimental results prove that the proposed method is able to give a good recognition quality and a high accuracy rate.

***Keywords*—3D face recognition; salient points; deformed mesh model; facial curvatures; Gabor wavelet; SVM**

I. Introduction

3D human face recognition is a very various and wide field in artificial intelligence. The human face has a great variety of motions and expressions. Every single human face is characterized by its own deformations. So that we describe a face as a combination of attached rigid, semi-rigid and non-rigid areas, where only rigid areas are the stable and the constant parts for any expression and over time. The other parts are easy, soft and effortless zones when there is even a simple facial expression.

Recently, 3D face recognition has become a substantial issue in computer vision and image processing. For this reason, many researchers are working on developing several 3D face recognition techniques in different domains. In literature, researches and contributions in the 3D human face recognition field are various. We select the approaches that provide the most significant concepts, similarly to our work.

Yinjie et al. [1] proposed a 3D face recognition approach that employed local geometrical signatures known as Angular Radial Signatures (ARS) and used Kernel Principal Components (KPCA) combined to Support Vector Machine (SVM) to extract and identify 3D faces. Another research presented by Sajad et al. [2] applied Zernike Moments (ZM) calculations with Hermite Kernels (HK) to extract global features from 3D images with different facial expressions. Since human face is a rich source of behavioral expressions, Hsun et al. [3] developed a Hidden Markov Model (HMM) based method to separate non-rigid facial expressions from rigid regions. Hengliang et al. [4] described and developed a Local Binary Pattern (LBP) framework to identify 3D faces under multiple expressions. Dalila et al. [5] introduced the use of 3D mesh vertices located in the contour of the face shape. In [6] face-tree was presented as a 3D face shape model.

Due to expensive 3D scanners and complex computational operations on 3D databases, 3D to 2D transformation has proven its effectiveness in face recognition. In practical intelligent face recognition applications, operating on 2D images is still widely performed. In [7], cross dimensional comparison was implemented to solve pose variety issue, where 2D rendered models were constructed from 3D images with different angles.

Most multimodal approaches confirm the great benefit from the fusion of 3D and 2D modalities in order to raise the recognition rate and to boost the authentication results. Many researchers have studied the 3D to 2D model transformation. Zhe et al. [8] presented a multi-pose 3D face recognition method based on the construction of a discrete conformal map from a 3D domain. The main task is to map 3D facial surfaces onto a 2D planar domain. Consequently, 2D face recognition techniques are applied easily. Hei-Sheung and al. [9], encoded 3D facial features by introducing series of translations, rotations and space scaling to plant an alignment transformation on polygonal meshes. Then, a genetic algorithm (GA) was implemented to select the most significant landmarks. The obtained results were compared to PCA and LDA algorithms through several 3D databases and showed a great recognition rate about 80%.

However, model-based processes suffer from some drawbacks such as exposure to local minima, pose and

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illumination. As a solution to adjust these deficiencies. Jaeik et al. [10] designed a solid algorithm combining a 3D morphable model and a facial structure from motion block. Then, sparse representation classification was tested on multiple-view 3D range images. The proposed method had overcome the disadvantages caused by facial expressions, occlusions and different pose variations and elevated computational costs. We have used 3D triangular mesh where all facets are constructed through three edges connecting each three vertices. In order to succeed in 3D mesh modeling, there are several mathematical proceedings described by Coupez et al. [11] where mesh connectivity notations and topology optimization are introduced.

During the last few years, researchers had developed a robust differential geometry graphics. Among 3D landmarks differential detection techniques, principal curvature has proven its forcefulness in spotting salient points on 3D meshes [12,13]. The purpose of adopting principal curvature is its effectiveness in measuring how this surface could bend, so that is a great way to calculate the curvature in each point.
A systematic analysis was undertaken using Riemannian tensor to prove that curvature computed in a given point is an invariant geometric quantity. Mio et al. [14] proved that computing Gaussian curvature needs to minimize the discrete Ricci energy which is strictly convex.
The global objective of this manuscript is developing 3D face recognition method by employing a 3D to 2D transformation based on 3D mesh vertices projection. Then, we propose to perform feature extraction using Gabor wavelet technique through surface curvatures analysis. In the other hand, this study focuses on further increasing the 3D recognition accuracy rate and on further decreasing the computational complexity and the computational time.
The report is organized as follows. In section 2, we deeply presented the proposed method. The experimental results are given in section 3. Some conclusions are made in section 4.

