Efficient Representation of Range Face Images Using Vectorfaces

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ABSTRACT

Advancement in scientific representation should accelerate the processing of images if it is more relevant and worthy with the experiment. Scientific visualizing of data (here, face images) has an enormous impact on exploring detailed inner content of images. Hence, the quality of processing depends on the quantity and informative data that might be accumulated, preserved as well as visualized in a particular image. In this paper, authors have described a novel technique for representation of range face image by 'Vectorfaces', which is proved to be more effective towards better recognition purpose in terms of recognition rate. Range face image is particularly important for 2D visual images for accomplishing depth data from 3D images. Other than an efficient representation of 'Vectorfaces' images, authors have also emphasized its significance for selecting better features compared to conventional range images. The major goal of the present work reported in this article is to evaluate, visualize and compare the role of 'Vectorfaces' over range face images. Change of tracks for different mathematical notations to visualize the images are noted. Moreover, Mean-Maximum curvature image pair is accumulated from range image as well as 'Vectorfaces' for extraction of features. SVD, followed by a feed-forward backpropagation neural network have been used for recognition purpose. In this work, 3D face images from Frav3D database have been considered. A statistical evaluation of this investigation is also given in the case study section.

Keywords

Scientific representation, 3D face image, range face image, Vectorfaces, Surface extraction, Mean-Maximum curvature, Face recognition.

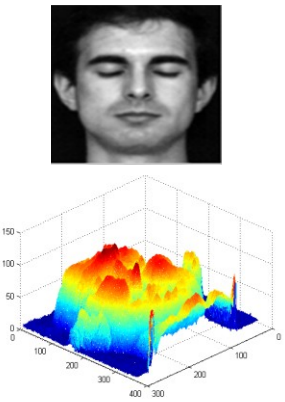
1. INTRODUCTION

In recent years, 3D images have gained much attention of the researchers for its underlying crucial information. Unlike 2D images, 3D images are used to accumulate data points along X, Y and Z axes. Now, to process 3D images more effectively, it is important to accumulate required information that can be analyzed by quantitative as well qualitative fashion. Before quantitative analysis, it is very much required to know how to process the information that are already belonging to it. Hence, image representation (i.e. qualitative observation) methods are becoming more important to explore the hidden information.

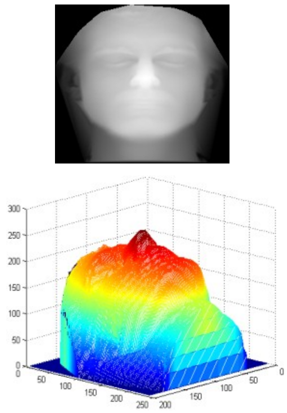
The idea to visualize the depth-oriented technique is popular and well accepted in terms of range image [1]. Other than range face image, authors have developed a novel face representation technique for depth data, i.e. 'Vectorfaces'. In general, range image preserve normalized depth data. Therefore, Vectorfaces is another approach to visualizing a range face image that exhibits depth data more than 2.5 D range image [2-3].

In practice, it is easy to learn and analyze any image by different appearance and selecting appropriate representation mechanism, which encourages the researchers to apply suitable techniques for further processing. In this article, various representation mechanisms of range image and Vectorfaces illustrate its suitable applications in the domain of computer vision especially in face recognition.

In general, any three-dimensional face image contains the data in the form of points rather than intensity of conventional 2D face image. The depth data (i.e. Z) in X-Y plane renders the valuable surface information from a face that is not supported by 2D. In addition, due to the presence of depth in the 3D image, the external illumination and shades do not affect its content. Further, facial pose registration for rotated face images by the available data across three axes is an additional feature of 3D scanned face image. In figure 1, the phenomenon of intensity vs. depth data of a randomly selected person from Frav3D database is illustrated.



