Journal of Engineering and Applied Sciences 13 (19): 8034-8042, 2018
ISSN: 1816-949X

A Critical Comparative Analysis for 2D and 2.5D Face Recognition Techniques

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Abstract: During the past few years, face recognition techniques has received a significant attention. Face recognition is considered a non-threatening, natural and commonly accepted biometric technique. These techniques depend on the analysis of frontal or profile images of the face that are often effective without the participant's cooperation. In this study, face recognition techniques are discussed and reviewed in two different sections and have gone some way towards enhancing our understanding of the various approaches applied for face recognition and their advantages and disadvantages to date. This study, provides an up-to-date investigation of face recognition researches as regards to 2D and 2.5D image based face recognition techniques. As a result, this study, suggests compensating for the problems and the limitations of 2D based image techniques by substituting them with 2.5D range images because 2.5D approaches have proven themselves to outperforming 2D based image approaches. To validate this study, a set of experiments using OPSO-SVM face recognition technique are applied on a property 2.5D face dataset.

Key words: Face recognition, 2D image based, 2.5 image based, face recognition, biometric, Iraq

INTRODUCTION

Biometric recognition is the task of identifying someone by using some of his or her unique biometric information including either person's physiological characteristics such as iris, face and finger print or his or her behavior patterns such as key-stroke pattern, voice and even, a hand-writing (Rathgeb and Uhl, 2011). By having various applications at automated teller machine, physical access control and credit card industry to name a few, biometric recognition considered as one of the most powerful, dependable and convenient means of person authentication. Owing to the increasing concerns of terrorism and access security, this area of research has been given much attention as regards to security and privacy of the biometric data itself (Blackburn, 2001). That is behind the reason that a cornucopia of developments has been made to increase the biometric data security in the deploying of a biometric system (Adini *et al*., 1997). Among all, face is considered as one of the most chief features in biometric recognition (Prabhakar *et al*., 2003). Face recognition scenario can be classified as face verification and face identification (Abdulameer *et al*., 2013). Face verification is concerned with a one-to-one matching (1:1) that compares image of a face with a template face images whose identity is being claimed. Face identification, on the other hand is a one-to-many matching (1:N) that compares image of a face with all image templates in a face database in order to identify the identity of the query face (Abate *et al*., 2007). Regardless to the type (either face verification or face identification), however, many factors can negatively affect this image analysis of face recognition performances. This study is divided into two different sections namely, 2D face recognition, 2.5D face recognition and this has been visualized in Fig. 1.

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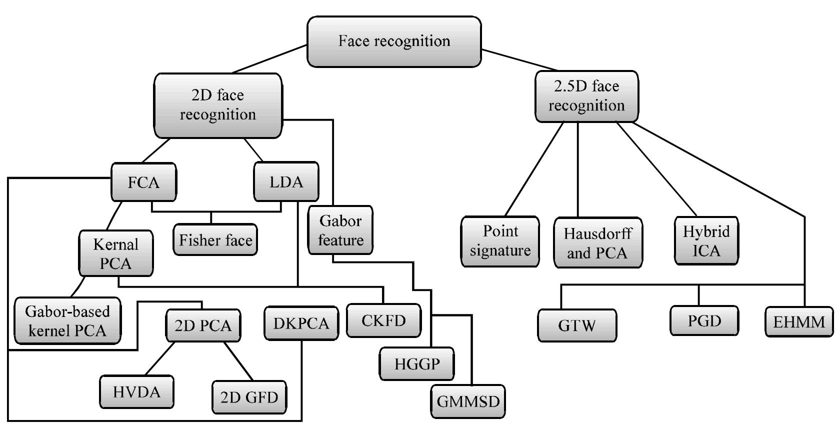

