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A hybrid image similarity measure based on a new combination of different similarity techniques

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ABSTRACT

Image similarity is the degree of how two images are similar or dissimilar. It computes the similarity degree between the intensity patterns in images. A new image similarity measure named (*HFEMM*) is proposed in this paper. The *HFEMM* is composed of two phases. Phase 1, a modified histogram similarity measure (*HSSIM*) is merged with feature similarity measure (*FSIM*) to get a new measure called (*HFM*). In phase 2, the resulted (*HFM*) is merged with error measure (*EMM*) in order to get a new similarity measure, which is named *(HFEMM*). Different kindes of noises for example Gaussian, Uniform and salt & pepper noise are used with the proposed methods. One of the human face databases (*AT&T*) is used in the experiments and random images are used as well. For the evaluation, the similarity percentage under peak signal to noise ratio (PSNR) is used. To show the effectiveness of the proposed measure, a comparision anong different similar technique such as *SSIM, HFM, EMM* and *HFEMM* are considered. The proposed *HFEMM* achieved higher similarity result when PSNR was low compared to the other methods.

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1. INTRODUCTION

Image similarity in recent years has become a key point in image processing applications for example monitoring, restoration and other applications [1]. Similarity can be characterized as the contrast between two images, and the similarity measure is a numerical difference between two dissimilar images under comparison [2]. When the two images match up to the maximum similarity, the similarity degree between two signals is required to test the system and in order to make a decision [3]. Similarity measure methods can be classified into: information theoretical techniques and statistical techniques [4]. Several studies related to similarity techniques have been presented recently. In 1995, proposed a new information-theoretic approach (Mutual Information) [5]. In 2004, the researchers presented a scale called (*SSIM*) based on the information of the structure [6]. In 2014, introduced a new measure called (*HSSIM*) that based on 'joint histogram'. The measure outperforms statistical measure (*SSIM)* [7]. On the other hand, in 2017, the researchers proposed measure similarity called (*NMSE*) depened on normalized mean square error [8]. A New likeness measure based on 'Affinity Propagation' introduced in 2018 [9]. As well, in 2018 introduced likeness measure based on "joint histogram-Entropy" [10]. In 2019, intrduoced ahybrid measure for similarity of images [11]. In this paper, proposed a hybrid measure for image similarity called (*HFEMM*). The rest of this paper is organized as follow: the similarity techniques is presented in section 2, the research method is explained in section 3, section 4 presents the results and discussions and the conclusions is presented in section 5.

2. SIMILARITY TECHNIQUES

Techniques that used for Similarity can be classified into: the statistical and the information theoretical techniques [4, 7].

2.1. Statistical similarity techniques

It is possible to obtain valuable information from the image via calculating 'statistical measurements' for example 'Mean', 'Variance' and (SD) where SD means standerd divation. This information can be utilized to calculate similarity of image [12].

2.1.1. Structural similarity measure (SSIM)

In 2004, the authors introduced a new statistical measure for image quality index called Structural Similarity Index Method (*SSIM*) [6, 13] that utilized distance function to measurement the likeness relied upon statistical features [12]. The measure can be display in (1)**:**

$$SSIM(p,q) = \frac{(2\mu_p\mu_q+C1)(2\sigma_{pq}+C2)}{(\mu^2{}_p+\mu^2{}_q+C1)(\sigma^2{}_p+\sigma^2{}_q+C2)} \tag{1}$$

Where µp, µq are the 'means' and $\sigma^2{}_p$, $\sigma^2{}_q$ are the 'variance'; σ_{pq} is the 'covariance', *C1* and *C2* are constants ($C1=(R1P)^2$, $C2=(R2P)^2$, *R1* and *R2* are constants, *P* is maximum pixel value).

