Useful Application of Noise: a Novel Approach to Content-Based Image Retrieval System

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Abstract— Noise is an unwanted signal which tends to corrupt a desired signal. Image noise is caused by the imperfections in the systems used for image acquisition, processing, storage and transmission. Image de-noising is therefore an essential image pre-processing task. Can noise be useful? Yes, noise can be useful. Useful application of noise for the development of a Novel Content-based Image Retrieval System (Novel CBIRS) is presented. Salt and Pepper Noise (SPN) with noise density of 0.2% is added to the Query Image to generate a noisy version of the Query Image which serves as the reference image. The Peak Signal to Noise Ratio (PSNR) of the Query Image relative to the reference image is compared with the PSNR of each of the images in the Database relative to the reference image. PSNR is thus the only feature adopted for image retrieval. Euclidean distance is the similarity measure for feature natching. For only one feature, Euclidean distance is equivalent to absolute difference. The Novel CBIRS is tested with the Columbia Object Image Library which is a Database of 7,200 images. Additional 400 external images are used for system's performance evaluation. The accuracy of the Novel CBIRS is found to be satisfactory with 100% Recall ratio and 100% Precision ratio. The Novel CBIRS is less complex because it uses only one feature compared with other CBIRS schemes that use more features to achieve the same result. Noise has been put to useful application in image retrieval.

Index Terms— Noise, Image Retrieval, Signal to Noise Ratio, Similarity Measure, Feature Matching, Euclidean distance, Precision ratio, Recall ratio.

1 Introduction

HUGE amount of images exist in large Databases in arts, sciences, social sciences, schools, universities, hospitals, aviation, remote sensing, industries and digital libraries for record keeping, management, medical diagnosis, treatment and follow up, educational, entertainment and economic purposes. Efficient and accurate image retrieval system has been an active area of research in image processing [1], [2], [3], [4]. Text-Based Image Retrieval System (TBIRS) was in vogue for some time. TBIRS makes use of text as tags to distinguish one image from the other for image retrieval purpose. For large Databases, TBIRS requires many tags or keywords and is found to be time consuming and inefficient [1], [3], [5].

Content-Based Image Retrieval System (CBIRS) has been introduced to overcome the limitations of TBIRS. As the name implies, image retrieval in CBIRS is based on the content of the image [6], [7], [8], [9]. Image content refers to image features which include textures, shape, edges, color, first-order statistics, and second-order statistics [10], [11], [12]. Image retrieval is the process of retrieving the most closely Matched Image to a given Query Image by comparing the features of the Query Image to similar features of all the images in the Database. Similarity measures like Euclidean distances of the Query Image from each of the images in the Database are computed [13], [14], [15]. The image in the Database having zero Euclidean distance from the Query image is selected as the retrieved image. The retrieved image can link the user to more information stored in the Database about the identity of the Query Image. Images in the Database having short Euclidean distances from the Query image are also identified as being close to the Query Image.

Several image features have been employed and are being employed for CBIRS [3], [4], [6], [7], [16], [17], [18]. Histogram, color moment, Gray Level Co-occurrence Matrix (GLCM), and Tamura texture features were used as features in CBIRS developed in [16]. Color moment gave the highest Recall ratio of 66% and the Highest Precision ratio of 33% [16]. The Gray Level Co-occurrence Matrix based CBIRS is found to have a Precision ratio of 44% [17]. A Precision ratio of 81% was recorded with CBIRS based a combinations of features [17]. Fifteen (15) second-order statistics derived from the Gray Level Co-occurrence Matrix (GLCM) were combined as the basis of the CBIRS developed in [18]. 100% Recall ratio and 100% Precision ratio were recorded with this combination [18].

Signals are affected by the systems used to acquire, transmit, or process them. These systems are imperfect and introduce noise, distortion, or other artefacts [19]. Noise is defined as unwanted signal tending to corrupt a desired signal. The main task in Electronic communication and most Digital Signal Processes is elimination or suppression of noise. Image noise can be caused by atmospheric inhomogeneity, relative motion between camera and object, and defects in charge coupled devices [20]. Image de-noising is also an active area of research [20], [21], [22], [23], [24], [25], [26]. The research question in this work is "Is it possible to put noise to useful service in Digital Signal Processing or Digital Image Processing?".

In this work, a novel approach to Content-Based Image Retrieval System (CBIRS) is presented. Noise is applied as a useful tool in image retrieval.

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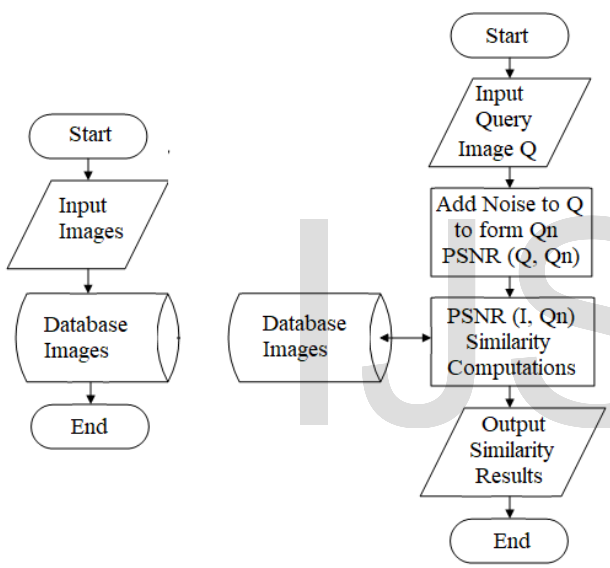
2 Development of a Novel Content-Based Image Retrieval System

2.1 Novel CBIRS

The novel Content-Based Image Retrieval System (Novel CBIRS) is described by the flowchart of Fig. 1. Fig. 1(a) describes the loading of images to the Database which is simple. Fig. 1(b) describes the querying of the Database. Querying the Database begins with the input of the Query Image Q. A noisy version of the Query Image Qn is generated by adding noise to the Query Image. The Peak Signal to Noise Ratio (PSNR) of the Query Image relative to its noisy version Qn is evaluated. PSNR of each Image I in the Database is also evaluated relative to the noisy version of the Query Image Qn is also evaluated. The PSNR of Q relative to Qn is compared with the PSNRs of all the images in the Database relative to Qn and similarity measures are computed. The algorithm output the similarity results.