Fig. 1: 2D and 2.5D at a glance

MATERIALS AND METHODS

The 2D face recognition techniques: Face recognition studies have recently been applied in various fields including computer vision and pattern recognition. Furthermore, as a result of rising number of real world applications, a great number of face recognition techniques have been developed. One of the most key developments in this regard was a 2D image that its texture information was capable of providing detailed information for interpreting facial image (Kusuma and Chua, 2011). For a long time only 2D images have been available for recognition resulting at many techniques in that context. For example, Sirovich and Kirby (1987) and its sequel further in 1990 used PCA to efficiently represent pictures of human faces. They indicated that any face image could somehow be constructed again as a weighted sum of a small collection of images that define a facial basis (Eigenimages) and a mean image of the face (Yang *et al*., 2004). Concurrent with this, Turk and Pentland (1991) presented the recognized method of Eigenfaces for face recognition. Since then, PCA has become a burgeoning area for investigation and gained so much popularity among approaches that were applied for face recognition (Grudin, 2000; Valentin *et al*., 1994). Like any other approaches applied, however, there were also shortcomings that needed to be overcome when applying PCA.

One of the very first researches that applied PCA was conducted by Wiskott *et al*. (1997). In dealing with the shortcomings of PCA, they indicated that one of the most crucial prerequisites for capturing even the simplest invariance in PCA is that for the information to be explicitly provided in the training data. For that to be overcome, they suggested a technique called elastic bunch graph matching that could help the system to recognize human faces from single images out of a large database containing one image per person. However, it is worth mentioning that the information that is provided by a single image for each person in the galleries cannot be sufficiently enough to handle in depth analogous rotations. In another study focused on PCA-based vision systems (Zhao and Yang, 1999) tried to justify for arbitrary illumination effects for a pose of an object. In order for the approach to be applied directly to an arbitrary number of poses of an arbitrary number of objects, first an analytic closed-form formula of the covariance matrix for a special lighting condition was generated and then all possible illumination effects were analyzed and finally an equation called the illumination equation was derived in order to account for arbitrary illumination effects. While dealing with the shortcomings of PCA, LDA (Linear Discriminant Analysis) was born as a better alternative (Martinez and Kak, 2001). LDA could not only deal with the input data in their entirety but also was capable of following the underlying structure by expressly providing discrimination among the classes. LDA was professionally designed to find a base of vectors facilitating best discrimination among the classes, to maximize the between-class differences and minimize the within-class differences. However, owing to the high dimensions of scatter matrices, computationally, LDA is costly (Zhi and Ruan, 2008). On top of that because of the limited number of high-dimensional training samples, Chen *et al*. (2000) asserted that LDA suffers from the so-called Small Sample Size‘ (SSS) problem. However, a solution in line with this problem was made earlier on by Belhumeur *et al*. (1997) who believed that SSS problem could be solved by Fisher face which is the method based on a two-phase framework: PCA plus LDA.

Yang (2002) applied kernal PCA for face feature extraction and recognition and came to the conclusion that the advantages of kernel eigenfaces method outweigh those of classical eignfaces method. To deal with the problems related to nonlinearity of the distribution of face patterns (Lu *et al*., 2003) proposed a method based on the kernel discriminant analysis. One of the most important features of this method was its ability to successfully overcome the problem of SSS which was mentioned earlier. One year later, Liu (2004) proposed a new method called Gabor-based kernel PCA that had fractional power polynomial models for frontal and pose-angled face recognition. This method was specialized to deal with the variations that had caused by illumination and facial expression changes by driving the desirable facial features characterized by spatial frequency and locality as well as orientation selectivity. The kernel PCA method is then amplified to take in fractional power polynomial models for enhanced face recognition performance. However, the variation of facial expression in approach was limited with two facial expressions such as neutral and smile.

In 2005, a Complete Kernel Fisher Discriminant analysis (CKFD) algorithm comprises of Kernel Principal Component Analysis (KPCA) plus Fisher Linear Discriminant Analysis (LDA) was also, proposed by Yang (2002). Their proposed algorithm was a more powerful discriminator capable of carrying out the discriminant analysis in double discriminant subspaces by making full use of two kinds of discriminant information,