2.2.2. Feature similarity measure (FSIM)

Feature Similarity Measure is a statistical measurement of image quality estimation. FSIM offered by [14]. FSIM computation consists of two phases: the first phase calculates the similarity of local (S_L) as follows:

$$S_L(x_1) = \left[S_{pc}(x_1)\right]^{\propto} \times [S_G(x_1)]^{\beta} \tag{2}$$

Where S_{Pc} represents the Phase Congruency similarity

$$S_{PC}(x_1) = \frac{2PC_1(x_1)\times PC_2(x_1)+R1}{PC_1{}^2(x_1)\times PC_2{}^2(x_1)+R2} \tag{3}$$

$$PC(x_1) = \frac{R(x_1)}{\in+\sum_n A_n(x_1)}\ , R(X1) = \sqrt{K1^2(x_1) + H1^2(x_1)}, A_n(x_1) = \sqrt{[e_n{}^2(x_1) + o_n{}^2]} \tag{4}$$

Where

$$H1(x_1) = \sum_n O_n(x_1), K1(x_1) = \sum_n e_n(x_1), O_n(x_1) = \varepsilon(x_1) * M_n{}^e,\ e_n(x_1) = \varepsilon(x_1) * M_n{}^o \tag{5}$$

S_G represents the GM similarity

$$S_G(x_1) = \frac{2G_1(x_1)\times G_2(x_1)+R1}{G_1{}^2(x_1)\times G_2{}^2(x_1)+R2} \tag{6}$$

$$G = \sqrt{G_p{}^2(x_1) + G_q{}^2(x_1)} \tag{7}$$

The second phase is to calculate the *FSIM* between $F1(x)$ and $F2(x)$:

$$\mathrm{FSIM}\{\mathrm{F1}(\mathrm{x}_1), \mathrm{F2}(\mathrm{x}_1)\} = \Phi\{\ \mathrm{F1}(x_1), \mathrm{F2}(x_1)\} = \frac{\sum_{\mathrm{x}\in\Omega} \mathrm{s_l}(\mathrm{x}_1)\times \mathrm{pc}(\mathrm{x}_1)}{\sum_{\mathrm{x}\in\Omega} \mathrm{pc_m}(\mathrm{x}_1)} \tag{8}$$

Where $PC_{max}(x_1)$ is MAXimum (MAX) between '$PC_1(x_1)$' and '$PC_2(x_1)$'[15].

2.2. Information-theoretic similarity techniques

Information-theoretical similarity technique is used to get the similarity depended on intensity values [16, 17].

2.2.1. Histogram similarity measure

Histogram Similarity Measure is the measurement that depends on information theoretical technique via using conventional histogram and common histogram H_{ij} [7]. HSSIM suggested previously as SSIM scale cannot be well-implemented under signifcant noise. In (HSSIM) the researcher applied the common histogram and combined it with the conventional histogram as follows [18, 19]:

$$L(p,q) = \sqrt{\frac{\sum_i \sum_j \left[(H_{ij} - H_{ji})\frac{1}{h_i + C1}\right]^2}{2L^2}} \quad (9)$$

Where, h_i is the conventional histogram and $C1$ is a constant. L(p,q) can be normalize by using $L1(p,q)$ which represent the maximum value of the error estimate in very low PSNR as follows:

$$LL(p6,q6) = \frac{L(p,q)}{L1(p,q)}, r1(p,q) = 1 - LL(p6,q) \quad (10)$$

3. RESEARCH METHOD

The merhod and proposed Measure (HFEMM) is depicted in Figure 1.