II. THE PROPOSED METHOD

In this paper, we present a new approach of 3D face recognition, the Gabor filter applied to 3D-2D deformed model. Our method consists first on performing geometrical transformation to 3D mesh in order to obtain 2D deformed model projected and fitted into 2D plane. Then, a bunch of Gabor wavelet is applied to the deformed model to extract the mean Gabor curvatures which simplifies facial salient point detection. The final step is to classify 3D-2D data by SVM and to present our experimental results tested on 3D AJMAL database. Next, we propose to measure accuracy rate and compare our results with similar work.
In Fig. 1 we present the global architecture of our adopted 3D face recognition method based on 3D database analysis.
3D data could be a 3D mesh, 3D range image or 3D point cloud. In case two and three, a mesh processing is applied in order to perform our algorithm.

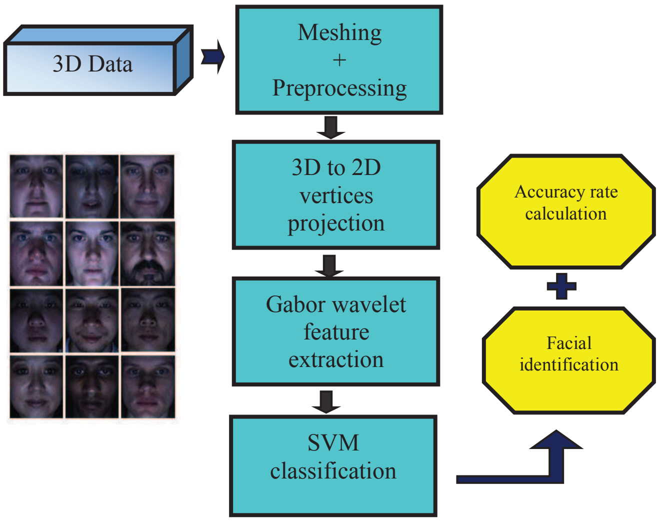

Fig. 1. Our proposed 3D face recognition algorithm.

A. 3D mesh preprocessing

In this segment, we present the preprocessing operations adapted in order to prepare the mesh dataset to feature extraction. 3D facial images scanned by laser cameras are sensitive to high frequency noises and gaps provoked by illuminations variety, for this reason, we first practice a median filter to shut out the annoying noises. Second, we apply an interpolation as a filler to the holes resulting from lack of information during 3D scanning. Third, a low pass filter is used to smoothen and strengthen mesh surface. Fig. 2 shows preprocessing tasks applied on a 3D model from 3D AJMAL database captured under illumination and poses variations with different expressions.

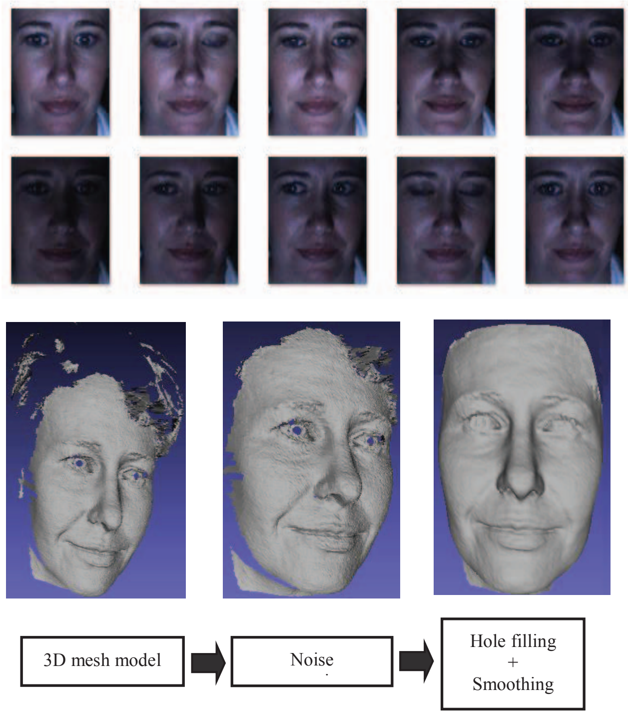

Fig. 2. A preprocessed 3D AJMAL database.