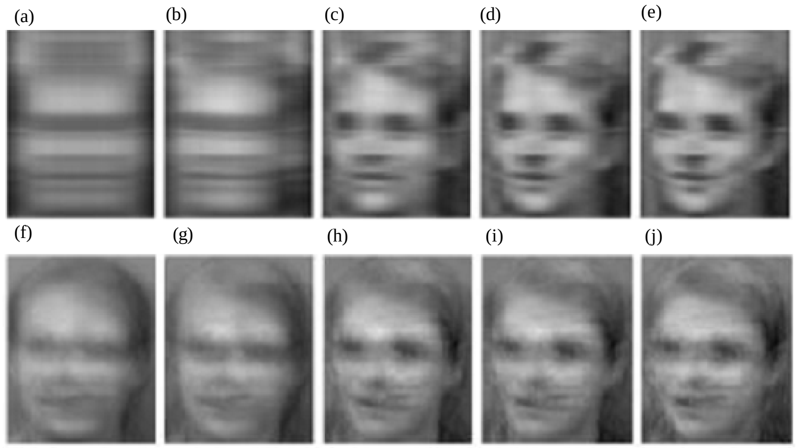

Fig. 2: The 2DPCA approach (2DPCA (upper) and PCA (lower)) (Yang *et al*., 2004): a) d = 2; b) d = 4; c) d = 6; d) d = 8; e) d = 10; f) d = 5; g) d = 10; h) d = 20 and i) d = 30; d = 40

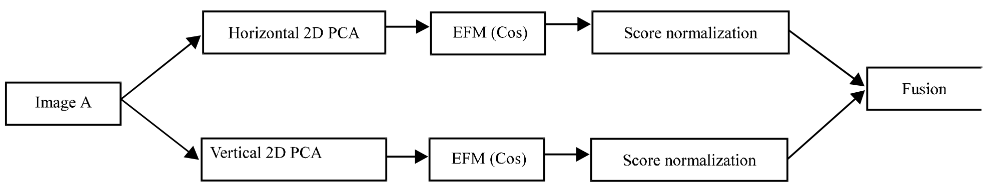

Fig. 3: HVDA frameworks (Yang and liu, 2007)

regular and irregular. It is worth mentioning that by using the FERET face database and the CENPARMI handwritten numeral database (Yang *et al*., 2004) tested and evaluated this algorithm and came to the conclusion that CKFD performs better than other KFD algorithms. However, Mika *et al*. (2003) posit that solving an M×M sized eigen problem (or generalized eigen problem) makes a very large sample size M that makes CKFD become very computationally intensive. Finally, Xie and Lam (2006) proposed a combination of Gabor-based kernel Principal Component Analysis (PCA) and doubly nonlinear mapping PCA (DKPCA) in order to perform feature transformation and face recognition.

Having explained the rationale for and the manner in which PCA was applied and improved, so, far, it therefore, follows that we should now discuss what 2DPCA is and how it has been outperform conventional PCA (eigenfaces) to date. The 2DPCA, a two-dimensional principal component analysis was developed by Yang *et al*. (2004). Unlike in 1D vector that the image matrix need to be transformed into a vector prior to feature extraction, this analysis is based on 2D image matrices that allows image covariance matrix to be built directly from the original image matrices andits Eigenvectors from image feature extraction. Figure 2 shows some of reconstructed images based on 2DPCA. As compared to PCA, 2DPCA made it more popular for image feature extraction usage because it was simpler and more straightforward, gave more promising results in terms of recognition accuracy, its ability to considerably increase image feature extraction speed and was computationally more efficient. However, it should be pointed out that 2DPCA-based image representation was not as effective as PCA as regards to storage requirements because 2DPCA requires more coefficients for image representation than PCA.

Since, the original 2DPCA only worked in the row direction of face images (Yang and Liu, 2007) extended it to two-directional 2DPCA that worked simultaneously in the row and the column directions of face images reducing the number of coefficients for face representation and recognition. Later, rows and columns image information was combined with a discriminant analysis framework in order to create a Horizontal and Vertical 2DPCA-based Discriminant Analysis (HVDA) method for face verification (Yang and Liu, 2007). This method could compensate for the high computational complexity in traditional PCA and high dimensional image vectors in Fisher Linear Discriminant Analysis (LDA) based methods by applying horizontal and vertical 2DPCA. Figure 3 illustrates the structure of HVDA.