(a) Loading the Database (b) Querying the Database

Fig. 1 Novel Content-based Image Retrival System (Novel CBIRS).

Salt and Pepper Noise (SPN) is selected for this work. Any other type of image noise can be used. SPN belongs to the group of fixed valued impulse noise [10], [12], [19], [20], [23], [27]. SPN is due to defects in the Charged Coupled Device (CCD) which cause d% of the pixels' intensity values to be wrongfully recorded and transmitted as '0' or '255' while the remaining (100-d)% pixels' intensity values are recorded and transmitted correctly [20], [23], [27]. d is said to be the noise density. Only very few pixels of Q are corrupted with SPN as described in (1). d is fixed as 0.2; 2 pixels out of every 1000 pixels are corrupted with SPN. A corrupted pixel's intensity value is set to '0' or '255' as shown in (1).

$$Qn = \begin{cases} Q(m,n) & \text{for } (100\text{-d})\% \text{ of the pixels} \\ \eta \quad \text{where} \in [0,255] & \text{for d\% of the pixels} \end{cases} \qquad (1)$$

2.2 Peak Signal to Noise Ratio (PSNR)

The Query Image Q is corrupted to obtain the noisy version of The Query Image Qn. The degree of corruption or degradation of Qn relative to Q is measured with the Peak Signal to Noise Ratio (PSNR) as shown in (2) [23], [28]. If Qn is exactly the same as Q, the PSNR will be equal to ∞. The higher the noise quantity, the lower is the PSNR. The unit of PSNR is decibel (dB). PSNR can also be used to compare any image I in the Database with Qn as shown in (3).

$$PSNR_Q = 10\log_{10}\left[\frac{255^2}{\frac{1}{3MN}\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{t=1}^{3}(Q(m,n,t)-Qn(m,n,t))\text{^}2}\right] \qquad (2)$$

$$PSNR_I = 10\log_{10}\left[\frac{255^2}{\frac{1}{3MN}\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{t=1}^{3}(I(m,n,t)-Qn(m,n,t))\text{^}2}\right] \qquad (3)$$

2.3 Test Image Database

The Columbia Object Image Library (COIL-100) is adopted as the test image Database [29], [30]. COIL-100 contains 7,200 images. The images are of dimensions 128-by-128-by-3. Each of the images has a unique name and a Serial Number (S/N) [18], [25], [26]. A look up table relates the S/N of a Database image with its unique name [18].

2.4 Feature Extraction

The feature adopted in this work for distinguishing one image from the other is the Peak Signal to Noise Ratio (PSNR). A 1-by-1 matrix **q** is used to store the $PSNR_Q$ of the Query Image Q relative to the noisy version of the Query Image Qn obtained from (2). A 7200-by-3 matrix **p** is used to store the data generated for the images in the Database. Row 1 and column 1 of **p** is used to store the Serial No (S/N) for the first Database image I. Row 1 and column 2 of **p** stores the $PSNR_I$ of the first Database image I relative to the noisy version of the Query Image Qn obtained from (3). Row 2 and column 1 of **p** is used to store the Serial No (S/N) for the second Database image I. Row 2 and column 2 of **p** stores the $PSNR_I$ of the second Database image I relative to the noisy version of the Query Image Qn obtained from (3). Similar data are stored in rows 3, 4, 5, …, 7200 of p for the 3rd, 4th, 5th, …, 7200th Database Image I respectively.

2.5 Feature Matching: Similarity Computation

Euclidean distance is the similarity measure of choice [13], [14], [15], [18], [31], [32]. The similarity between the first Database image I with the Query Image is obtained by calculating the Euclidean distance between $PSNR_I$ (in row 1 and column 2 of **p**) and $PSNR_Q$ (in row 1 and column 1 of **q**) as shown in (4); the result is stored in row 1 and column 3 of **p**. Since only one feature is involved, the Euclidean distance is equal to the absolute difference between $PSNR_I$ and $PSNR_Q$ as shown in (4). The similarity between the second Database image I with the Query Image is obtained by calculating the Euclidean distance between $PSNR_I$ (in row 2 and column 2 of **p**) and $PSNR_Q$ (in row 1 and column 1 of **q**) as shown in (4); the result is stored in row 2 and column 3 of **p**. Similarly, the Euclidean distances between the Query Image Q and the 3rd, 4th, 5th, …, 7200th Database Image I are stored in the column 3 of rows 3, 4, 5, …, 7200 of **p** respectively.

$$Ed = \sqrt{(PSNR_I - PSNR_Q)^2} = \left|PSNR_I - PSNR_Q\right| \quad (4)$$

2.6 Similarity Results

The rows in matrix **p** are sorted in ascending order of the Euclidean distances in column 3. The row with the shortest Euclidean distance becomes row 1 while row with the longest Euclidean distance becomes row 7200. The Database image corresponding to row 1 of **p** after sorting is the Best Match Image and is also the Retrieved Image if and only if the Euclidean distance is zero (0). The Database images corresponding to rows 2 to 9 of **p** after sorting are picked as the Next 8 Close Images. The unique names of these images can be obtained in a look up table with the help of their Serial Numbers (S/N) in column 1.