(a) Surface of 2D image



(b) Surface of 3D image

Figure 1. Intensity and Depth Comparison

From figure 1, it is observed that due to the variation of illuminated light source, the values that are having maximum intensity are represented by number of peaks in surface representation form of 2D visual image. Whereas for 3D face image (for frontal face) nose region (especially tip of the nose or 'pronasal') is having maximum depth value having a single peak. For establishing the meaningful comparison, authors have normalized depth data from 3D image and intensity data from the 2D image. The available data from 2D and 3D images have been normalized between 0 to 255. All the color 2D face images have been converted to grayscale by following the standard formula as shown in equation 1.

$$G_r = 0.2989 \times R + 0.5870 \times G + 0.1140 \times B \quad (1)$$

where, G_r is the output gray image and R, G and B are the three color channels of the input color image

However, representation of range face images in Vectorfaces is aimed towards processing the points that are available using the computation of normal vector on facial surface preserved by different depth values. Thus, in Vectorfaces surface of a 3D face is well represented in comparison to corresponding range face images and hence that will certainly improve the recognition task significantly. The principal contributions of this investigation are summarized below:

- A novel face image, 'Vectorfaces', is introduced to describe a face image, by computing normal component and tangent component at each point of a depth image (especially 2.5D range image). From every pair of normal and tangent components, surface normal is computed that has been again arranged together to form an intermediate matrix, processed by the bi-cubic interpolation. The resultant matrix is Vectorfaces for that input image.
- It uncovers the prime structure and emphasizes on the overall depth information of a 3D image.
- Visual representation of output images obtained from different mathematical formulations are also shown in this paper.
- Other than qualitative analysis by different representation mechanisms, authors have also applied curvature based face recognition technique from both the range and Vectorfaces to accomplish quantitative measurement.

The remaining discussion in this paper is arranged as follows. In section 2, the detailing of 'Vectorfaces' is done. Various representation techniques and their significance have been explained in section 3. A case study for this representation i.e. faces recognition using Vectorfaces has been discussed in section 4. Conclusion and future scope are in section 5.

2. VECTORFACES

On the face surface, $'p'$ is a point having two components, namely a tangent component and a normal component to derive surface normal $'V'$. The vector $'V'$ is the summation of these two components as shown in equation 2.

$$V = V_t + V_n \quad (2)$$

To calculate the normal components for surface normal, unit normals on the face surface, let 'F', is considered. The unit normal is actually the unit vector ($\hat{n}$) that is perpendicular to 'F' at any point say $'p'$. Now, V_n has been calculated as described in equation 3.

$$V_n = (V.\hat{n}).\hat{n} \quad (3)$$

here '$.$' is used to denote dot product operation

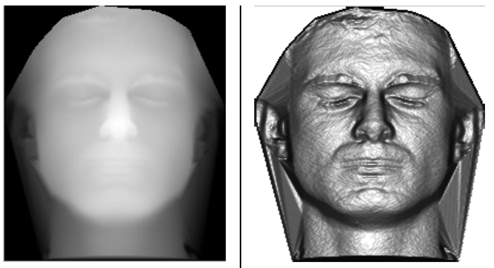
The remaining component i.e. tangential component has been calculated by following equation 4.

$$V_t = -\hat{n} \times (\hat{n} \times V) \quad (4)$$

here '$\times$' is used to denote cross product operation

Now, for accomplishing Vectorfaces from surface normal, at first it has been processed by bicubic interpolation [4] method. During interpolation mechanism, some missing links have been restored. Thus, some points have been restored, and a visual representation is accomplished. For the desired output, authors have chosen the value of the parameter (σ), with an iterative approach. Here, 'σ' is considered as 3. Finally, the smoothed matrix grid is termed as 'Vectorfaces' as shown in figure 2.

Hence, the basis of such face image is surface normal vector, and every mathematical formulation are done following a vector operation, authors have termed the ultimate resultant matrix as 'Vectorfaces'.



(a) Range Image | (b) Vectorfaces

Figure 2. Representation of range image and Vectorfaces.