B. 3D-2D deformed mesh model

Many existing studies rely on converting 3D face images to 2D space [15,16,17]. In [9] a 3D-2D transformation was established based on applying 3D manipulations to the facial surface by 3D rotation, translation and space scaling to facial and profile poses.

In this paper, we reveal our method based on 3D projection to 2D space. Since the facial surface is prepared to the feature extraction and considering our framework being established for the 2D face deforming, we define (M) a mesh in a 3D space, designed with a set of vertices related with edges to form the mesh facets. The basic objective from deforming a given mesh is to project the vertices coordinates into the 2D plane. The first step in deforming the 3D model is to extract the tri-dimensional data of the mesh triangles using barycentric coordinates. Every triangle is composed of three vertices. The triplet (x, y, z) are the coordinates of a given vertex v and p_1, p_2, and p_3 are three barycentric coordinates that figure out whether a point is located inside or outside the main triangle. After segmenting the mesh surface by the barycentric points, we perform the 2D plane representation to project the mesh triangles using least square fitting. Fig. 3 explains with the meanface of 3D AJMAL dataset our adopted process.

The equation of the new plane designed is defined as:

$$\alpha x + \beta y + \mu z = 0 \qquad (1)$$

Where (α, β, μ) are the coordinates of an orthonormal non-zero vector. Considering the n points with the coordinates (x_i, y_i, zi) segmented using the barycentric coordinates. The representation of the equation (1) in least square is defined by:

$$\begin{pmatrix} x_1 & y_1 & z_3 & 1 \\ x_2 & y_2 & z_2 & 1 \\ : & : & : & : \\ x_n & y_n & z_n & 1 \end{pmatrix} \begin{pmatrix} \alpha \\ \beta \\ \mu \\ \lambda \end{pmatrix} = M\psi \qquad (2)$$

Where λ is a constant. The second step is to discard z coordinates of the triangle vertices and solve the new z using the parameters of ψ to produce 2D meshes with new depth coordinates. Consequently, we design the whole 2D deformed model by repeating the 3D-2D deforming process to all triangles of the data mesh. The final step is to perform mesh subdivisions which is a great modeling tool that permits high flexibility in controlling sharp-cornered mesh surface.

In Fig. 3 the 3D AJMAL meanface contains 62 487 vertices and the 2D deformed model consists of 630 vertices which is a 99.17% vertex reduction. This reduction do not decrease the 2D mesh quality, it simplifies feature extraction and facilitates the 3D farce recognition process. As the Gabor wavelets give strong response with respect to spatial location and orientation which are the characteristics of an image, it's the most suitable for feature extraction.

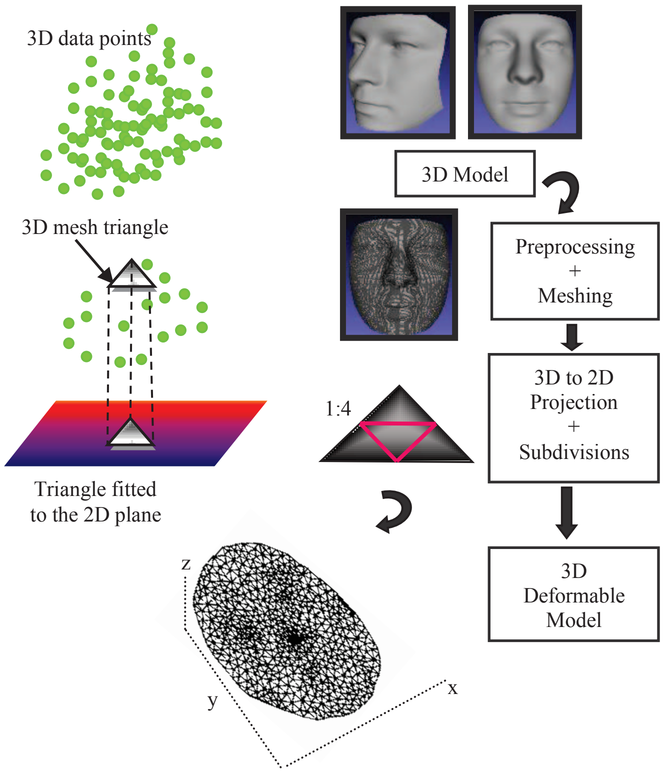

Fig. 3. Schematic diagram of the proposed 3D-2D deformed model.