The Novel CBIRS algorithm outputs the Best Matched Image and the Next 8 Close Images and their corresponding Euclidean distances. The algorithm declares the Best Match Image as the Retrieved Image if the Euclidean distance of the Best Match image is equal to zero (0). The algorithm declares that there is no Retrieved Image and that the Query Image is not in the Database if the Euclidean distance of the Best Match Image is greater than zero (0).

2.7 System's Performance Evaluation

Image retrieval results are classified as true positive (tp), false positive (fp), true negative (tn), and false negative (fn) as described in Table 1. Green background color in Table 1 means accurate retrieval results. Red background color in Table 1 means erroneous retrieval results. The system's performance or reliability is measured in term of Recall, Precision, and F-Measure as shown in (5), (6), (7) and (8) [18], [32], [33], [34].

TABLE 1
CLASSIFICATION OF RETRIEVAL RESULTS

S/N	Origin of the Query Image	Description of Result	Class of Result
1	from the Database	There is a Retrieved Image and the correct image is retrieved.	true +ve (tp)
2	from the Database	There is a no Retrieved Image or a wrong image is retrieved.	false -ve (fn)
3	not from the Database	There is a Retrieved Image but a wrong image is retrieved.	false +ve (fp)
4	not from the Database	There is a no Retrieved Image.	true -ve (tn)

$$Precision = Confidence = \frac{tp}{pp} = \frac{tp}{tp + fp} \quad (5)$$

$$Recall = Sensitivity = \frac{tp}{pc} = \frac{tp}{tp + fn} \quad (6)$$

$$Specificity = Inverse\ Recall = \frac{tn}{nc} = \frac{tn}{tn + fp} \quad (7)$$

$$F\text{-}Measure = \frac{2(Precision)(Recall)}{(Precision + Recall)} \quad (8)$$

3 Results and Discussions

3.1 Sample Tests on Novel CBIRS

Six sample tests were carried out on the Novel CBIRS Algorithm. The Query Images for Tests 1, 2, and 3 were picked from the Database. The Query Images for Tests 4, 5, and 6 were not from the Database. A Database Image with unique name ('obj51__70.png') and Serial Number (S/N = 3379) was modified to produce the Query Image for Test 4. Another Database Image with unique name ('obj2__60.png') and Serial Number (S/N = 1649) was modified to produce the Query Image for Test 6. The results of the Tests 1, 2, 3, 4, 5, and 6 are presented in Figs. 2, 3, 4, 5, 6, and 7 respectively. Tables 2, 3, 4, 5, 6, and 7 show the $PSNR_Q$ and the first 9 rows of matrix **p** after **p** was sorted for Tests 1, 2, 3, 4, 5, and 6 respectively.

TABLE 2
SAMPLE TEST 1 RESULTS: DATA FOR THE BEST MATCH IMAGE AND THE NEXT 8 CLOSE IMAGES

	Column No	1	2	3
Row No	Corresponding Image Name	Image S/N	$PSNR_I$ (dB)	Euclidean Distance
1	'obj48__315.png'	3074	34.75	0.00
2	'obj48__320.png'	3075	21.49	13.27
3	'obj48__310.png'	3073	20.13	14.62
4	'obj48__325.png'	3076	17.08	17.67
5	'obj48__305.png'	3072	16.65	18.10
6	'obj48__330.png'	3077	15.89	18.86
7	'obj48__335.png'	3078	15.09	19.66
8	'obj48__300.png'	3071	15.00	19.75
9	'obj48__340.png'	3079	14.41	20.34
	$PSNR_Q$ = 34.75 dB	First 9 rows of matrix **p** at the end of Image Retrieval Sample Test 1.		

The Euclidean distance obtained for the Best Match Image is zero (0) for Tests 1, 2, and 3 as shown in Figs. 2, 3, and 4 respectively and as shown in Tables 2, 3, and 3 respectively. Therefore, the Best Match Image is the same as the Retrieved Image for Tests 1, 2, and 3. The Retrieved Images in Tests 1, 2, and 3 are found to tally with the Query Images as shown in Figs. 2, 3, and 4 respectively and as shown in Tables 2, 3, and 4 respectively. Therefore, the retrieval results in Tests 1, 2, and 3 are classified as true positive results (tp). If there were no Retrieved Images or if the Retrieved Images do not tally with the Query Images, the results would have been classified as false negative results (fn) because the Query Images were from the Database.

TABLE 3
SAMPLE TEST 2 RESULTS: DATA FOR THE BEST MATCH IMAGE AND THE NEXT 8 CLOSE IMAGES

	Column No	1	2	3
Row No	Corresponding Image Name	Image S/N	$PSNR_I$ (dB)	Euclidean Distance
1	'obj97__345.png'	6968	36.29	0.00
2	'obj97__340.png'	6967	25.34	10.95
3	'obj97__350.png'	6970	24.65	11.64
4	'obj97__355.png'	6971	20.67	15.62
5	'obj97__335.png'	6966	20.35	15.94
6	'obj97__0.png'	6913	18.77	17.52
7	'obj97__330.png'	6965	17.70	18.59
8	'obj97__5.png'	6974	17.64	18.65
9	'obj97__10.png'	6914	16.99	19.30
	$PSNR_Q$ = 36.29 dB	First 9 rows of matrix **p** at the end of Image Retrieval Sample Test 2.		