It can be noticed that, from the Vectorfaces facial shapes, as well as different facial objects (like: eyes, nose, lips etc.), are accurately detectable than range images. This quality has proven to be more significant for face recognition than range images. It has been explained later in section 4 of the paper. Moreover, Vectorfaces preserves more information content that has been observed from two different mathematical measures, like entropy and mean of standard deviations. Entropy [5] is used to compute the amount of information it preserves. The more data it contains, the more entropy can be noted. Whereas, evaluation of mean of standard deviations is used to measure the average of standard deviations that has been calculated from each column of the face image. Standard deviation defines the amount of variations in the data. The mean of standard deviation over all the columns of the image is the measurement of average variation from the image. It has been observed that, the entropy of range image shown in figure 2(a) is 0.7069 whereas from Vectorfaces (displayed in figure 2(b)) it is 4.9790. Besides this, the mean of standard deviations of a range image is 38.4320 and for Vectorfaces the value is 0.2556.

From this analysis, it can be concluded that, although the entropy of the Vectorfaces is much higher than range image, it is having very less average variations among data it preserves. It signifies that Vectorfaces accumulates images in much informative and correlated way and an excellent way of representation for preserving facial features.

3. VECTORFACES VS. RANGE IMAGE

In this section, authors are concerned to explain the efficient methods and their representation that explains the significance of Vectorfaces of range face images. Representation of 3D face image cannot be usually seen. Here, in figure 3, authors have displayed a 3D face image in a reference plane. There are data points for X-Y grid to represent Z as depth values.

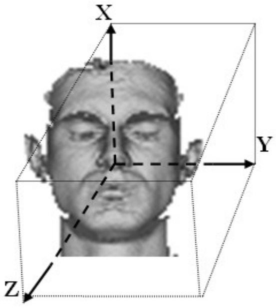


Figure 3. A 3D is a referential image.

Now, to emphasize the implication of Vectorfaces, authors have considered all the data points that are along the side of three axes. Rendering three volumes of datasets from three axes, authors have determined various surface metrics, like line, area, curves, etc. from face surface using depth data. Hence, to process and visualize these metrics authors have applied some methods, such as curvature analysis, shape index, and curvedness index.

3.1. Curvature analysis

In general curvature is used to define the amount by which the surface of any object deviates from a line or plane. Among two types of curvatures, like: extrinsic and intrinsic, Mean curvature belongs to the extrinsic property whereas Gaussian curvature is having the intrinsic property of face surface. Mean curvature (H) describes the curvatures of the local face region. It has also been noticed that the mean curvature values are the trace of second fundamental form, and that has been computed by equation 5. It can also be computed from principal curvatures by simple averaging them.

$$H = \frac{(1+f_x^2)f_{yy} - 2h_x h_y h_{xy} + \left(1+f_y^2\right)f_{xx}}{\left(1+f_x^2+f_y^2\right)^{3/2}} \quad (5)$$

Gaussian curvature (K) is computed by taking the product of principal curvatures. The alternative definition that the authors have followed here is shown in equation 6.

$$K = \frac{f_{xx}f_{yy} - f_{xy}^2}{(1+f_x^2+f_y^2)^2} \quad (6)$$

The principal curvature at any point on face surface is the minimum and maximum values of the curvature that can be denoted by P_{max} and P_{min} and they are perpendicular to each other if they are not equal. Now, it has been computed from Gaussian and mean curvature values using equation 7 and 8.

$$P_{max} = H + \sqrt{H^2 - K} \quad (7)$$

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$$P_{min} = H - \sqrt{H^2 - K} \qquad (8)$$

In these equations, f_x and f_y is the first derivative of f, such that $Z = f(x, y)$, with respect to X and Y axes. f_{xx} and f_{yy} are the second derivative of f with respect to X and Y axes. f_{xy} represent the mixed derivative.

In this investigation process authors have also implemented these mathematical derivations for Vectorfaces for suitable comparison with corresponding range face image. In Table 1, the curvature points for both the images from the various analysis are displayed with quantification using number of points it preserves. The images in table 1 are of binary type. The white points are the representation of the detected curve points from individual curvature analysis.

(i) H	(ii) K	(iii) P_{max}	(iv) P_{min}
			
No. of points: 34190	No. of points: 25223	No. of points: 30705	No. of points: 29708
(a) From range face image			
			
No. of points: 38085	No. of points: 35472	No. of points: 36938	No. of points: 36624
(b) From Vectorfaces			

Table 1. Observation of curvature points on range and Vectorfaces image

From this type of analysis and corresponding representation highlights that the number of curvature points are accumulated by various curvature maps from Vectorfaces than range images. Hence, it proves that Vectorfaces would be more useful for further processing.