Figure 3 HVDA frameworks (Yang and Liu, 2007). From what it can be inferred from Liu and Wechsler (2000)'s study, we can argue that although, the verification rate in HVDA is 78%, it is still lower than EFM. When comparing HVDA with EFM, Liu and Wechsler (2000)'s findings show that although the verification rate in HVDA is high 78%, it is still lower than EFM. Using Gabor wavelets, 2DPCA was then extended to 2-Dimensional Gabor Fisher Discriminant (2DGFD) to extract facial features for image representation and recognition (Mutelo *et al.*, 2008). The advantages of this approach outweigh the previously mentioned approaches because PCA was directly applied on the Gabor transformed matrices. This was done in order to remove redundant information from the image rows. Then the redundant information was further removed by a new direct 2-Dimensional Fisher Linear Discriminant (direct 2DFLD) method forming a discriminant representation more applicable for face recognition. This in turn, made 2DGFD outperform 2DPCA because of its larger dimensions and 2DFLD in terms of recognition accuracy in all tasks (pose, expression and illumination) because of its ability to treat each of the 40 different orientations and scales separately due to its Gabor features. To encode the phase variation with the orientation changing of Gabor wavelet at a given scale on one hand andto make the connection among local neighborhoods of the Gabor phase information on the other hand (Zhang *et al.*, 2007) proposed a novel object descriptor, named HGPP. In their approach, objects are modeled as an ensemble of spatial histograms. However, it is worth pointing out that this method has high dimensional histogram features owing to the increasing of Gabor features. As regards to Gabor features, Min (2009) introduced a new Gabor-based Median Maximum Scatter Difference (GMMSD) method by replacing within-class mean with within-class median as well as holding Gabor superior representation properties for face recognition. The recognition rate, however, reported still low by two CAS-PEAL and FERET databases that he used in this approach. To search for the optimal parameters of support vector machine, Abdullah *et al.* (2017) introduced OPSO-SVM approach where OPSO is used to find the optimal parameters for SVM. The 2D face datasets FERET and YALE are used in their experimental results and the method achieved good recognition rate using the 2D face images.

The 2.5D face recognition: It has been argued that 2.5D based face recognition outperformed 2D and 3D as well because of its ability to stay independent to any illumination conditions (Liu *et al.*, 2009, 2013). This is firstly due to its extra dimension information and secondly

Fig. 4: The 2.5D image (Abate *et al.*, 2007)

to its shorter capturing time by taking range information from a single viewing angle shot as compared to 3D based face recognition (Hajati *et al.*, 2010, 2012). Face recognition technique can use 3D face scans within two different categories. In the first category, commercial 3D scanners (e.g., Minolta Vivid series) capture the 2.5D images from a single view of the face. This image is located at the face surface points in 3D space as at most one depth value (z direction) is available for every point in the (x, y) plane (Lu *et al.*, 2006). However, it is worth mentioning that owing to the self-occlusion, some parts of the face may not be captured in a 2.5D image. In the second category, this problem has been compensated by 3D Models that are provided by merging several 2.5D images from different views. In real applications, 3D sensors can capture only partial views (2.5D images) of objects. So, using the 2.5D images in face recognition researches is more acceptable. Figure 4 illustrates an example of 2.5D face image.

To be able to recognize frontal face scans with different facial expressions, Chua *et al.* extended the use of point signature in their experiment. Their study shows promising results in terms of the applied algorithm. However, one should be very careful while generalizing such data when only six human subjects, each with four different facial expressions all of its frontal used as a data for this study. A year later, Pan *et al.* (2003) proposed an approach which consisted of facial range data registration and comparison for full automatic 3D face verification from range data. They utilized the partial directed Hausdorff distance to align and match two range images for verification. Their findings show that if facial range data has low-resolution, the outcome will be more