C. Feature extraction using Gabor wavelet

In this study, we are particularly interested in feature extraction based on 2D Gabor wavelet transformation. Gabor wavelet is an outstanding theory for both of 2D and 3D face recognition.

Involving curvature Gabor wavelet theories into the heart of salient points extraction has led to prosperous results with different orientations and scales in face authentication.

A Gabor filter is simply a linear filter described by a frequency and a particular orientation whose impulse response is a sine wave modulated by a Gaussian envelope.

We define the conventional equation of the Gabor wavelet kernel:

$$\psi(\vec{\chi};\upsilon) = \frac{\kappa^2}{\sigma^2}\exp\left(\frac{-\kappa\,\|\vec{\chi}\|^2}{2\sigma^2}\right)\times\left[\exp(i\kappa x)-\exp\left(\frac{-\sigma^2}{2}\right)\right] \qquad (3)$$

$$\left(\vec{\chi}\right) = \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} x\cos\theta + x\sin\theta \\ x\cos\theta - x\sin\theta \end{pmatrix} \qquad (4)$$

Where $k=2^{-(\upsilon+2)/2}\pi$, $\sigma = 2\pi$, θ={0,…,4} defines a set of 5 frequencies and γ={0,…,7} defines a set of 8 orientations. We design x and y as the coordinates of a given pixel in a 2D image. The Gabor wavelet kernel equation is:

$$\psi(x, y, \upsilon, \gamma) = \frac{\kappa^2}{\sigma^2}\exp\left(-\frac{\kappa^2(x^2+y^2)}{2\sigma^2}\right)$$

$$\times\left[\exp(i\,\kappa(x\cos\theta+y\sin\theta))-\exp\left(-\frac{\sigma^2}{2}\right)\right] \qquad (5)$$

Global analysis of the face using Gabor wavelet is settled by the convolution of the 2D face with a Gabor filter family of different resolutions and orientations. The result of this convolution is a 40 magnitude map and 40 phase map. Only magnitude responses are providing us with useful information related to the features positions. Gabor wavelet analysis is suitable for detecting curved shape components of the human face. Nose, eyes and lips do not have straight lines, for this reason their curvature edge information such as pit and peak surface types are detected using Gabor filters. In these regions of the face, most of the feature points are heavily localized [18]. In [19,20], Gabor filters were employed to extract tumors from 2D scanner images. In [21], the filters were used with a PCA technique on different 3D shapes. In the next part, we present our experimental results compared to other face recognition methods.

III. EXPERIMENTAL RESULTS

In order to evaluate 3D face recognition rate of our adopted approach, we explore the 3D AJMAL Faces database. Ajmal database was built from 4347 images of 106 subjects using 3D Minolta laser scanner. Each subject was scanned under varying illumination, poses and facial expressions. Then, 3D facial models were constructed based on the different range images using desktop optics. 3D models are stored in VRML file format (Virtual Reality Modeling Language) which is a 3D object and scene description commonly adopted in 3D modeling. In our work, we tested our 3D face recognition using a Support Vector Machine classifier.

SVM is a kernel based machine learning prototype essentially used for regression and classification tasks. It constructs a hyperplane to separate the training-data points and builds a margin between the two data classes. The functional margin is maximized in order to optimize the 3D recognition rate. To lower the error rate of the classifier, the margin must be maximized. Thus, the 3D to 2D transformation based Gabor-SVM method is a well-established technique for feature face detection and identification with excellent performance.

First, we perform our 3D triangular mesh on the 3D AJMAL database. Second, we fill up the holes and apply a laplacian filter to smoothen the new surface. Next, the whole mesh is filtered to illuminate annoying noises. Then, we convert the 3D face meshes into 2D aligned models. Finally, the proposed Gabor-SVM technique is performed to the database.

Fig. 4 shows the result of convolving a 2D deformed model with four different Gabor filters. Facial curvatures are clearly observed in light lines where pit and peak regions are heavily concentrated.

