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RATIONAL STRUCTURAL-ZERNIKE MEASURE: AN IMAGE SIMILARITY MEASURE FOR FACE RECOGNITION

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Abstract— Image similarity or image distortion assessment is the underlying technology in many computer vision applications, and is the root of many algorithms used in image processing. Many similarity measures have been proposed with the aim of achieving a high level of accuracy, and each of these measures has its strength as well as its weaknesses. In this paper, we present a highly efficient hybrid measure for image similarity that is based on structural and momental measures. We propose a similarity measure called the rational structural-Zernike measure (ZSM), to determine a reliable similarity between any two images including human faces images. This measure combines the best features of two structural measures, the well-known structural similarity index measure (SSIM) and the feature similarity index for image quality assessment (FSIM), with Zernike moments (ZMs), which have proven effective in the extraction of image features. Simulation results show that the proposed measure outperforms the SSIM, FSIM , ZMs and the state-of-art measure Feature-Based Structural Measure (FSM) through its ability to detect similarity even under distortion and to recognise the similarity between images of human faces under various conditions of facial expression and pose.

Keywords—Structural Similarity Measure (SSIM); Feature Similarity measure (FSIM); Zernike moments (ZMs); Feature-Based Structural Measure (FSM); Face Recognition;

I. INTRODUCTION

The measurement of image similarity is an important issue in real-world applications, and measures of similarity play a vital role in digital image processing.

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This technique can be applied to improve the quality of the image and to optimise parameters in many digital image processing applications, for instance, image enhancement, image compression, and image restoration. The aim of image similarity measurement is to produce methods for the objective assessment of quality, as opposed to subjective human evaluations of image quality [1]. The conventional methods for measuring the similarity between two images, such as using pixel-by-pixel errors, previously called mean-square errors, have become obsolete since they are not efficient ways to compare two images. An important feature of natural images is that they contain highly structured signals and are highly correlated; this correlation between the image signals provides information about the relationship between the signals, and image comparison between these images, therefore, needs a correlative measure of quality [2].

Many studies have been presented in the field of image similarity. Numerous methods have been proposed in this area, each of which has particular features and weaknesses, but the only method that has resonated widely in the world of image similarity and is still used by many applications is SSIM [3], which is based on the structural similarity between images and uses mathematical statistical measures such as mean and variance. This method gives good results under noise-free conditions, but goes to zero when noise is increased; in other words, its determination of the similarity between two different images is dependent only on the statistical features of these images, which may have certain correlations. SSIM cannot reveal all the structural properties of an image, and we, therefore, need to develop more specific measurements that are image-dependent. In 2009, Sampat et al. [4] presented an improvement on SSIM that was based on wavelet coefficients, extracted at the same spatial locations in the same wavelet sub-bands of the two images under consideration. The results given by this method are less sensitive to small geometric variations such as rotation, translation, and differences in scale. Dan et al. [5] presented an image quality assessment technique based on SSIM and the discrete cosine transform (DCT). This method involves a structural comparison that weights the frequency components depending on the sensitivity of the human eye. In 2011, an improved version of SSIM was proposed by Zhang et al. [6]. This measure was called feature similarity index for image quality assessment (FSIM), in an effort to emphasise its use in recognition, and is dependent on the low-level features of images. In this measure, the dimensionless and gradient magnitudes are the main features, and these play complementary roles in characterising the image. However, FSIM produces confusing results in certain cases; for example, it may detect a similarity between dissimilar images, or a non-trivial amount of similarity between two different poses.

There are many studies that associate image similarity with human facial recognition. The recognition of human faces is considered to be one of the most demanding issues in the field of image similarity, due to the significant challenges involved such as head poses, different types of illumination and different facial expressions [7]. Face recognition is also one of the most important applications in the field of image similarity; this is to adopt the face recognition entirely on detecting the similarity between two faces images. This issue is currently of great consequence, especially in the area of security, as surveillance cameras are now ubiquitous. We, therefore, test the efficiency of our proposed measure in terms of its ability to both recognise human faces and to find similarities between images of human faces [8]. In an attempt to develop similarity measures and to use them for face recognition, Hu et al. proposed a similarity measure for face recognition based on the Hausdorff distance. This measure can provide information on the similarity or dissimilarity of two objects and can compare them, such as faces with different illumination conditions and facial expressions. Their measure gives better performance than measures based on the conventional Hausdorff distance and eigenface approaches [9]. Hashim and Hussain [10] proposed a new similarity measure for face recognition by combining global and local information in different poses. This measure is based on ZMs and SSIM, with local and semi-global blocks. Hassan et al. [11] presented a new measure for face recognition based on a similarity comparison of images using SSIM. This measure was called ISSIM and was based on a joint histogram. The goal of this work was to present a simplified approach for face recognition that may work in real-time environments, and ISSIM outperformed the well-known, statistical-based SSIM. Shnain et al. [12] presented a new similarity measure for face recognition, with the aim of resolving the shortcomings of the previous measures, by combining SSIM with a feature similarity index measure and incorporating edge detection as a distinctive structural feature. In 2017 an image similarity measure for face recognition was proposed based on the high order statistic (kurtosis and skewness) [13]. Aljanabi et al. [14] presented an image similarity measure also for face recognition based on information theory (entropy with joint histogram). Besides that, ZMs also use a statistical-based method and a facial feature descriptor in face recognition systems. This method has several advantages such as geometrical invariance, ability to capture distinct features, robustness to noise, and attractive traits such as minimum redundancy [15]. Many face recognition methods are therefore based on ZMs. Lajevardi and Hussain [16] used ZMs in facial expression recognition under conditions of rotation and noise, and the results indicated that the higher-order ZM features are robust for images affected by noise and rotation. Farajzadeh et al. [17] compared the accuracy of ZMs, pseudo-ZMs and orthogonal Furrier-Mellin moments (OFMMs) in a face recognition system. The results indicated that the ZMs outperformed both pseudo-ZMs and OFMMs.