3.2. Shape index and Curvedness index

The curve points are mainly focused on global curvedness whereas shape index (SI) is used to calculate local features that might also be useful during the face recognition task. The curvedness index (CI) is also computed to measure the magnitude of the curvedness at any point on face surface that are particularly dependent on principal curvatures of the surface. The SI and CI are followed by equation 9 and 10. These particular descriptors from both the face images are displayed in figure 4.

$$CI = \sqrt{\frac{P_{max} + P_{min}}{2}} \qquad (9)$$

$$SI = -\frac{2}{\pi}\tan^{-1}\frac{P_{max} + P_{min}}{P_{max} - P_{min}} \qquad (10)$$

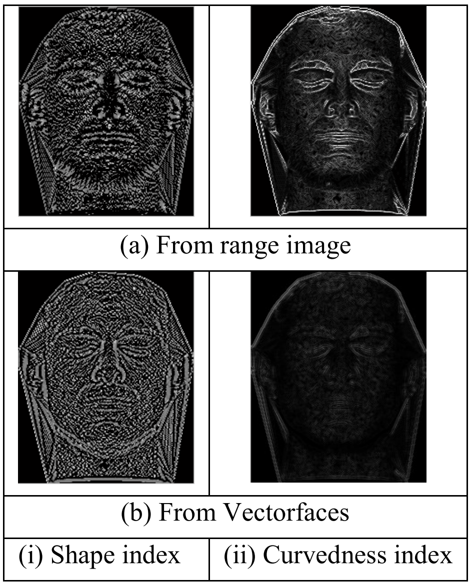


Figure 4. SI and CI from face images.

3.3. H-K classification and SI range

Here, authors have represented various facial surface's regions from H-K classification [6] and SI range [6]. H-K table is useful to describe various surface information for instance, concave and convex cylinder, planer, valley ridge, rut, dome etc. following a conditional parameters of H and K. Though much work has been progressed using curvatures, authors have planned to explain the significance of Vectorfaces with suitable representations. In Table 2, various surface information from range face image as well as Vectorfaces using H-K table is described. In addition, the values of SI (shown in equation 10) can be interpreted between -1 to 1 that specifically describes more local information than H-K. In Table 3, facial surfaces from SI are also described for both the images.

From such analysis, described in table 1, 2 and 3, it is proved that Vectorfaces is capable to accomplish more global as well as local facial features than conventional range face images. The efficient representation of Vectorfaces implies that it contains more number of effective data points than range face images and as a matter of fact it accomplishes other tasks in the sequence, typically face recognition with much higher success rate.

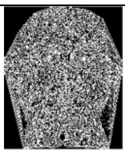
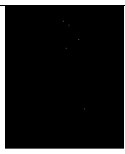
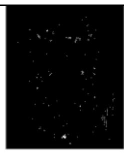
K<0 & H<0	K=0 & H<0	K>0 & H<0	K<0 & H=0	K=0 & H=0	K<0 & H>0	K=0 & H>0	K>0 & H>0
							
(a) From range image							
							
(b) From Vectorfaces							

Table 2. Representation of facial surfaces using H-K table

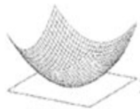
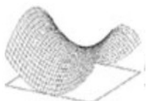
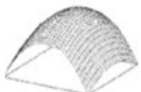
					
[-1,-0.625) **Spherical cup**	**[-0.375,-0.125)** **Saddle Rut**	**[-0.125,0.125)** **Saddle**	**[0.125,0.375)** **Saddle Ridge**	**[0.375,0.625)** **Ridge**	**[0.625,1)** **Dome**
(a) Various surface description from SI					
					
(b) Extraction of various face surfaces from range image					
					
(c) Extraction of various face surfaces from Vectorfaces					

Table 3. Facial surfaces from SI range

Various representations in these tables of face images from both the image types are binary images. Here also the white points used to visualize the validate points from H-K table and SI. Here, the term 'validate' means the valid points that are within the range of H-K table and SI.