An important question regarding Gabor wavelet technique is its robustness to noise factor. Not many studies considered the effect of applying Gabor filters under high frequency noises circumstances. To evaluate the robustness of our algorithm, we added a set of Gaussian noise levels with standard deviations to the 3D AJMAL models. Experimental results have proven that facial proposed algorithm is highly descriptive and robust to Gaussian noise under different levels.

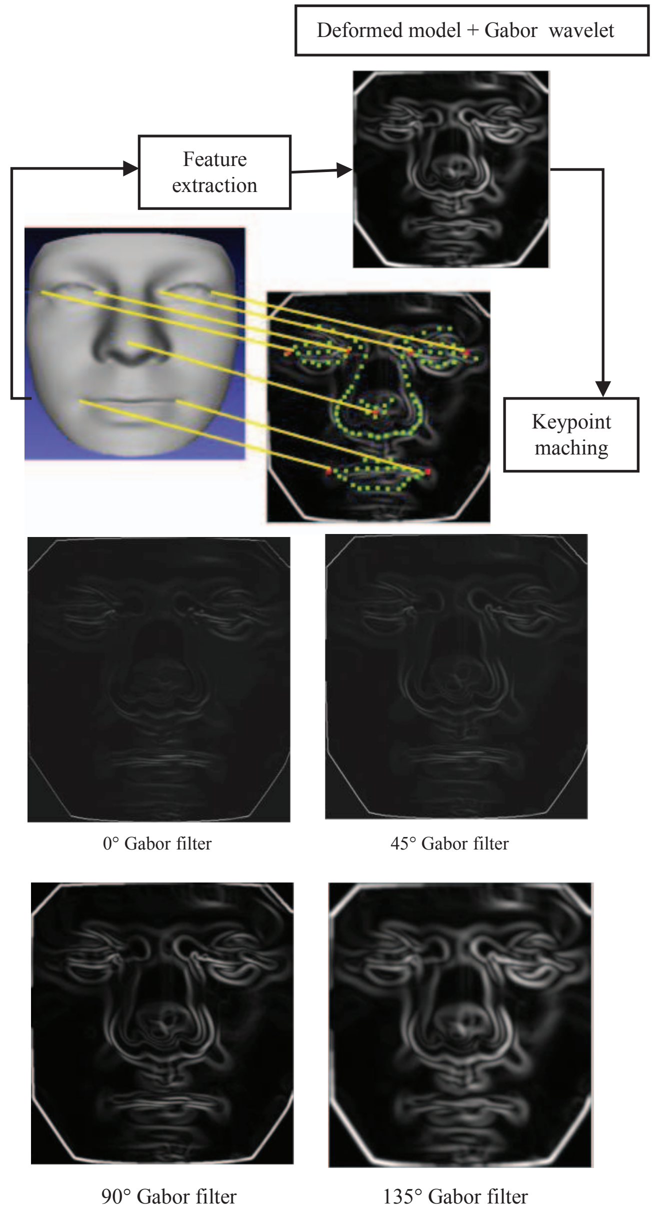

Fig. 4. Gabor filters applied on 2D deformed AJMAL meanface.

Fig. 5 shows two examples of subjects with concave curvatures (in red) and convex curvatures (in green) embossed by the Gabor kernels under normal environment and under Gaussian noises. Salient points are densely distributed in the curve's lines.

We compared our work to [18] experimental results. [18] evaluated the performance of curvature extended Gabor face recognition by employing just 60×80 resolution normalized images and a feature vector of only 1400 features. In this case, [18] achieved 90.97% recognition rate when manipulating only mid-resolution images.