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In [18] and[19], the authors proposed feature extraction methods based on ZMs, and discussed the rotation invariance of ZMs. Shi et al. [20] proposed a method for extracting features based on pseudo-ZMs, followed by LDA for dimensionality reduction. The main aim of the current work is to design an efficient similarity measure that can contribute to solving the problem of high-suspicion situations, which is prevalent in previous measures, in order to generate more confidence in detecting similarity and face recognition. The proposed measure combines the best features of the SSIM and FSIM structural measures with a momental measure (ZMs) to achieve a good overall performance. These measures are combined using a balanced equation to give a powerful similarity measure. The robustness of the proposed measure is derived from that of its elements, such as the statistical (structural) properties provided by SSIM and extraction of image features provided by ZMs. The proposed measure, ZSM, gives a reliable measure of the similarity between any two images, even under conditions of disruption, such as different types of illumination or background, and variations in facial expressions, head poses and hair styles. Such properties are highly desirable in security applications that check the identity of a specific face image from a large database.

II. SIMILARITY MEASURES

Image similarity measurement is a fundamental problem in image processing applications. It is a primary task of Human Visual System (HVS) to notice the similarities and differences between images, rank a set of images or perceive the quality of images based on similarity. Moreover, a perceptual similarity measure can be used to evaluate perceived image quality by measure the similarity between the reference and distorted images [21]. Similarity measure is the distance (based on a specific norm) between various data points; the performance of any similarity measure is based on choosing a good distance function over an input data set. In this paper an effective measure is proposed, it combines the distinctive features of structural and momental measures. The previous measures that have been compared with the proposed measure as follow:

A. Structural Similarity Measure (SSIM) considers a great step in image similarity; it's widely used for image quality assessment and many algorithms of image processing systems. This measure has been proposed in 2004 by Wang and Bovik [3]; it's based on statistical measurements like mean and standard deviation to find a definition for a distance function. The Authors considered image distortion as a combination of three kinds: correlation, luminance and contrast. SSIM measure has been put into the form:

$$S(x,y) = \frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)} \quad (1)$$

where $S(x,y)$ represents the similarity between x and y images, x reference image and usually y is a corrupted version of x, while μ_x, μ_y and σ_x, σ_y respectively are the statistical means and variances of images x and y. The variable σ_{xy} is the statistical co-variance between pixels in images x and y. The constants C_1 and C_2 are given by $C_1 = (K_1L)^2$ and $C_2 = (K_2L)^2$, with K_1 and K_2 are small constants and L = 255 (maximum pixel value).

B. Feature Similarity Measure (FSIM) considers an improved version of structural similarity index measure (SSIM), this measure has been proposed by Zhang et al [6] in an effort to be used in recognition. It depends on the fact that visual perception of human recognises an image according to the low-level features based on two phases: congruency (PC) which is a dimensionless measure for the significance of a local structure, and gradient magnitude (GM); these phases are playing complementary roles in image characterizing. FSIM between images f_1 and f_2 has been put into the form:

$$F\{f_1(x), f_2(x)\} = \frac{\sum_{x\in\Omega} S_L(x)\cdot PC(x)}{\sum_{x\in\Omega} PC_m(x)} \quad (2)$$

C. Zernike Moments (ZMs) a type of moment function; considers an efficient global image descriptors. It is mapping an image onto a set of complex Zernike polynomials; these polynomials are orthogonal to each other. The orthogonality of Zernike moments can appear the properties of an image without any redundancy or overlap of information between the moments, this characteristic makes each moment to be unique of the information in an image. Due to these properties, Zernike moments have been used as feature sets in applications such as pattern recognition, content-based image retrieval, and other image analysis systems. In this work we will extract various Zernike moments (Zernike domain) as face features, then define a similarity measure after imposing a distance measure in this domain. The distance measure will be Euclidean distance metrics. The ZMs of an image function f(r, θ) with order n and repetition m are given as[22]:

$$Z_{nm} = \frac{P+1}{\pi}\int_0^{2\pi}\int_0^1 R_{nm}^*(r)\, e^{jm\theta} f(r,\theta) r dr d\theta \quad when\ |r| \le 1 \quad (3)$$

The radial polynomial $R_{nm}(r)$ is given in this equation:

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$$R_{nm}(r) = \sum_{k=0}^{\frac{n-|m|}{2}} (-1)^k \frac{(n-k)!}{k!\left(\frac{n+|m|}{2}-k\right)!\left(\frac{n+|m|}{2}+1-k\right)!} \quad (4)$$

When $0 \le |m| \le n$ and $n-|m|$ is even.

The discrete approximation of equation (3) is defined as:

$$Z_{nm} = \lambda_z(P,N) \sum_{i=0}^{n-1} \sum_{i=0}^{n-1} R_{nm}(r_{ij}) e^{-jm\theta_{ij}} f(i,j) \quad (5)$$