TABLE 4
SAMPLE TEST 3 RESULTS: DATA FOR THE BEST MATCH IMAGE AND THE NEXT 8 CLOSE IMAGES

	Column No	1	2	3
Row No	Corresponding Image Name	Image S/N	$PSNR_I$ (dB)	Euclidean Distance
1	'obj55__160.png'	3616	36.58	0.00
2	'obj55__165.png'	3617	25.96	10.62
3	'obj55__155.png'	3615	24.90	11.68
4	'obj55__170.png'	3618	21.81	14.77
5	'obj55__150.png'	3614	20.94	15.64
6	'obj55__175.png'	3619	20.01	16.57
7	'obj55__180.png'	3620	18.98	17.59
8	'obj55__145.png'	3612	18.28	18.30
9	'obj55__185.png'	3621	18.14	18.44
	$PSNR_Q$ = 36.58 dB	First 9 rows of matrix **p** at the end of Image Retrieval Sample Test 3.		

TABLE 5
SAMPLE TEST 4 RESULTS: DATA FOR THE BEST MATCH IMAGE AND THE NEXT 8 CLOSE IMAGES

	Column No	1	2	3
Row No	Corresponding Image Name	Image S/N	$PSNR_I$ (dB)	Euclidean Distance
1	'obj51__70.png'	3379	23.74	11.86
2	'obj51__250.png'	3348	20.17	15.43
3	'obj51__75.png'	3380	20.13	15.48
4	'obj51__65.png'	3378	19.32	16.28
5	'obj51__245.png'	3346	18.58	17.03
6	'obj51__255.png'	3349	18.55	17.05
7	'obj12__255.png'	253	17.36	18.25
8	'obj51__60.png'	3377	17.34	18.26
9	'obj51__260.png'	3350	17.25	18.35
	$PSNR_Q$ = 35.61 dB	First 9 rows of matrix **p** at the end of Image Retrieval Sample Test 4.		

TABLE 6
SAMPLE TEST 5 RESULTS: DATA FOR THE BEST MATCH IMAGE AND THE NEXT 8 CLOSE IMAGES

	Column No	1	2	3
Row No	Corresponding Image Name	Image S/N	$PSNR_I$ (dB)	Euclidean Distance
1	'obj25__90.png'	1295	13.05	24.04
2	'obj25__100.png'	1227	13.02	24.06
3	'obj25__50.png'	1287	13.01	24.07
4	'obj25__75.png'	1292	13.00	24.08
5	'obj25__65.png'	1290	13.00	24.08
6	'obj25__80.png'	1293	13.00	24.09
7	'obj25__145.png'	1236	12.99	24.09
8	'obj25__110.png'	1229	12.99	24.10
9	'obj25__130.png'	1233	12.98	24.10
	$PSNR_Q$ = 37.08 dB	First 9 rows of matrix **p** at the end of Image Retrieval Sample Test 5.		

TABLE 7
SAMPLE TEST 6 RESULTS: DATA FOR THE BEST MATCH IMAGE AND THE NEXT 8 CLOSE IMAGES

	Column No	1	2	3
Row No	Corresponding Image Name	Image S/N	$PSNR_I$ (dB)	Euclidean Distance
1	'obj2__60.png'	1649	33.20	3.91
2	'obj2__55.png'	1648	30.87	6.24
3	'obj2__65.png'	1650	28.91	8.21
4	'obj2__50.png'	1647	28.12	9.00
5	'obj2__70.png'	1651	27.77	9.35
6	'obj2__45.png'	1645	26.25	10.86
7	'obj2__75.png'	1652	25.86	11.26
8	'obj2__80.png'	1653	24.87	12.24
9	'obj2__40.png'	1644	24.53	12.58
	$PSNR_Q$ = 37.11 dB	First 9 rows of matrix **p** at the end of Image Retrieval Sample Test 6.		

The Euclidean distances obtained for the Best Match Images in Tests 4, 5, and 6 are 11.86, 24.04, and 3.91 respectively as shown in Figs. 5, 6, and 7 respectively; and also as shown in Tables 5, 6, and 7 respectively. These values are greater than zero (0). Therefore, there are no Retrieved Images in Tests 4, 5, and 6. The algorithm has detected correctly that the Query Images for Tests 4, 5, and 6 were not from the Database. These results are classified as true negative results (tn). If there were Retrieved Images, the results would have been classified as false positive results (fp) because the Query Images were not from the Database.

The Query Images for Tests 4 and 6 were not from the Database but are modified versions of Database Images 'obj51__70.png' (S/N = 3379) and 'obj2__60.png' (S/N = 1649) respectively. The Best Match Images in Tests 4 and 6 are 'obj51__70.png' (S/N = 3379) and 'obj2__60.png' (S/N = 1649) respectively as shown in Figs. 5 and 7 respectively and as shown in Tables 5 and 7 respectively. If a Database image is

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altered in one way or the other, and is presented to the Novel CBIRS algorithm, the algorithm can pick the original Database image as the Best Match Image and can pick very similar Database images as the Next 8 Close Images.

3.2 Novel CBIRS Performance Evaluation

The Novel CBIRS was tested 7,600 times with different Query Images; 7200 Query Images were from the Database and 400 Query Images were external to the Database. All 7,200 Tests with Query Images from the Database gave true positive (tp) results; Query Images were accurately retrieved. All 400 Tests with Query Images which were not from the Database gave true negative (tn) results; the algorithm correctly detected the images as not being from the Database. None of the 7600 Tests gave false positive (fp) results and none of the 7600 Tests gave false negative (fn). Therefore, the Precision, the Recall, and the F-Measure are found to be 100% using (5), (6), (7) and (8).