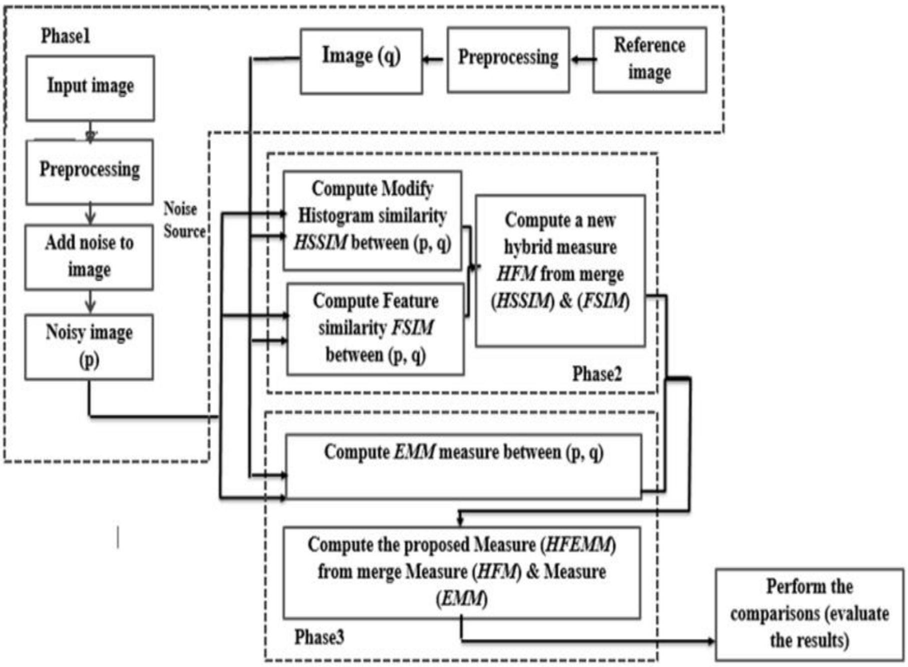

Figure 1. The similarity between two images (verification) by the proposed similarity measure

3.1. Phase one

In this phase, preprocessing performed on both images (refrence and input) to prepare the images. Furthermore, different kinds of noise are added to the input image from a variety of sources [20, 21, 22].

3.2. Phase two

In this phase, Modify Histogram Similarity measure is merged with Feature Similarity measure to get a new hybrid measure (*HFM*) as in (11):

$$HFM(p,q) = \sqrt{H(p,q)K + FSIM(p,q)(1-K)} \quad (11)$$

H (p,q) is Histogram Similarity measure but with a simple change as follows:

$$H1(p,q) = \sqrt{\sum_i \sum_j \left[(H_{ij} - H_{ji})\frac{1}{h_i + c1}\right]^2} \quad (12)$$

H1 (p,q) can be normalize by using $H2(p,q)$ which represent the maximum value of the error estimate in signifcant noise as follows:

$$HH(p\ \ ,q) = \frac{H1(p,q)}{H2(p,q)} \quad ,H(p,q) = 1 - \ HH(p,q\ \ ) \tag{13}$$

FSIM(p,q) is Feature Similarity Measure as in equation (8) .K is very small constant.

3.3. Phase three s

The other measure is the Error Mean Measure $EMM(p,q)$ between image p and q (derived from Mean Square Error [23]) as follows:

$$EMM = 1 - [\frac{1}{\mathrm{NM}} \sum_{\mathrm{n}=0}^{\mathrm{N}-1} \sum_{\mathrm{m}=0}^{\mathrm{M}-1} [\mathrm{p(n,m)} - \mathrm{q(n,m)}]^2 \ /(\sum_{n=0}^{N-1} \sum_{m=0}^{M-1} q(n,m))^{\frac{1}{2}}] \tag{14}$$

By combining the resulted measure from phase two (*HFM*) and the Error Mean measure (*EMM*), we will get a new similarity measure called (*HFEMM*). The (15) is summaries the new measure as form:

$$HFEMM(p,q) = (HFM(p,q)(1-U) + EMM(p,q)(U))^{1/2} \tag{15}$$

Where U is very small constant, $0 \leq \ HFEMM(p,q) \leq 1$. Finally, perform the comprasions. Algorithm (1) shows the method and proposed measure (*HFEMM*) for similarity.

Algorithm (1) HFEMM
Inputs: p isrefrence image and q is noisy image, K and U are very small constant
Outputs: a number between 0 and 1 that represent the similarity.

- Step 1: transform the colour images in to grayscale images.
- Step 2: transform the images into double.
- Step 3: Compute *H*

$$H1(p,q) = \sqrt{\sum_i \sum_j \left[\left(H_{ij} - H_{ji}\right) \frac{1}{h_i + c1}\right]^2}$$

- Step 4: Set $H2(p,q)$= *H1(p,q)* when noise is maximum.
- Step 5: Normalization: *HH=H1/* $H2$.
- Step 6: Set *H =1-HH*.
- Step 7: Compute FSIM

$$FSIM(p,q) = \frac{\sum_{\mathrm{x}\ \in ℶ}\ S_L(x\ \ ).PC_{max}(x)}{\sum_{\mathrm{x} \in ℶ} PC_{max}(x\ \ )}$$