Where $\lambda_z(P,N) = \frac{P+1}{N+1}$; and $\theta_{ij} = tan^{-1}\{\frac{y_j}{x_i}\}$ when $y_j = \frac{2j}{N-1} - 1$; $x_i = \frac{2i}{N-1} - 1$

$$r_{ij} = \sqrt{x_i^2 + y_j^2} \quad (6)$$

The features of an image x can be represented by a vector of selected Zernike moments Z_x and the features of y image can represent by a vector Z_y. The Euclidean Metric is the distance measure which is applied to feature vectors Z_x, Z_y of two images in the Zernike domain as in following equation:

$$d_E(X,Y) = \sqrt{\sum_{i=1}^{n} |x_i - y_i|^2} \quad (7)$$

D. Feature-Based Structural Measure (FSM) is an efficient state-of-art similarity measure [12], based on combining the best features and statistical properties provided by SSIM and FSIM, trading off between their performances for similar and dissimilar images. While Canny edge detector added a distinctive structural feature, where (after processing by Canny's edge filter [23]) two binary images, gx and gy, are obtained from the original two images x and y. FSM can be given by:

$$\mathcal{F}(x,y) = \frac{(a+c) \cdot R(g_x, g_y) \cdot \Phi(g_x, g_y) + b \cdot R(g_x, g_y) + e}{(a+b) \cdot \rho(g_x, g_y) + c \cdot R(g_x, g_y) \cdot \Phi(g_x, g_y) + e} \quad (8)$$

where, $\mathcal{F}(x,y)$ represents the proposed similarity between two images x and y; usually, x represents the reference image and y represents a corrupted version of x; Φ represents the feature similarity measure (FSIM); and ρ represents the structural similarity measure (SSIM). The constants are chosen as a =5, b=3 and c=7, while e=0.01 is added to balance the quotient and avoid division by zero. The function $R(x,y)$ refers to the global 2D correlation between the images, as follows:

$$R(x,y) = \frac{\sum_i \sum_j (x_{ij} - x_0)(y_{ij} - y_0)}{\sqrt{\left[\sum_i \sum_j (x_{ij} - x_0)^2\right]\left[\sum_i \sum_j (y_{ij} - y_0)^2\right]}} \quad (9)$$

where x_0 and y_0 are the image global means. This function is applied here as $R(g_x, g_y)$ on the new images obtained from the application of edge detection to the original images x and y.

E. The Proposed Measure (ZSM) One intractable problem that generally faces researchers in the field of image similarity measurement is a high-suspicion situation of similarity between the reference image and other images in the database, especially when the image contains disruption in terms of changes to the illumination or background. These suspicious situations often occur for human faces, due to changes in facial expressions, head poses and hair styles. Currently, there is no guarantee that any security system that relies on face recognition is entirely reliable, and this is a serious problem in terms of security. In this paper, we therefore present a contribution to the field of image similarity measurement at the same time it recognising the human faces based on detecting the accurate similarity among the faces images, in order to solve this significant challenge. We propose a new similarity measure that can determine the similarity among all images (face images and non-face images) with more reliability, accuracy and confidence than previous similarity measures. This new measure derives its robustness by combining the best properties of structural and momental features; since ZMs can render the properties of an image without redundancy or overlap of information between the moments, this characteristic means that each moment is unique for the information in a particular image. In addition, statistical (structural) features are provided by SSIM, and feature detection of the images is carried out using FSIM.

The proposed measure is given by this equation:

$$R(x,y) = \frac{a * S(g_x, g_y) + b * Z(g_x, g_y) + c * F(g_x, g_y) + d}{(a+b) * S(g_x, g_y) * Z(g_x, g_y) * c * F(g_x, g_y) + d} \quad (10)$$

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Where, $R(x,y)$ represents similarity between two images x and y, always x represents the reference image and y represents a corrupted version of x; $F(g_x, g_y)$ represents the feature similarity measure (FSIM), $Z(g_x, g_y)$ represents Zernike moments, $S(g_x, g_y)$ represents structural similarity measure (SSIM). The constants are chosen as a =3, b=2 and c =5, while d=0.01 is added to balance the quotient and avoid division by zero. The objective of creating this balanced equation is to design an efficient similarity measure for the purpose of face recognition; also, can be used in case of non-face images. This measure draws its strength from powerful elements such as the statistical (structural) properties provided by SSIM and extraction of the features of an image offered by ZMs. The main features of the proposed measure are the High performance, accuracy and more confidence as compared to existing measures. Although other measures may have the ability to detect the similarity among images (even for face recognition), the proposed measure has a high confidence by giving almost a near-zero value when the images are dissimilar, while other measures give a non-trivial amount of similarity when comparing dissimilar images.

III. EXPERIMENTAL RESULTS AND PERFORMANCE

A. Image Database: All Image similarity systems are based on a comparison between the reference image and training set images saved in memory as a database. In our experiments, we used two databases for algorithm validation. TID2008 database is used for comparison the image with its complex distorted versions. The TID2008 contains 25 reference images and 1700 distorted images (25 reference images x 17 types of distortions x 4 levels of distortions) [24]. In this paper, we used 13 reference images of the TID2008 database for implementation; six complex distorted versions are used as image poses to test, compare, and prove that the proposed ZSM outperforms the other measures. The second database is AT&T database of human faces images is used for face recognition. AT&T [25] database contains 400 images for 40 individuals; each person has 10 poses at different illuminations, facial expressions and facial details like glasses, we used whole AT&T images in our experiments.