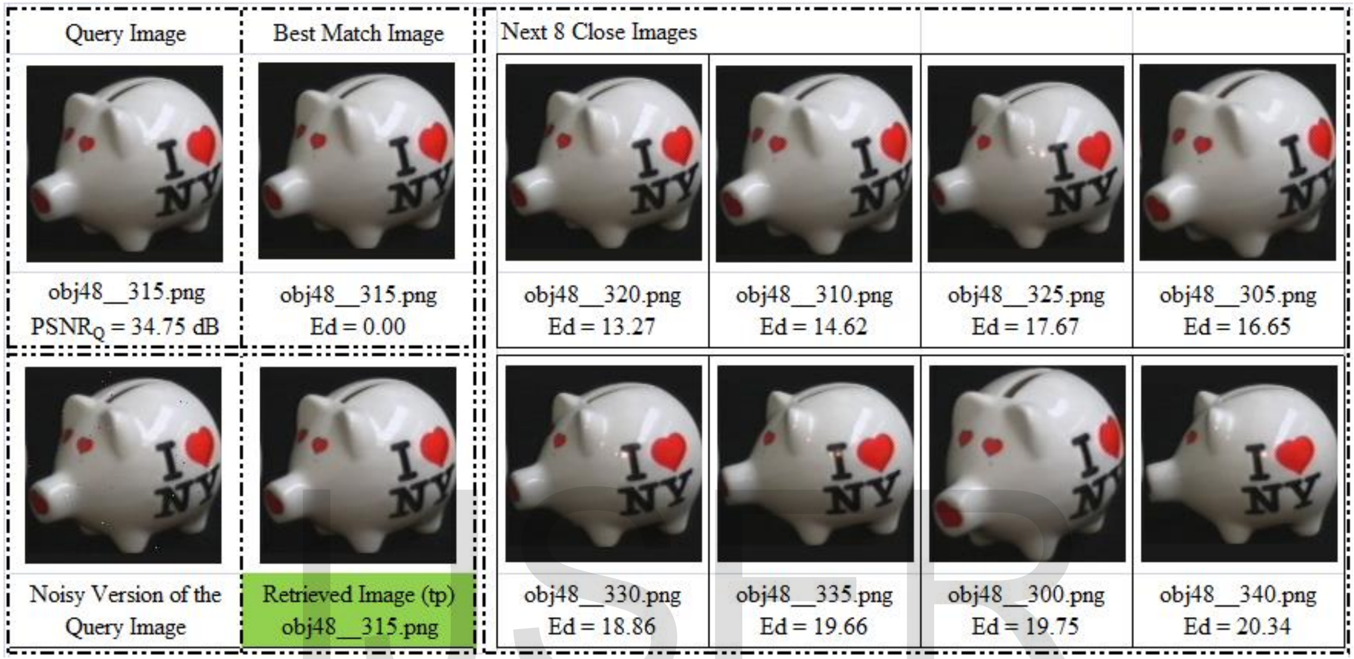

Fig. 2 Results of Sample Test 1.

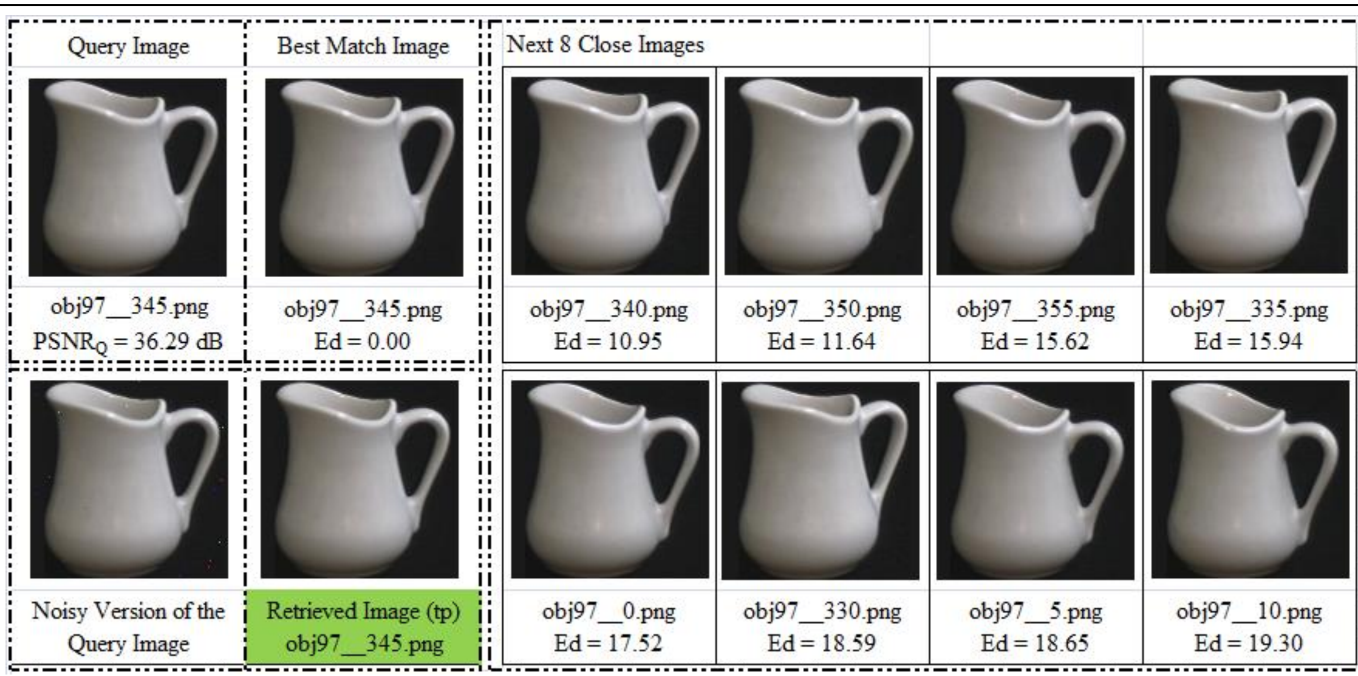

Fig. 3 Results of Sample Test 2.