- Step 8: Compute *HFM*

$$HFM = \sqrt{H(p,q) \times K\ +\ FSIM(p,q) \times (1-K)}$$

- Step 9: Compute *EMM*

$$EMM(p,q) = 1 - [\frac{1}{\mathrm{IJ}} \sum_{\mathrm{n}=0}^{\mathrm{N}-1} \sum_{\mathrm{m}=0}^{\mathrm{M}-1} [\mathrm{p(n,m)} - \mathrm{q(n,m)}]^2 \ \ /(\sum_{n=0}^{N-1} \sum_{m=0}^{M-1} q(n,m))^{\frac{1}{2}}\ ]$$

- Step 10: Compute HFEMM

$$HFEMM(p,q) = (HFM(p,q)(1-U) + EMM(p,q)(U))^{1/2}$$

- Step 11: Perform the comparisons (evaluate the results)
- Step 12: End of Algorithm

4. RESULTS AND DISCUSSIONS

The proposed meaures implemented using 'MATLAB' environment and a human face database called AT and T was used in testing the proposed methods. Moreover, different kinds of random image are also used for the evaluation. The range of similarity measures among (0 and1). If value is (1), then its displays the ideal match between the images, Else if its value is (0), then there is no match between images [24].

4.1 AT&T data base

The AT&T is an American Telephone & Telegram: Laboratories from Cambridge comprises a set of various human faces images were taken in (April 1992 and April 1994) at the database lab. It comprises of 10 dissimilar images (poses) of every person, image size (92×112) pixels **[**25].

4.2. Evaluation the proposed measure on AT&T dataset

This first of evaluation includes implementing the similarity measure under different kinds of noise such as Gaussians, salt and pepper and uniform noise. Diffent types of images from AT and T database are adopted and tested, for example an image as in the Figure 2 below was tested using Gaussians noise. Table 1 and Figure 3 are show the similarity results between the proposed measure and other measures such as (*SSIM, EEM, HFM*) under Gaussian noise.

In addition, the second test shows the implementation under salt and pepper noise as shown in Figure 4. Table 2 and Figure 5 shown similarity result between the proposed measure and another measures unde salt & pepper noise. So as to show the steadiness and adequacy of the proposed measure, we applied the proposed measure under a combination of noises (Gaussian and Uniform noise, Gaussian and salt and pepper noise) which will be more noisy, and As show in the follwing Figure 6. The Figure 7 shows the performance under Gaussian noise and slat and pepper noise Table 3 shown similarity result between the proposed measure and another under Gaussian and Uniform noise. Table 4 show the similarity result between the proposed measure and another under Gaussian and salt and pepper noise.

4.3. Evaluation the proposed measure by using different kinds of images

In this section, we used different kinds of image to display the effectiveness and efficiency of that the proposed measure. As illustrated in Figures 8-10. Comparisons of similarity measures under Gaussian and uniform noise a shown in Figure 11

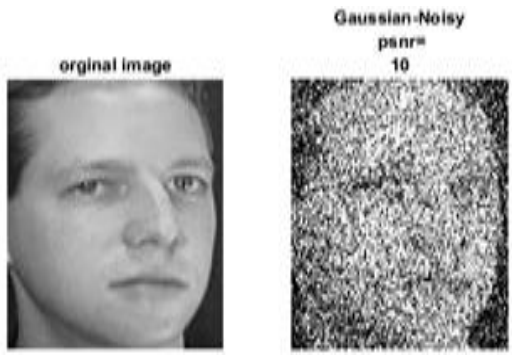

Figure 2. Original image and noisy image with Gaussian noise

Table 1. Comparisons of similarity measures for same images under Gaussian noise (Higher noise ratio 100% when psnr =100)

Ratio of Noise	*SSIM*	*EMM*	*HFM*	*HFEMM*
65% (PSNR-50)	0.0020	0.0001	0.3072	0.4293
52% (PSNR-30)	0.0020	0.0008	0.2990	0.4465
38% (PSNR-10)	0.0034	0.0830	0.3924	0.5383
32% (PSNR 0)	0.0141	0.2155	0.5605	0.6891
28% (PSNR 10)	0.0633	0.5469	0.7871	0.8824
1% (PSNR 50)	0.9831	0.9999	0.9996	1.0000