B. Testing: It is necessary to evaluate the quality of the measure; because the quality and efficiency of recognition varies from one measure to another. Here we are using three testing methods to evaluate the quality and superiority of our proposed measure: At the beginning we calculated the average similarity difference using all database images as a reference image and again all images as test images. In this case, similarity difference is (best match of reference image)-(second best match within any other images). The global average of similarity can be obtained by the mean of all these sub-averages. To calculate the similarity average for database we supposed s_{ik} denote the similarity confidence when the image i with the distorted version of it, and k is the reference image. Let N refers to the number of all images in database (original images and distorted images) . Let M refers to the number of versions for each image while d denote to the number of original images in the database. Then the global confidence average is taken as:

$$s_{av} = \frac{1}{N}\sum_{k=1}^{M}\sum_{i=1}^{d} s_{ik} \tag{11}$$

According to equation (11) we can extract the the global confidence average for TID2008 database $s_{av} = \frac{1}{78}\sum_{k=1}^{6}\sum_{i=1}^{13} s_{ik}$; table 1 shows the performance of the proposed ZSM versus other methods by using TID2008 database. The global similarity average for AT&T database will be $s_{av} = \frac{1}{400}\sum_{k=1}^{10}\sum_{i=1}^{40} s_{ik}$; table 2 show the performance of the proposed measure ZSM versus other measures by using AT&T database. The second test to evaluate the performance of our proposed measure (ZSM) is the ROC graph (Receiver Operating Characteristics); which is a 2-D graph consists of true positive rate (tpr) and false positive rate (fpr); ROC graph essentially shows the relationship between advantages (true positives) and disadvantages of the classifier (false positives) [26]. Figures 9 and 10 show ROC graph by using TID2008 database and AT&T database.

$$tpr = \frac{Positives\ correctly\ classified}{Total\ positives} \tag{12}$$

$$fpr = \frac{Negatives\ incorrectly\ classified}{Total\ negatives} \tag{13}$$

The third performance evaluation test is the quality measure based on confidence for face recognition; confidence is the best matching of similarities between the test image and the corrupted image (in the database). The confidence in face recognition at level k of similarity is defined as follows:

$$C_k = \frac{(1-k)}{n_k} \tag{14}$$

where n_k is the number of persons with k-level of similarity $s_k > k$ [12].

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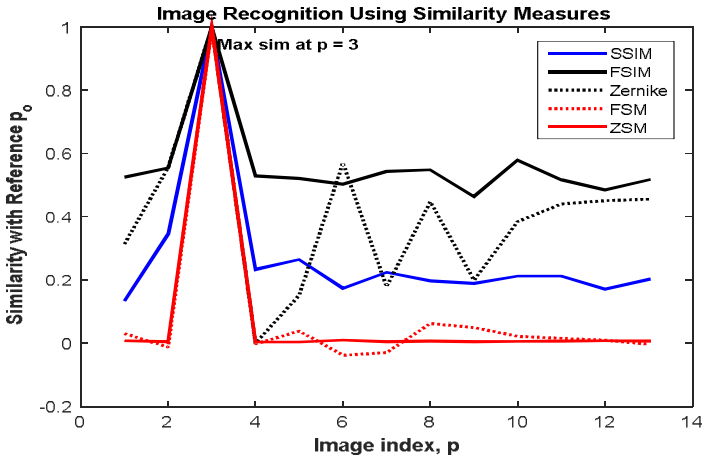
C. Results and Discussion: At the beginning we implemented the new measure ZSM as per equation (10) with well-known measures SSIM as per equation (1), FSIM as per equation (2), Zernike Moments as per equation (3) and FSM as per equation (8). These five methods are implemented together on two databases TID2008 and AT&T to compare the performance. The distance between the maximum similarity curve (peak) and second curve used for all similarity measures; more distance means more confidence in the decision of recognizing the target image. The difference in the values of the peaks is a new feature showing the high performance; if the distance between the highest match and the second-best match is higher, that means the measure has better performance; and vice versa, i.e., if the distance is less, that means the measure has been confused in deciding the best match by giving a non-trivial similarity between the different images. Figure (1) shows the original image from TID2008 database and its distorted version in parts (a) and (b) of figure 1; while the performance of the similarity measures is shown in part (c) of figure 1. Figure (2) shows the original image from TID2008 database in part (a) and its distorted version in part (b); while the performance of the similarity measures is shown in part (c) of figure 2. It is clear that the proposed measure ZSM has a larger peak that means the proposed measure ZSM produces fewer suspicion situations and more confidence in similarity detection. Figures (3) and (5) show the poses of person no. 5 and person no.10 in AT&T database each person has 10 poses, used for testing and the reference images are indicated. In figures (4) and (6) show the similarity test results between the reference image and training set images in the database which consist of 40 individuals and for each person 10 poses; the most similarity pose among the other poses is considered. In figures (4) and (6) it's clear that the proposed ZSM gives better performance (by get the largest peak) in terms of detecting the similarity and giving more confidence to decide the target person from a database. Despite the other measures SSIM, FSIM, and Zernike moments correctly decide the target person with maximum similarity, they give low confidence in their decision because there are many cases of suspicion (big probability of similarity with wrong images).

(a)

(b)



(c)

Fig.1 Performance of similarity measures using original image and its distorted version; (a) The original image; (b) The distorted version of it (c) Performance of SSIM, FSIM, Zernike moments and proposed ZSM using TID2008 database. Confidence in similarity recognition for SSIM=0.6543, FSIM=0.4206, Zernike moments =0.4293, FSM=0.9377,ZSM=0.9903.

(a)

(b)

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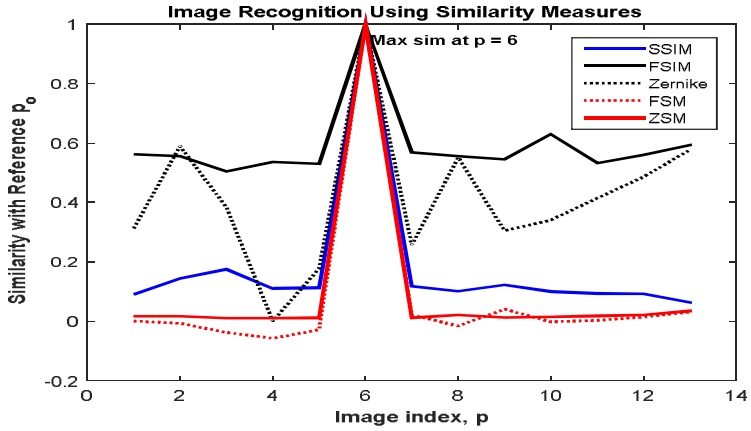

(c)

Fig. 2 Performance of similarity measures using original image and its distorted version; (a) The original image; (b) The distorted version of it (c) Performance of SSIM, FSIM, Zernike moments and proposed ZSM using TID2008 database. Confidence in similarity recognition for SSIM=0.8256, FSIM=0.3702, Zernike moments=0.4110, FSM=0.9598 ,ZSM= 0.9661.