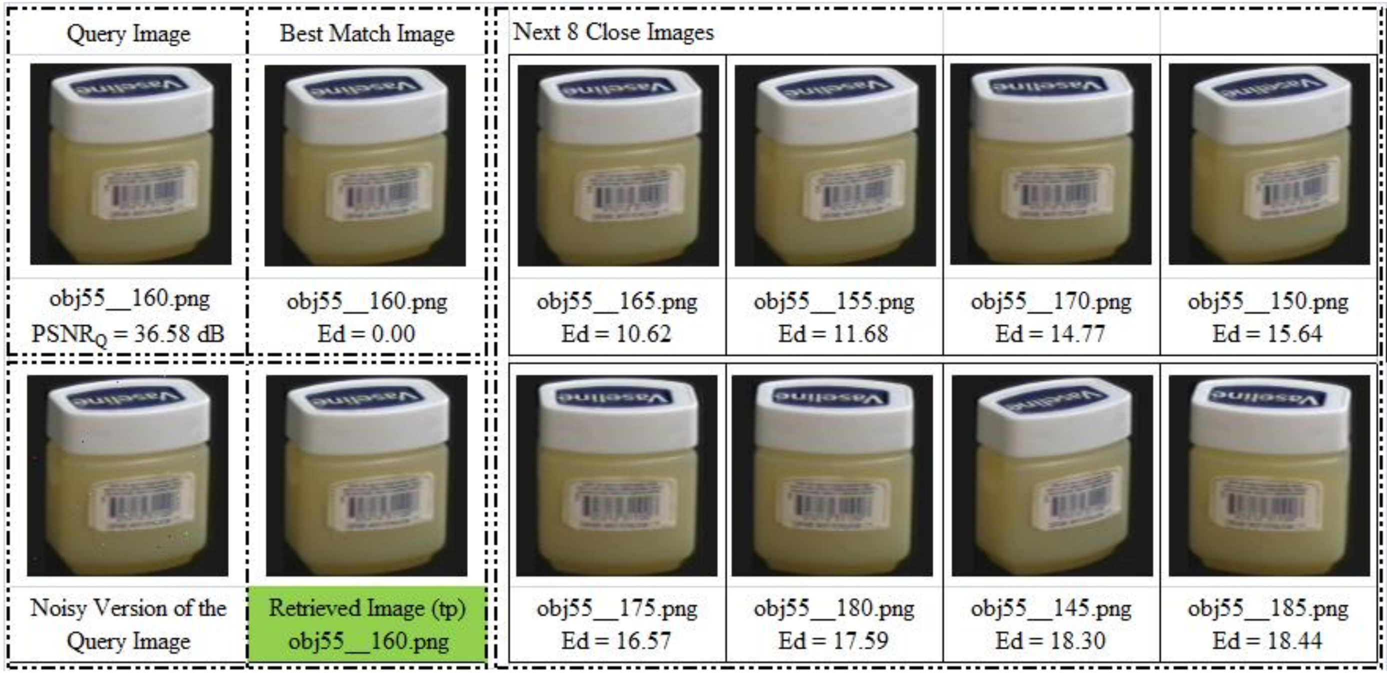

Fig. 4 Results of Sample Test 3.

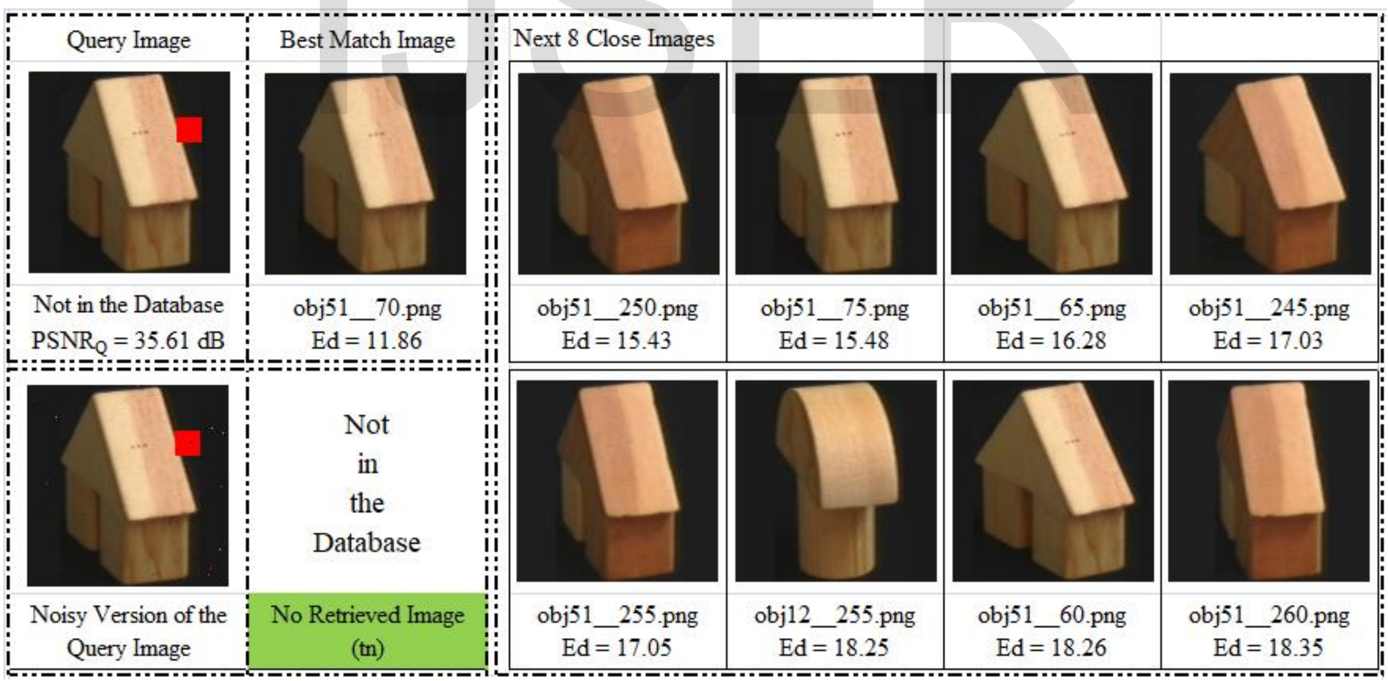

Fig. 5 Results of Sample Test 4.