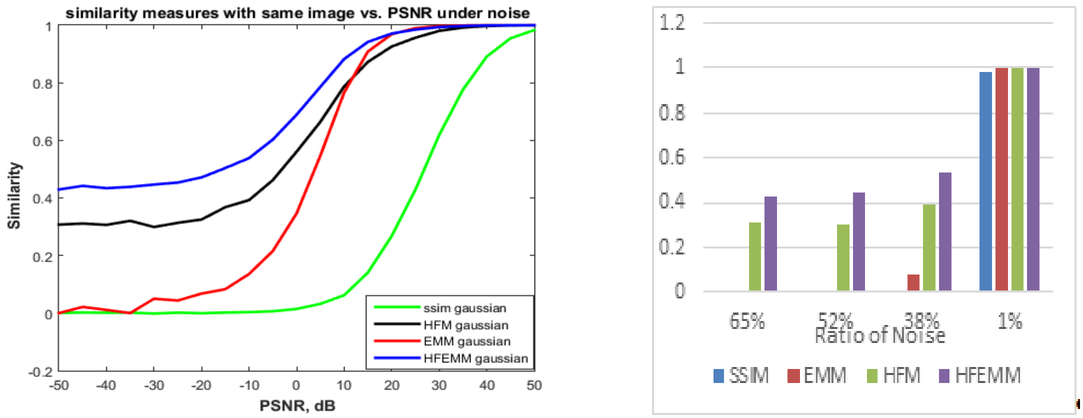

Figure 3. Comparisons of similarity measures for same imagesu under Gaussian noise

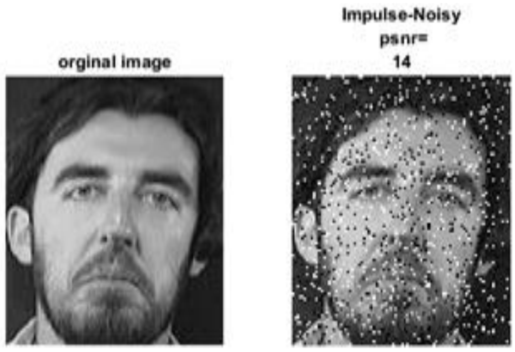

Figure 4. Original image and noisy image with salt and pepper noise

Table 2. Comparisons of similarity measures for same images under salt and pepper noise

Ratio of Noise	*SSIM*	*EMM*	*HFM*	*HFEMM*
27% (PSNR 9.9650)	0.0930	0.6511	0.7735	0.8512
22% (PSNR 15.3765)	0.2963	0.8972	0.9176	0.9536
18% (PSNR 20.4279)	0.5835	0.9676	0.9716	0.9849
16% (PSNR 23.7130)	0.7289	0.9848	0.9854	0.9925
12% (PSNR 28.8983)	0.9067	0.9954	0.9957	0.9978
8% (PSNR 32.4168)	0.9527	0.9984	0.9983	0.9991