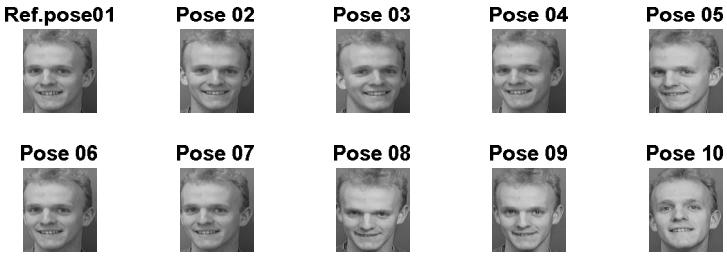

Fig.3 Poses for Person no.5 in AT&T database used in the test.

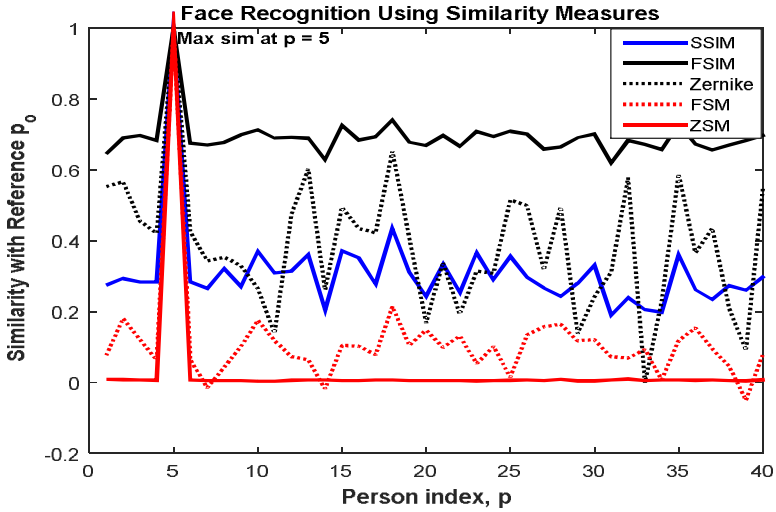

Fig. 4 Performance of similarity measures using person no. 5. in the AT&T database .When the confidence in similarity recognition for SSIM= 0.6396, FSIM= 0.2769, Zernike moments= 0.4289, FSM= 0.7545,ZSM= 0.9809.

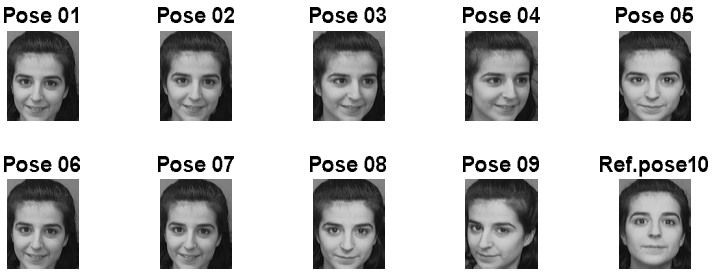

Fig. 5 Poses for Person no.10 in AT&T database used in the test.

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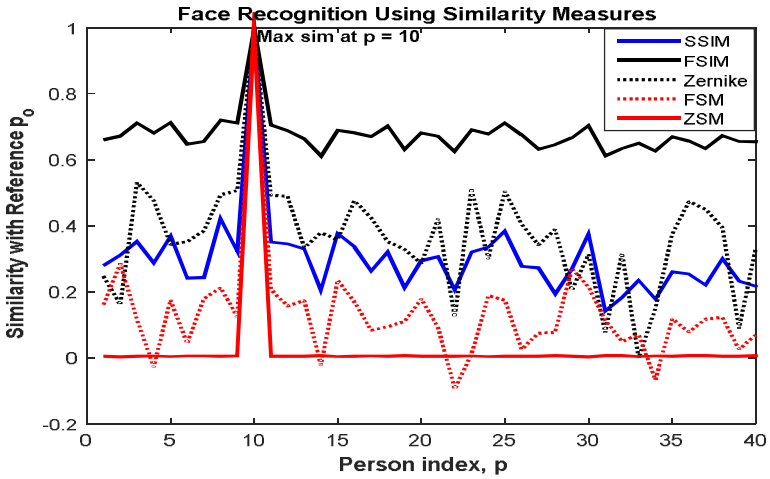

Fig. 6 Performance of similarity measures using person no. 10. in the AT&T database. When the confidence in similarity recognition for SSIM= 0.5773, FSIM= 0.2803, Zernike moments= 0.4684, FSM= 0.7145,ZSM= 0.9843.

To confirm the efficiency of the proposed measure versus the other measures we calculated the average of similarity for each image in database first as a reference image and again as a test image. We got the global mean of all these sub-averages as per equation (11). The results in tables 1 and 2 show that the similarity average of the proposed measure ZSM is higher than averages of other measures. This indicates to the efficiency of the proposed measure ZSM and its high ability to detect the similarity among the images versus other measures.

TABLE I - THE GLOBAL SIMILARITY AVERAGE FOR TID2008 DATABASE.