4. EXPERIMENTAL STUDY

In this section, authors have presented a case study to underline the significant role of Vectorfaces over range face images in performing face recognition. Face recognition is an interesting and challenging research domain that has been studied during the past decades. In addition, there is numerous holistic as well as feature-based techniques for robust and accurate recognition purpose. Therefore, an effective visualization and representation would be one of the key contributions for implementing the successful face recognition system. Hence, to select the suitable feature set from input face images it is very much required to discover the underlying information for more robust recognition purpose. In figure 5, the role of

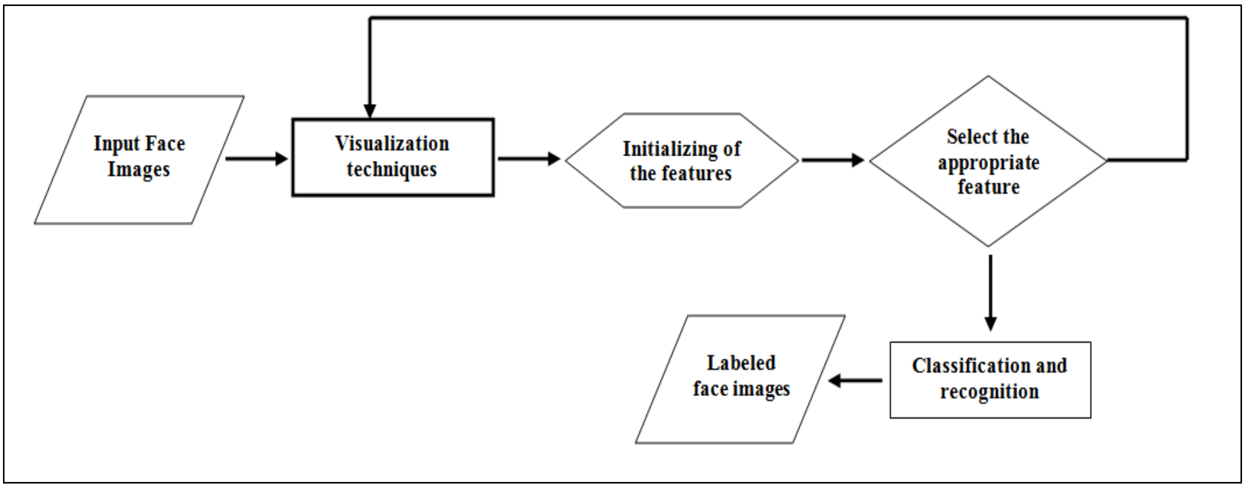


Figure 5. Importance of Representation techniques in face recognition scheme.

Representation techniques for executing an efficient recognition algorithm has been illustrated. In this figure, a feedback loop between feature selection and representation techniques blocks implies the cohesive relationship. A better representation of the data points is very much advantageous for selecting better features that ultimately results in better recognition rate.

In connection with the qualitative assessment, in terms of representation or representation, the said case study have been followed by the authors. In figure 6, an overall sketch of the recognition algorithm for quantitative evaluation of these images is illustrated.

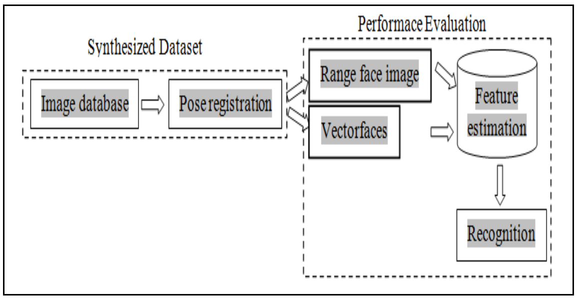


Figure 6. Sketch of the quantitative estimation.