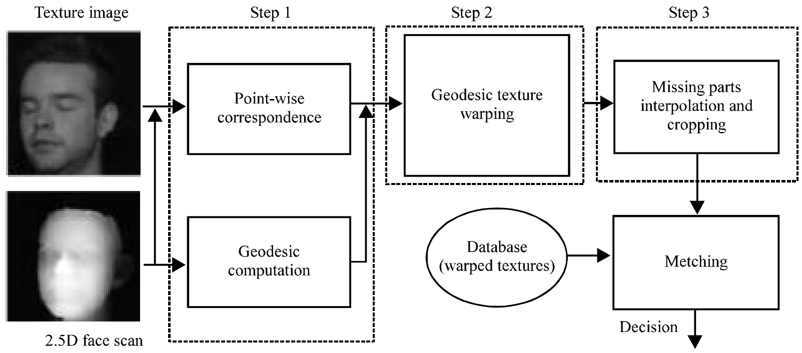

Fig. 5: Geodesic Texture Warping (GTW) algorithm scheme (Hajati *et al.*, 2010)

promising. Finally, they concluded that their approach could perfectly deal with variation of pose and some changes of expression.

Combing 2D and 3D for face recognition, Malassiotis and Strintzis (2005) used 2.5D face images to compensate pose variations in corresponding texture images. Like the previous mentioned studies, they could compensate for the pose of input face images by matching the input 2.5D image with a reference model using the ICP algorithm. Under variation of pose and illumination, another face recognition system was proposed by Lu *et al.* (2006). Their proposed system did have the ability to match 2.5D scans of arbitrary poses with lighting and expression variations to a database of neutral expression frontal 2.5D scans. With the aim of having better registration performance, they applied hybrid ICP scheme to combine two classical ICP algorithms and they reported encouraging results in terms of existed challenges of recognizing faces with arbitrary pose and illumination. However, it has to be taken in to consideration that using a scanner for the high speed of record face scan is very costly. The computational cost could be reduced greatly in another study conducted by Hajati *et al.* (2010) by applying GTW which is a texture warping method to recognize pose varying 2.5D faces. In their proposed method, geodesic information is used to warp the texture on a rotated 2.5D face image to that of a frontal one to perform matching. They showed promising results as regards to pose variations using 2.5D. Figure 5 shows the proposed Geodesic Texture Warping (GTW) algorithm and the matching block.

A 2 years later by Hajati *et al.* (2012) proposed a novel Patch Geodesic Distance (PGD) approach to transform the texture map of an object through its shape data for robust 2.5D object recognition. Using 2.5D face images and covered face recognition under expression and pose changes, they repeatedly confirm that PGD outperform the standard geodesic distance under the

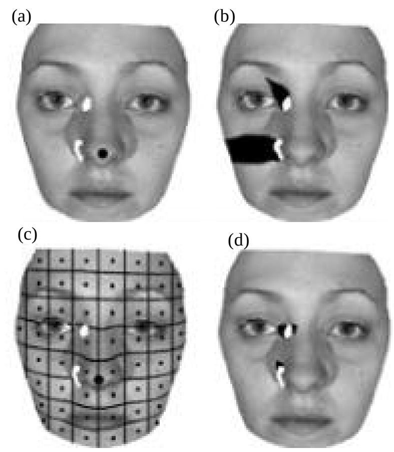

Fig. 6: Comparison between patch geodesic distance and the traditional geodesic distance: a) A face surface with missing data; b) Regions with invalid traditional geodesic distances; c) The partitioned face surface in patch geodesic distance and d) Regions with invalid patch geodesic distances (Hajati *et al.*, 2012)

expression and pose changes. Figure 6 demonstrate the comparison between the traditional geodesic distance and their proposed patch geodesic distance with the missing data.