Measures	**SSIM**	**FSIM**	**ZMs**	**FSM**	**ZSM**
Similarity Average, s_{av}	5.4378	2.4745	2.4375	6.4670	6.5794

TABLE 2- THE GLOBAL SIMILARITY AVERAGE FOR AT&T DATABASE.

Measures	**SSIM**	**FSIM**	**ZMs**	**FSM**	**ZSM**
Similarity Average, s_{av}	0.0150	0.0066	0.0119	0.0192	0.0247

As a second test to prove that the proposed measure is better than the previous measures; we extracted the true positive rate (tpr) values and false positive rate values (fpr) as per equations 12, 13. The confidence measure here is a difference between the best match and the second-best match used to confirm that the test image belongs to the database. Thresholds of confidence are used as given by in the following vector: T=[0.1 .2 .3 .4 .5 .7 .9]. Then we used measure $1-d$ to confirm that the test image does not belong to the database, with the same thresholds above. Tabels (3-6) show the tpr and fpr by using the TID2008 database and AT&T database, while figures 7 and 8 show the ROC graph for these trp and fpr. we can note the position of the proposed measure (ZSM) in all thresholds (in the left corner or very near from it) that refers to the proposed measure has a highest true positive rate and zero or very close to zero false rate.

TABLE3 - THE TRUE POSITIVE RATE (TPR) ACCORDING TO THE THRESHOLD VECTOR OF CONFIDENCE BY USING AT&T DATABASE, WITH POSE 2 AS A REFERENCE IMAGE.

Thresholds	**SSIM**	**FSIM**	**Zernike**	**FSM**	**ZSM**
0.1	1	1	1	1	1
0.2	1	1	1	1	1
0.3	1	0.3250	1	1	1
0.4	1	0	1	1	1
0.5	1	0	0.8750	1	1
0.7	0.2500	0	0.2500	0.9500	1
0.9	0	0	0	0	1

TABLE4 - FALSE POSITIVE RATE (FPR) ACCORDING TO THE THRESHOLD VECTOR OF CONFIDENCE BY USING AT&T DATABASE, WITH POSE 2 AS A REFERENCE IMAGE .

Thresholds	**SSIM**	**FSIM**	**Zernike**	**FSM**	**ZSM**
0.1	0	0	0	0	0
0.2	0	0	0	0	0
0.3	0	0	0	0	0
0.4	0	0	0	0	0

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0.5	0	0	0.2500	0	0
0.7	0	0	1	0	0.0250
0.9	0.1750	0	1	0.5	0.0375

TABLE5 - TRUE POSITIVE RATE (TPR) ACCORDING TO THE THRESHOLD VECTOR OF CONFIDENCE BY USING TID2008 DATABASE, WITH POSE 1 AS A REFERENCE IMAGE .

Thresholds	SSIM	FSIM	Zernike	FSM	ZSM
0.1	1	1	1	1	1
0.2	1	1	1	1	1
0.3	1	1	1	1	1
0.4	1	0.4615	0.4615	1	1
0.5	1	0	0.3077	1	1
0.7	0.8462	0	0	1	1
0.9	0	0	0	0.8462	1

TABLE6 - FALSE POSITIVE RATE (FPR) ACCORDING TO THE THRESHOLD VECTOR OF CONFIDENCE BY USING TID2008 DATABASE, WITH POSE 1 AS A REFERENCE IMAGE.

Thresholds	SSIM	FSIM	Zernike	FSM	ZSM
0.1	0	0	0	0	0
0.2	0	0	0	0	0
0.3	0	0	0	0	0
0.4	0	0	0.0769	0	0
0.5	0	0	0.3077	0.0769	0
0.7	0.1538	0	1	0.4615	0.0307
0.9	0.5385	0	1	0.9231	0.0538

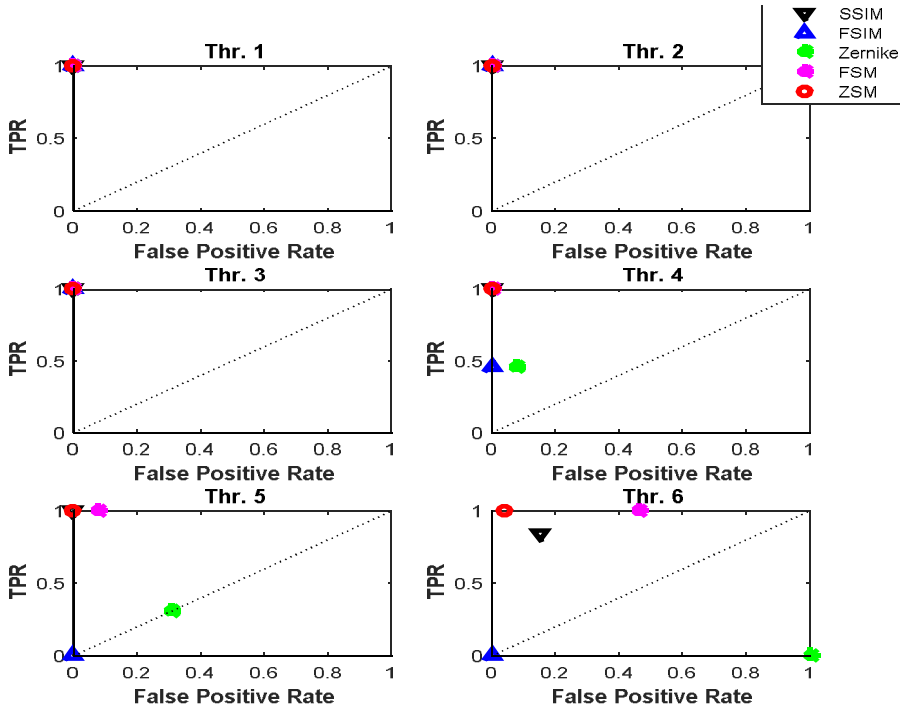

Fig. 7 ROC graphs for 5 similarity measures with 6 different confidence thresholds by using TID2008 database.