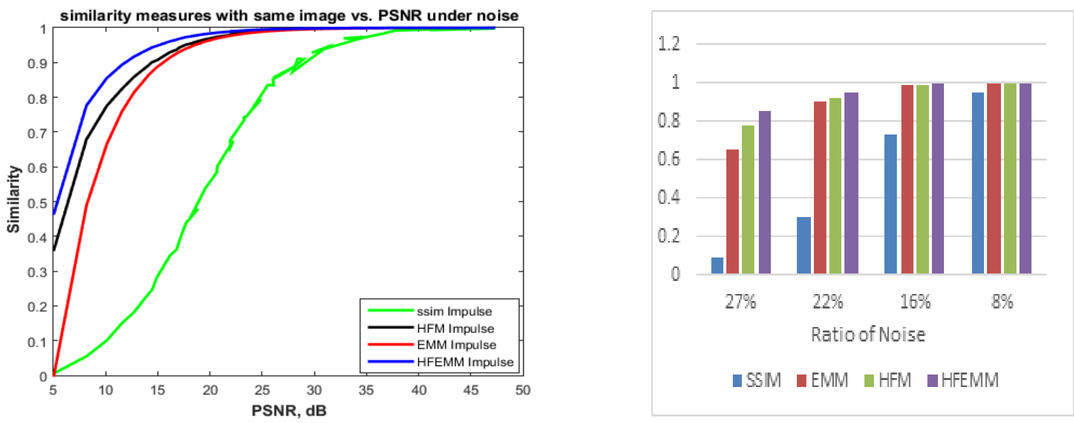

Figure 5. Comparisons of similarity measures for same images under impulse noise

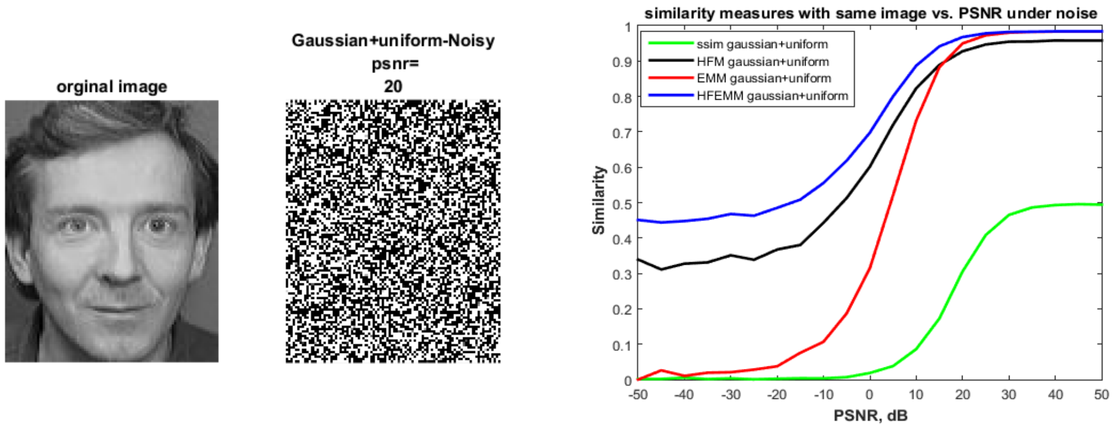

Figure 6. (P) Original image and noisy image (q) comparisons of similarity measures under Gaussian+uniform noise

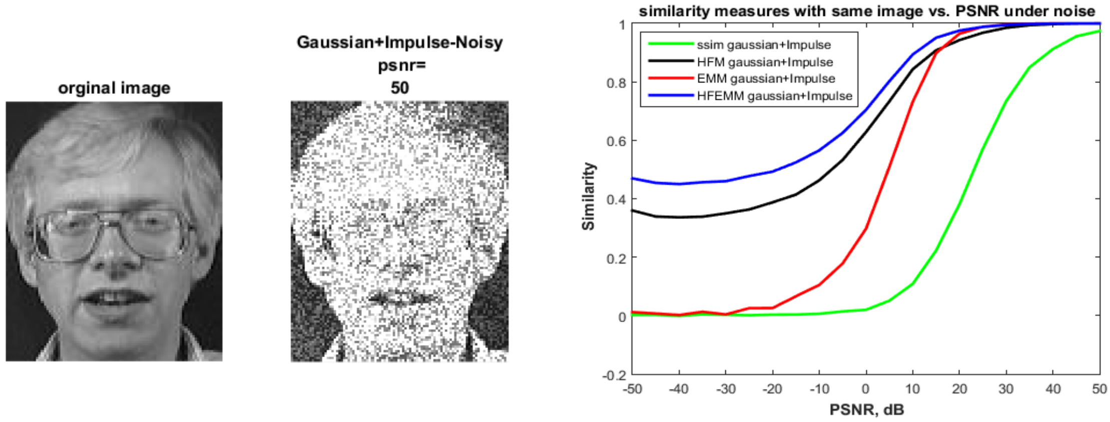

Figure7. (P) original image and noisy image (q) comparisons of similarity measures under gaussian+salt and pepper noise

Table 3. Comparisons of similarity measures for same images under Gaussian and uniform noise