In an experimental study, Conde *et al.* (2006) did compare the performance of 2D color images, 2.5D range images and 3D meshes. Their very beginning steps began by applying PCA and SVM classifier on 2D and 2.5D images. Next in order for the 3D meshes to be matched, they used ICP algorithm. The findings of their study show that 2.5D images were significantly better than 2D range images and 3D meshes with 99.9% success rate. Furthermore, their result also shows that with illumination variations, changes of illumination affect mainly 2D data while 2.5D and 3D remains same. Likewise, using modern

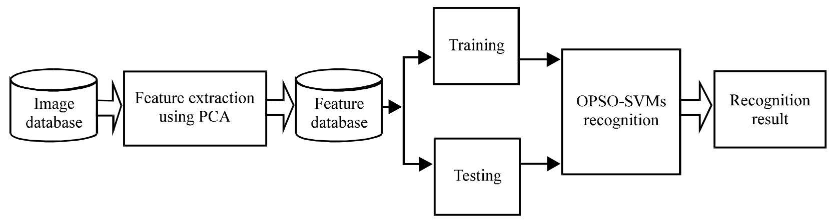

Fig. 7: The structure of OPSO-SVM technique

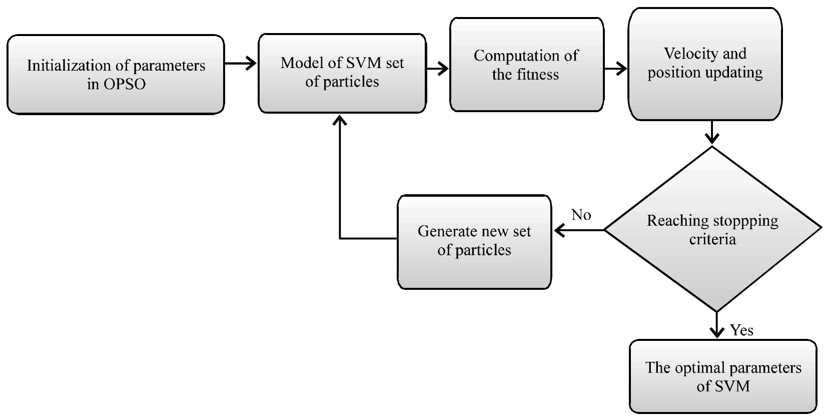

Fig. 8: SVM parameter optimization using OPSO

techniques, Zafeiriou and Petrou (2011) proposed EGM algorithm for capitalizing the available 2.5D facial information. Exploiting the facial geometry information, they applied some changes to matching techniques which led to incorporation of 2.5D information in a multi-scale morphological analysis. Their result indicates that by geodesic multi-scale morphological analysis, their approach is not sensitive to facial expression changes and poses variation. Finally, similar results are found in Charoenpong *et al*. (2010) study with their proposed algorithm for recognizing facial expressions. Like their pioneers, they also, came to the conclusion that 2.5D has a good feasibility for four facial expressions under their experiment. Abdulameer and his Colleagues have been utilized 2.5D images in three studies which were AAPSO-SVM in 2014 and the modified active appearance model in 2014 and their recent approach 2.5D facial analysis via. bio-inspired active appearance model which were in 2017. There outcome from using 2.5D face images was obviously outperform the 2D face images in all the three studies.

Opposition Particle Swarm Optimization and Support Vector Machine (OPSO SVM): One of the most newly advanced face recognition method is OPSO-SVM which was introduced by Hasan *et al*. In their method, the OPSO algorithm is used to search for the optimal parameters of SVM and the whole techniques (OPSO-SVM) is used for face recognition process. The structure of their proposed face recognition technique is illustrated in Fig. 7.

Furthermore, the parameter optimization process of SVM in their OPSO-SVM is explained in Fig. 8. In OPSO-SVM, two 2.D face images datasets are used to examine the performance of their proposed technique and they were FERET and YALE datasets. Nevertheless, we used a 2.5D face dataset (Abdulameer *et al*., 2014) in our experiments to analyze the performance of OPSO-SVM technique with 2.5D images for the first time instead of 2D face datasets.