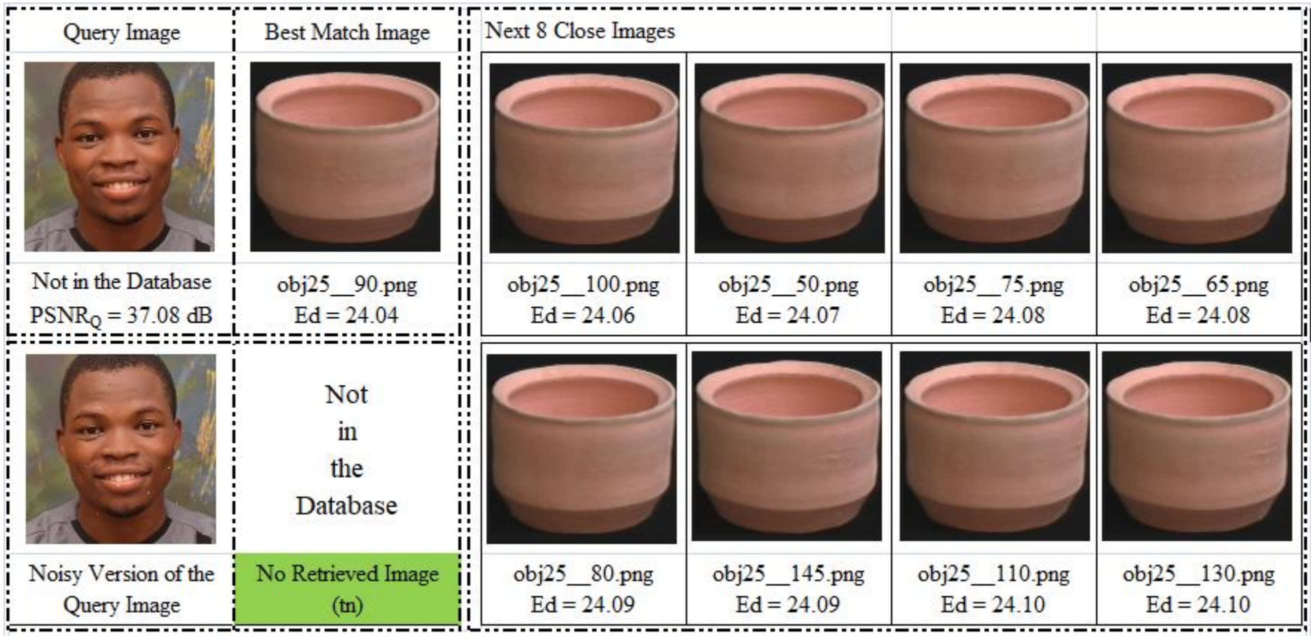

Fig. 6 Results of Sample Test 5.

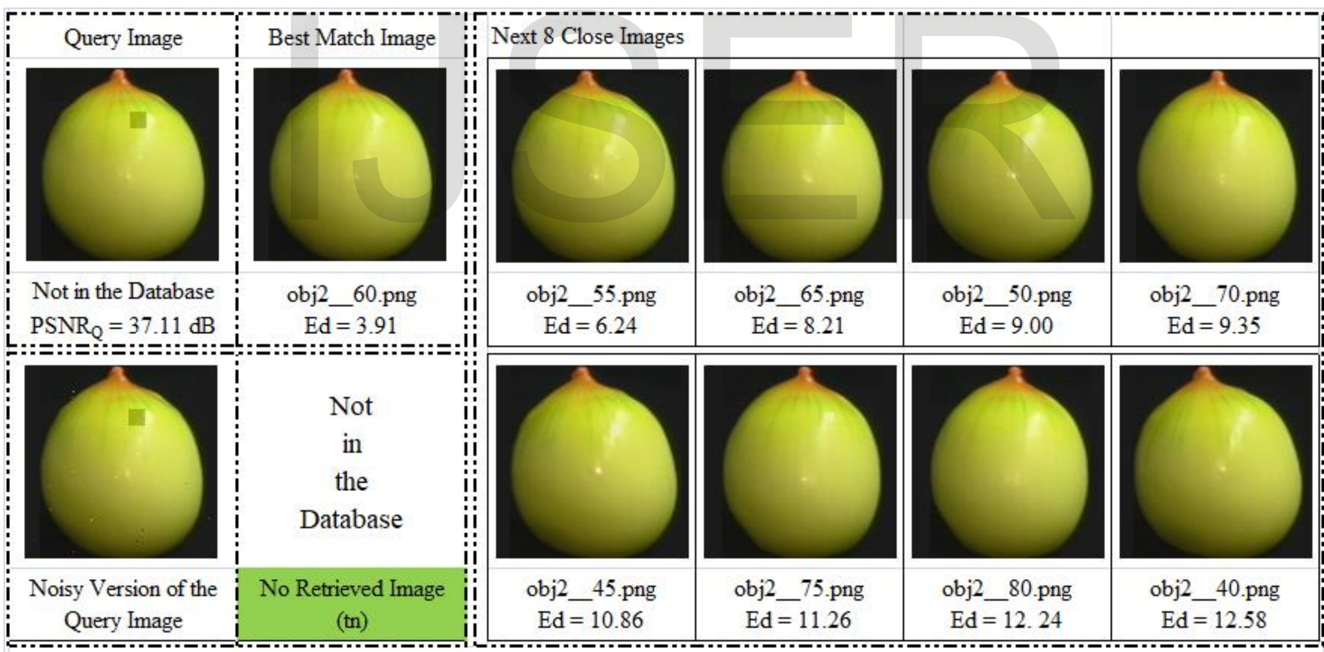

Fig. 7 Results of Sample Test 6.