Figures 9 and 10 show the confidence measure as per equation (20) to show the efficiency of the proposed measure. We can note that the proposed ZSM gives best performance versus the well-known SSIM, FSIM, and Zernike in terms of recognition confidence to decide the target person from a database; the confidence of the proposed measure ZSM almost may seem convergent with or a little more than the state-of-art measure FSM. The low confidence of other similarity measures is due to many cases of distrust in their decisions.

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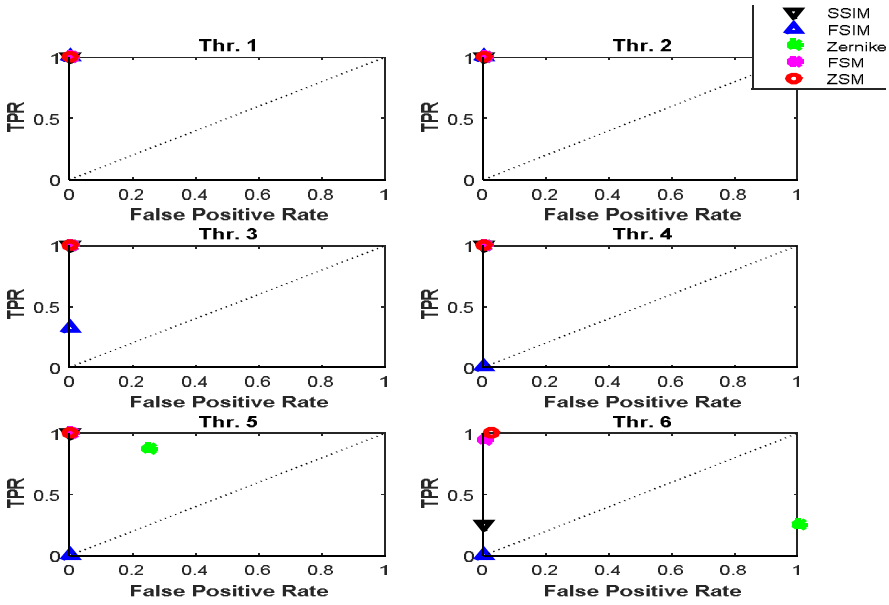

Fig. 8 ROC graphs for 5 similarity measures with 6 different confidence thresholds by using AT&T database.

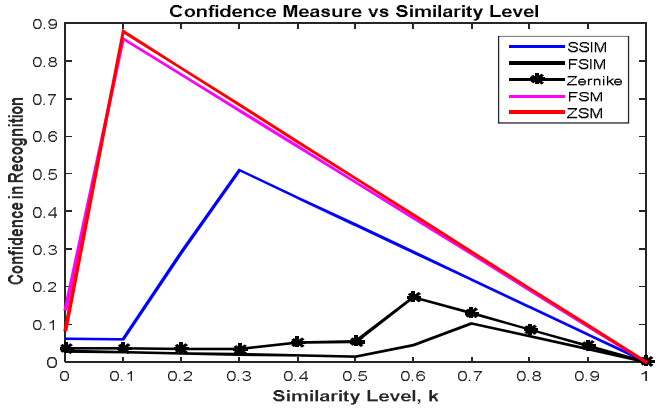

Fig. 9 The confidence measure for similarity measures SSIM, FSIM, Zernike, FSM and proposed ZSM by using the image no.6 in TID2008 database.

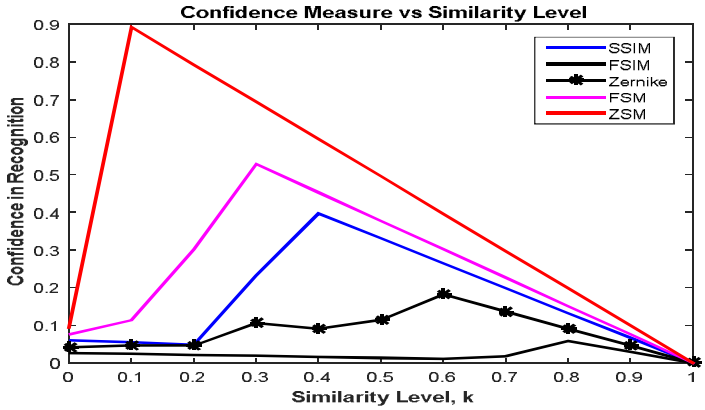

Fig.10 The confidence measure for similarity measures SSIM, FSIM, Zernike, FSM and proposed ZSM by using the poses of person no.5 in AT&T database.

IV. CONCLUSIONS

The proposed measure combines the characteristics of both structural and momental measures. The structural measures used are the well-known SSIM and FSIM approaches, which provide the statistical and structural properties of the image, while ZMs are used as the momental measures for feature extraction, giving strong global features. Experiments indicate that this combination of the features of both structural and momental measures leads to a reduction in their drawbacks, and gives a more powerful similarity measure with the ability to detect similarity even under conditions of distortion, and to recognise human face images under conditions of different types of illumination, facial expression and pose.

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In future work, the authors intend to extend this work on 3D image similarity and an image similarity measure based on image local analysis will handle soon and may extend the testing environment for assessing the performance of similarity measures to include modern communication systems, with focus on long-range channels [27, 28] and short-range systems [29].