RESULTS AND DISCUSSION

To validate this study, an OPSO-SVM face recognition technique is applied in the working platform of MATLAB 9.2. The evaluation is done using the property 2.5D face dataset that was used by Abdulameer *et al*. (2014) as shown in Fig. 8. The database consists of 2.5D TIFF images of 14 individuals, each individual have 11 images andthere is a total of 154 images. The performance of the technique is analyzed by conducting n-fold cross validation over each datasets and the equivalent statistical performance measures in term of accuracy, sensitivity and specificity are determined. To

Table 1: Recognition performance values from 2.5D dataset

Cross validation rounds	Accuracy	Sensitivity	Specificity
1	0.9	0.8	1.0
2	1.0	1.0	1.0
3	0.9	0.8	0.8
4	1.0	1.0	1.0
5	0.9	0.9	0.6
6	0.9	1.0	0.7
7	0.9	1.0	1.0
8	1.0	1.0	1.0
9	0.9	0.8	1.0
10	1.1	0.9	1.0
Average	0.94	0.93	0.9

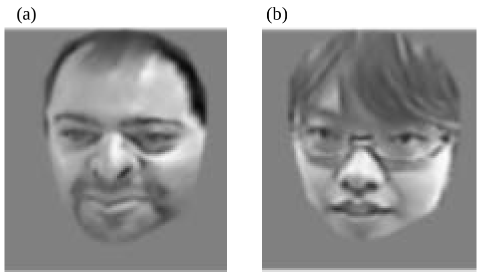

Fig. 9: Samples images from property 2.5D dataset

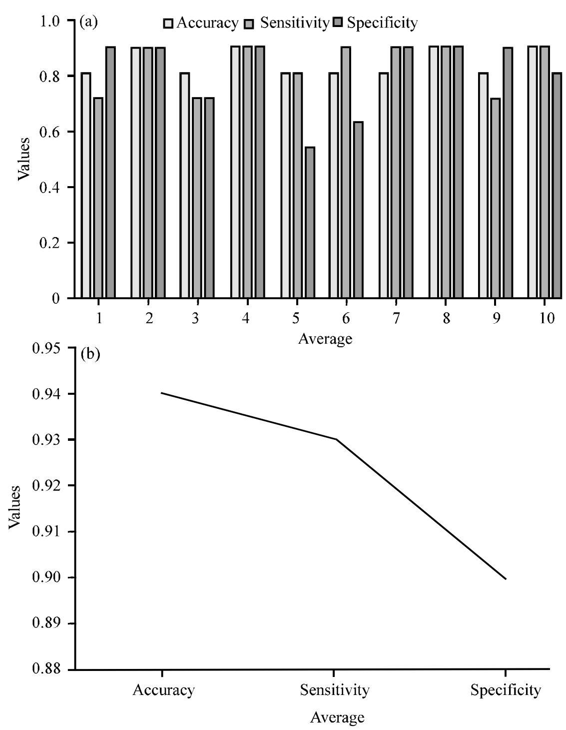

Fig. 10: a) Recognition performance in terms of accuracy, sensitivity and specificity and b) Average recognition performance for 2.5D face datase

perform n-fold cross validation, 10 folds of training and testing datasets are generated by folding operation. Table 1, Fig. 9 and 10 show the recognition performance over the 2.5D dataset.

CONCLUSION

This study has presented a critical analysis survey about face recognition techniques that comprise 2D and 2.5D face recognition. From this analysis, research efforts on 2D have shown that texture information in a 2D image provides detailed information for interpreting facial image. However, 2D face recognition is sensitive to illumination, pose variations, facial expressions. Owing to the aforementioned drawbacks existed in 2D, this study also reviewed 2.5D approaches that have proven themselves, so far to outperforming either 2D based image approaches. To date, researchers have been using 2.5D range images to describe a view of a person's face which is partway between a frontal view and a side view. From what has been reviewed, so far, it can be argued that 2.5D images are robust to the illumination variation because 2.5D images contain the extra dimension information which is the shape information that is independent to any illumination conditions. This independency indeed, make the 2.5D shape information to have an intrinsic property of the face which is invariant to illumination conditions. Experimental results on property 2.5D face dataset have been tested using OPSO-SVM technique and the results was an interesting and the 2.5D performance gave 0.94% accuracy.

SUGGESTIONS

Hence, this study suggests compensating for the problems of 2D by substituting them with 2.5D range images as an alternative solution for the 2.5D limitations. In the future research, we will test 3D face dataset and compare it with the 2.5D dataset.

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