Ratio of Noise	*SSIM*	*EMM*	*HFM*	*HFEMM*
65% (PSNR-50)	0.0005	0.0000	0.3391	0.4510
52% (PSNR -30)	0.0000	0.0207	0.3510	0.4679
38% (PSNR -10)	0.0053	0.1069	0.4431	0.5555
32% (PSNR 0)	0.0212	0.3146	0.6016	0.6977
28% (PSNR 10)	0.0885	0.7322	0.8231	0.8870
10% (PSNR 30)	0.4638	0.9727	0.9547	0.9823
2% (PSNR 50)	0.4945	0.9834	0.9580	0.9840

Table 4. Comparisons of similarity measures for same images under Gaussian and slat and pepper noise

Ratio of noise	*SSIM*	*EMM*	*HFM*	*HFEMM*
52% (PSNR -30)	0.0000	0.0118	0.3596	0.4695
38% (PSNR -10)	0.0020	0.0039	0.3469	0.4599
32% (PSNR 0)	0.0072	0.1050	0.463	0.5655
28% (PSNR 10)	0.0290	0.2973	0.6280	0.7041
8% (PSNR 50)	0.1045	0.7316	0.8430	0.8935
1% (PSNR 50)	0.7295	0.9964	0.9849	0.9947
65% (PSNR-50)	0.9774	0.9999	0.9996	1.0000

Figure 8. (P) original image and noisy image (q)

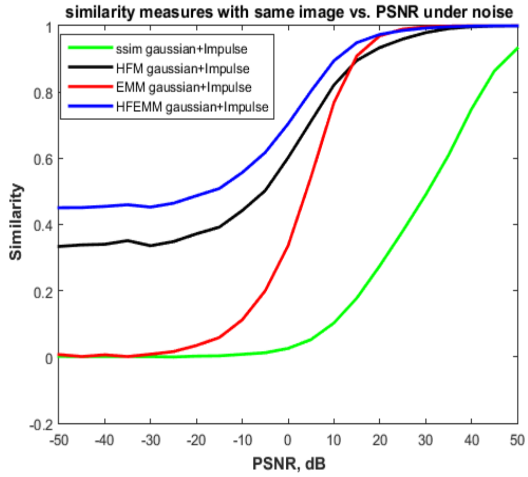

Figure 9. Comparisons of similarity measures under Gaussian and slat and pepper noise

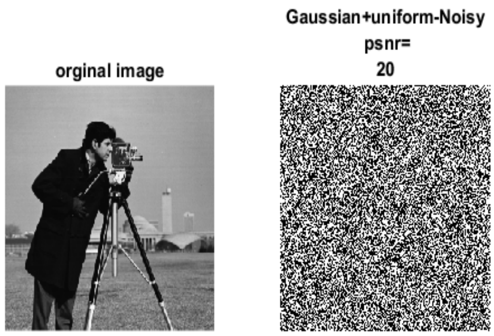

Figure 10. Original Image and noisy image

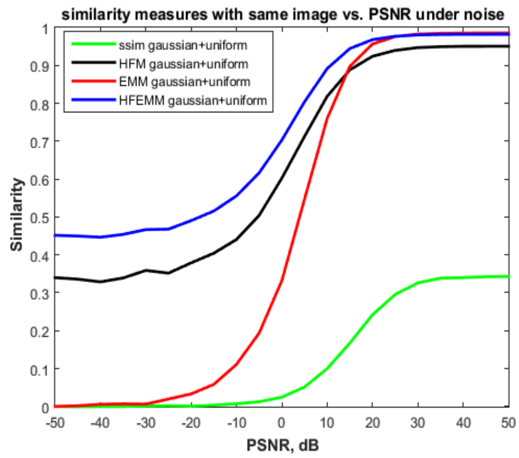

Figure 11. Comparisons of similarity measures under Gaussian and uniform noise

5. CONCLUSION

A hybrid similarity measure, called Histogram Feature Error Mean Measure, has been proposed. The proposed measure is depended on information theoretic features and statistical features. A joinit histogram' with original histogram have been used as information-theoretic tool, and Feature Measure with Error Mean have been used as a statistical tool. The proposed measure has been tested on AT and T and different types of images. We concluded that the new measure gave better performance (more similarity) than the other similarity measures such as (*SSIM*, *EMM*) under different kinds of noise when power of noise is highly high. The proposed measure can be used in a fundamental issue in real-world applications. Such as can be employed in found simlarity and different between image, verification, recognition (face, iris, and other pattern recognition systems).

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