4.1. State-of-the-art

For the motivation of such quantitative evaluation after qualitative discussion, authors have described the similar type of approaches that have already been considered by the researchers. In [7], Ganguly et al. researchers have compared the recognition performance of two paired curvature maps, such as Maximum Principal curvature-Mean and Gaussian-Mean. It is investigated that the features from the set of feature vector, better recognition is achieved by Maximum Principal curvature-Mean curvature pair. The key attributes from face image have been extracted using SVD based feature extraction mechanism. Later these features have been classified by five layers feed-forward backpropagation neural network. Lin et al. [8] also proposed curvature based 3D face recognition algorithm which are invariant of expression. Here, authors have mainly focused on Gaussian curvature maps. To create feature matrix, curvature points from various facial properties, like: nose, mouth eyes, etc. are considered. Later the feature vector is classified by distances between query image and gallery images. In [9], researchers have proposed PCA based face identification and verification process after successful detection and normalization of input 3D scan face image. Here, authors have used curvature values to detect whether the input image is facing for not. Mahoor et al. [10], proposed Hausdorff distance based face matching technique from surface ridge data. Surface ridge data has also been obtained from curvature analysis.

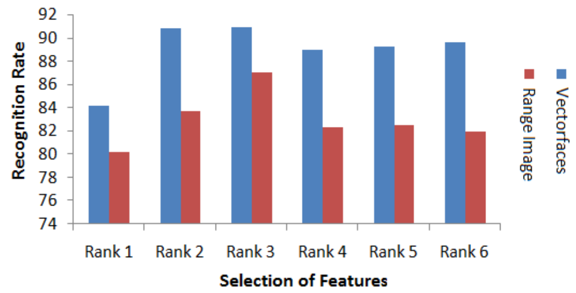
4.2. Discussion

Here, authors have followed and modified the recognition algorithm [7] for evaluation of Vectorfaces as well as range face image in terms of face recognition [14] rate. Since the algorithm proposed in [7], directly considers the curvature data as feature to discriminate the individuals, authors have followed this technique. Moreover, the data points accomplished by the curvature maps are more for Vectorfaces than corresponding range image. Therefore, aiming to compare the qualitative assessment, as well as quantitative measurement of same representation, has also inspired the authors to investigate the reorganization scheme from curvature maps.

In particular, authors have implemented and validated the algorithm using three layer feed-forward backpropagation neural network on synthesized face dataset from Frav3D database. In addition, unlike the algorithm [7], the concatenated features from paired curvature maps has not been sorted for this examination. Therefore, individual feature's position as well as its magnitude holds its important characteristics in the final feature vector. The synthesized dataset is accomplished by registering the rotated face images using ERFI model [11]. Other than registered face images, it contains face images with neutral as well as an expression.

In Table 4, the perceptible improvement of face recognition rate due to Vectorfaces is presented with a comparison of corresponding range face images. Here, rank based selection of features from SVD feature set is carried out for both the image types for recognizing 3D face images.

Feature Rank **(number of features from each curvature image of paired map)**	**From Vectorfaces**	**From Range Image [6]**
	Classification rate (%)	
Rank 1: 5	84.19	80.22
Rank 2: 10	90.87	83.75
Rank 3: 12	*91.01*	*87.1*
Rank 4: 15	89.01	82.35
Rank 5: 20	89.33	82.49
Rank 6: 25	89.67	82.01



Visual representation of the recognition rate

Table 4. Quantitative evaluation of Vectorfaces and range face image

From this tabular representation of the evaluation (in terms of recognition rate), it has been proved that the data points that are available in Vectorfaces is very much informative and useful for better recognition purpose. In Table 1, it has already been described that number of detailed points in the considered pair for Vectorfaces is much higher than range images. The recognition rates from the proposed mechanism also exhibit the same and support the qualitative measurement.

Although the said recognition rate is comparable with other's [12-13], authors have only tried to prove the importance of Vectorfaces by visualizing (i.e. qualitative fashion) and quantitative measurements (in terms of recognition rate).

5. CONCLUSION

During this investigation process, authors have established the role of Vectorfaces in the domain of 3D technology by qualitative as well quantitative assessment. Representation of the Vectorfaces in various fashion and relative importance establish that it would be effective for recognizing 3D face images like 2.5D range image.

Individual components of Vectorfaces, namely tangent and normal components can eventually be useful for further processing. Other than these investigations, Vectorfaces can be used to extract different facial properties, like nose, eyes, lips, etc. which might be eventually helpful for recognition purpose. Hence, it has certainly many useful applications in computer vision domain.

6. ACKNOWLEDGMENTS

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