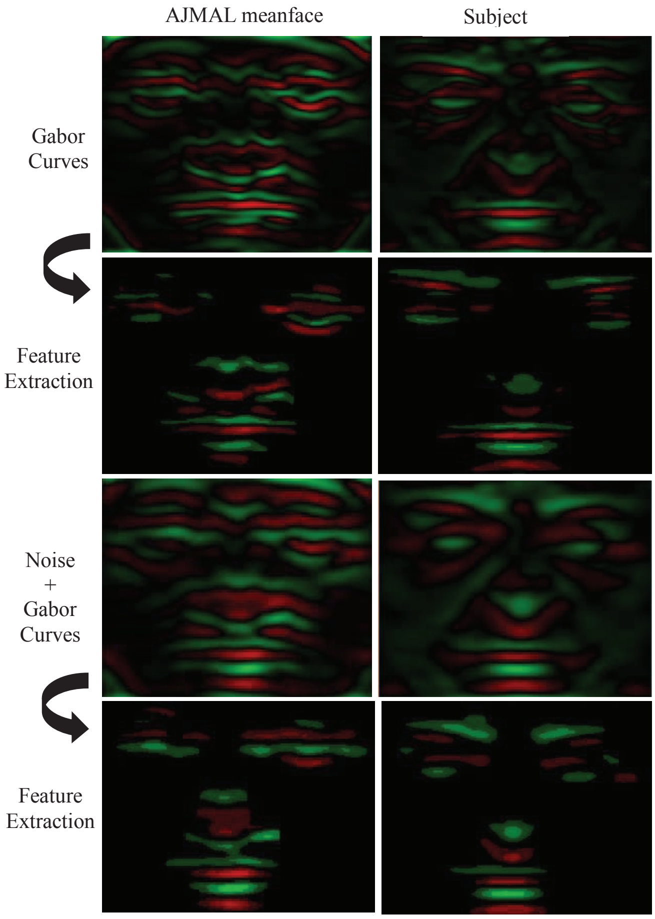

Fig. 5. Gabor curves, in red concave curves, in green concave curves.

It has been reported that the same method could not work on high-resolution images. In our experiment, our 3D-2D face recognition method allows us to reach the best accuracies using 250×270 and 440×440 3D to 2D transformed models without losing the dense curvatures information contained in our 2D transformed model. In the other hand, on Fig. 6 we conclude that the higher is the quality of the aligned model resolution the bigger is the computational complexity and the longer is the computational time. For this reason, we choosed finally to apply our algorithm to 250×270 high-resolution 3D-2D deformed models which is very sufficient to extract salient points from the Gabor curves rapidly. Our Gabor-SVM algorithm has excluded only one subject out of the 106 subjects due to the incomplete 3D AJMAL model. The best accuracy is about 99.05 % which is a high 3D recognition rate. We compare our algorithm to another work on 3D mesh models [22] accomplished only 96.2 % in face recognition tasks because it reduced excessively the 3D mesh data in order to obtain a simpler 2D surface. For example the study reduced the number of vertices from thousands to only 29 vertices. We minimize vertex number to hundreds which allows to exploit all the 3D information and inhibit facial feature lost.

In general, experimental results have demonstrated the solidness of Gabor feature extraction block against high frequency noises. Our Gabor curvatures still give us the salient points needed to our 3D facial. The fact that our accuracy rates shows high levels of face recognition confirm the efficiency of our 3D to 2D vertices projection and the efficacy of our deformed model in 3D face recognition.

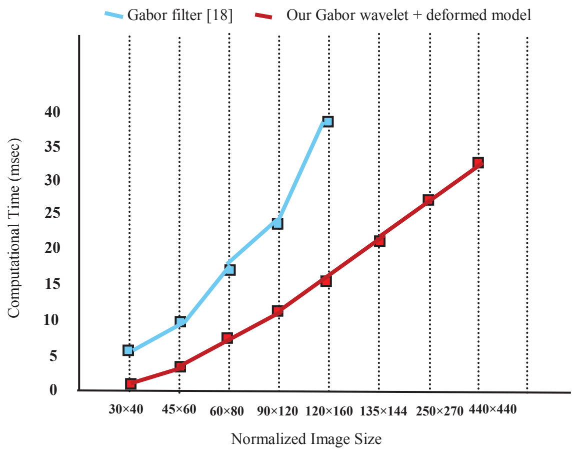

Fig. 6. Computational time and image resolution.

IV. CONCLUSIONS

This study presented a solid 3D face recognition algorithm based on 3D meshing, 3D to 2D deforming model and Gabor wavelet salient points detection. by projecting 3D mesh vertices into 2D space and applying different Gabor filters, we observed that facial curvatures are well captured which allowed us to exploit local features in face identification. Feature classification is performed by applying SVM to the 2D deformed and filtered model. Our 3D-2D face recognition technique is evaluated using 3D AJMAL database and experimental results shows superior accuracy rates.

Clearly, this work aims to a promising 3D face recognition method. To improve the performance of our technique we attend to introduce metaheuristic optimization and use more textured and animated databases.

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