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REFERENCES

1. Hassan, Asmhan F., Dong Cailin, and Zahir M. Hussain. "An information- theoretic image quality measure: Comparison with statistical similarity." (2014).
2. Hashim, A.N. and Z.M. Hussain. Novel imagedependent quality assessment measures. in J. Comput. 2014. Citeseer.
3. Wang, Z., et al., Image quality assessment: from error visibility to structural similarity. IEEE transactions on image processing, 2004. 13(4): p. 600-612.
4. Sampat, M.P., Z. Wang, S. Gupta, A.C. Bovik and M.K. Markey, 2009. Complex wavelet structural similarity: A new image similarity index. IEEE Trans. Image Proc., 18: 2385-2401. DOI:10.1109/TIP.2009.2025923
5. Dan, L., D.Y. Bi and Y. Wang, 2010. Image quality assessment based on DCT and structural similarity. Proceedings of the 6th International Conference on Wireless Communications Networking and Mobile Computing, Sept. 23-25, IEEE Xplore Press, Chengdu, pp: 1-4. DOI: 10.1109/WICOM.2010.5600663
6. Zhang, L., et al., FSIM: A feature similarity index for image quality assessment. IEEE transactions on Image Processing, 2011. 20(8): p. 2378-2386.
7. Zhao, W., et al., Face recognition: A literature survey. ACM computing surveys (CSUR), 2003. **35**(4): p. 399-458.
8. Barrett, W.A. A survey of face recognition algorithms and testing results. in Signals, Systems & Computers, 1997. Conference Record of the Thirty-First Asilomar Conference on. 1997. IEEE.
9. Hu, Y. and Z. Wang. A similarity measure based on Hausdorff distance for human face recognition. in Pattern Recognition, 2006. ICPR 2006. 18th International Conference on. 2006. IEEE.
10. Hashim, A.N. and Z. Hussain, Local and semi-global feature-correlative techniques for face recognition. IJACSA, 2014.
11. Hassan, A.F., Z. Hussain, and D. Cai-lin, An Information-Theoretic Measure for Face Recognition: Comparison with Structural Similarity. IJARAI. 2014.
12. Shnain, N.A., Z.M. Hussain, and S.F. Lu, A Feature-Based Structural Measure: An Image Similarity Measure for Face Recognition. Applied Sciences, 2017. 7(8): p. 786.
13. Shnain, Noor Abdalrazak, Song Feng Lu, and Zahir M. Hussain. "HOS image similarity measure for human face recognition." Computer and Communications (ICCC), 2017 3rd IEEE International Conference on. IEEE, 2017.
14. Aljanabi, Mohammed Abdulameer, Noor Abdalrazak Shnain, and Song Feng Lu. "An image similarity measure based on joint histogram—Entropy for face recognition." Computer and Communications (ICCC), 2017 3rd IEEE International Conference on. IEEE, 2017.
15. Teh, C.-H. and R.T. Chin, On image analysis by the methods of moments. IEEE Transactions on pattern analysis and machine intelligence, 1988. **10**(4): p. 496-513.
16. Lajevardi, S.M. and Z.M. Hussain, Higher order orthogonal moments for invariant facial expression recognition. Digital Signal Processing, 2010. **20**(6): p. 1771-1779.
17. Farajzadeh, N., K. Faez, and G. Pan, Study on the performance of moments as invariant descriptors for practical face recognition systems. IET Computer Vision, 2010. **4**(4): p. 272-285.
18. Ono, A., Face recognition with Zernike moments. Systems and Computers in Japan, 2003. **34**(10): p. 26-35.
19. Singh, C., N. Mittal, and E. Walia, Face recognition using Zernike and complex Zernike moment features. Pattern Recognition and Image Analysis, 2011. **21**(1): p. 71-81.
20. Shi, Z., G. Liu, and M. Du, Rotary face recognition based on pseudo Zernike moments. Emerging Comput. Inf. Technol. Educ. Adv. Intell. Soft Comput, 2012. **146**: p. 641-646.
21. Wang, Z. and E.P. Simoncelli. Translation insensitive image similarity in complex wavelet domain. in Acoustics, Speech, and Signal Processing, 2005. Proceedings.(ICASSP'05). IEEE International Conference on. 2005. IEEE.
22. Hwang, S.-K. and W.-Y. Kim, A novel approach to the fast computation of Zernike moments. Pattern Recognition, 2006. **39**(11): p. 2065-2076.
23. Canny, J., A computational approach to edge detection. IEEE Transactions on pattern analysis and machine intelligence, 1986(6): p. 679-698.
24. N. Ponomarenko, V. Lukin, A. Zelensky, K. Egiazarian, M. Carli, and F. Battisti, "TID2008—A database for evaluation of full-reference visual quality assessment metrics," Adv. Modern Radioelectron., vol. 10, pp. 30–45, 2009.

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25. AT&T Laboratories, The Database of Faces, Cambridge [online], ©2002 [accessed 10/09/2014]. Available from: http://www.cl.cam.ac.uk/research/dtg/attarchive/facedatabase.html
26. Tom Fawcett, "An introduction to ROC analysis," Pattern Recognition Letters, 2006.
27. Seedahmed S. Mahmoud, Zahir M. Hussain, and Peter O'Shea, "A Geometrical-Based Microcell Mobile Radio Channel Model," Wireless Networks, Springer, vol. 12, no. 5, pp. 653-664, 2006.
28. Seedahmed S. Mahmoud, Zahir M. Hussain, and Peter O'Shea, "Geometrical Model for Mobile Radio Channel with Hyperbolically Distributed Scatterers," IEEE International Conference on Communication Systems (ICCS 2002), Singapore, Nov. 2002.
29. Yuu-Seng Lau and Zahir M. Hussain, "A New Approach in Chaos Shift Keying for Secure Communication," Proceedings of the IEEE International conference on Information Theory and Its Applications (ICITA'2005), Sydney, Australia, 4-7 Jul. 2005.

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