3.3 Comparison of Novel CBIRS with Second-order Statistics based CBIRS

Second-Order Statistics based CBIRS Test results of Fig. 8 [18] and the Novel CBIRS Test results of Fig. 2 are similar as the same Query Image was used for testing both schemes. The 8 Close Images in the Novel CBIRS results are similar to the Query Image. For the Novel CBIRS, the 8 Close Images are the same object but different poses. The 8 Close Images in the Second-order Statistics based CBIRS results in Fig. 8 include objects that are different from the Query Image. For the Second-order Statistics based CBIRS, the 8 Close Images are three different objects with different poses. The Novel CBIRS is therefore better than the Second-Order Statistics based CBIRS as the Close Images are more similar to the Query Image in the former than the latter.

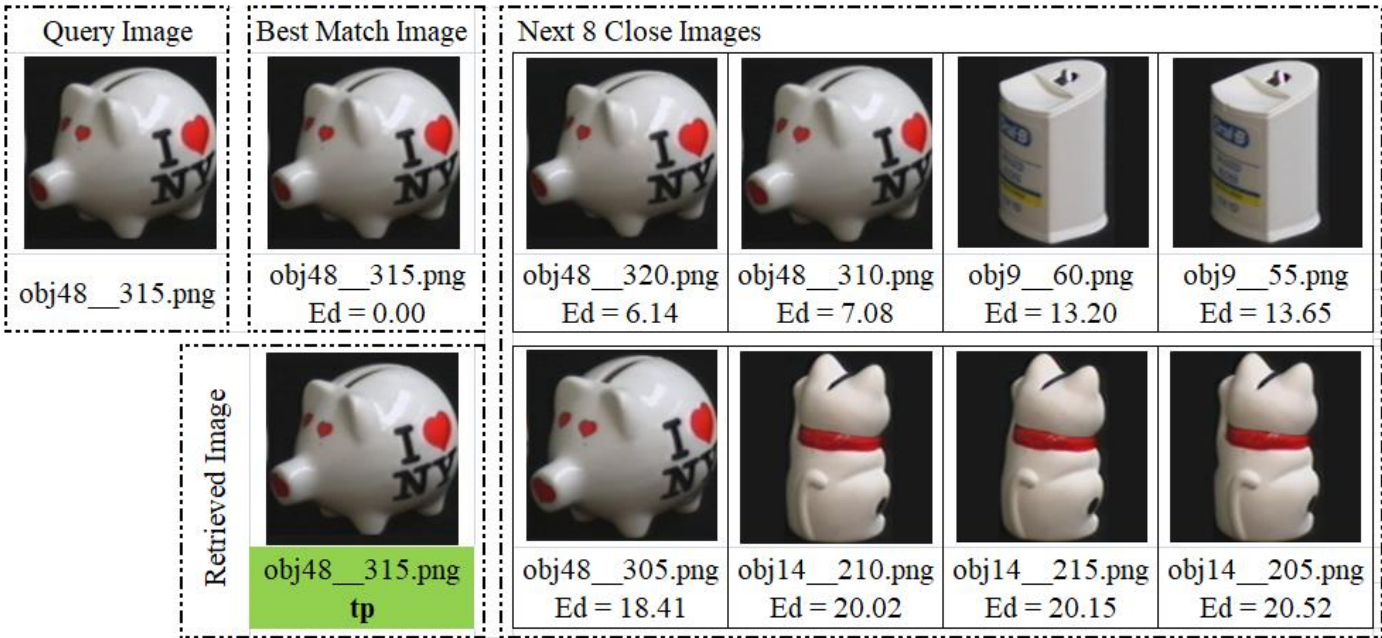

Fig. 8 Similar Test Results for Second-order Statistics based CBIRS [18].

The Novel CBIRS recorded 100% Precision, 100% Recall, and 100% F-Measure like the Second-order Statistics based CBIRS [18]. Novel CBIRS use only one feature whereas the Second-order Statistics based CBIRS uses fifteen (15) features. Matrix **p** has 17 columns in the Second-Order Statistics based CBIRS but it has only 3 columns in the Novel CBIRS. Therefore, the Novel CBIRS is less computationally complex compared with the Second-order Statistics based CBIRS.

4 Conclusion

Noise has been usefully employed for the development of a Novel Content-based Image Retrieval System (Novel CBIRS). The Novel CBIRS scheme adds Salt and Pepper Noise (SPN) to 2 pixels out of every 1000 pixels of the Query Image to create a noisy version of the Query Image which is used as reference image in the computation of the Peak signal to Noise Ratio (PSNR) of the Query Image and Database images. The system makes use of PSNR as the only feature for distinguishing one image from the other. Euclidean distance is employed as similarity measure for feature matching. The Novel CBIRS has been extensively tested and found to have 100% Recall ratio and 100% Precision ratio. The Novel CBIRS is found to be less computational complex compared with similar CBIRS schemes. Noise has thus been put to useful application.

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