Content-based Image Retrieval System using Second-Order Statistics

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ABSTRACT
The development of a Content-Based Image Retrieval System (CBIRS) is presented. The second-order statistics were adopted as image features by the system as a means of distinguishing between images. The numbers of co-occurrences of pairs of gray values in an image are recorded in the Gray Level Co-occurrence Matrix (GLCM). Five of the second-order statistics which usually have values greater than 1 were selected; Contrast, Dissimilarity, Entropy, Mean (μ), and Standard Deviation (σ). Thus, fifteen features were recorded for each image from the Horizontal GLCM, Vertical GLCM, and Diagonal GLCM. During Database querying, features of the Query Image are computed and compared with those of the Database images, and Euclidean distance is computed as a similarity measure. The system displays the Query Image, the Retrieved Image (if any), the Best Match Image, and Eight Close Images with their Euclidean distances from the Query Image. Columbia Object Image Library image collection of 7,200 images was selected as the test Database. The developed CBIRS system accurately detects and retrieves Exact Match Images to Query Images with Euclidean distance of the Best Match Image being zero. The system also accurately identifies Query Images which are not in the Database with Euclidean distance of the Best Match Image being greater than zero. The system recorded 100% Recall ratio and 100% Precision ratio.

General Terms
Digital Signal Processing, Digital Image Processing, Algorithm Development.

Keywords
Image retrieval, Second-order statistics, Gray Level Co-occurrence Matrix, Euclidean distance, Recall ratio, Precision ratio.

1. INTRODUCTION
One picture is worth more than ten thousand words in terms of information content [1]. Human beings receive, analyze, and process images throughout their lives. Images are used for domestic, social, educational, medical and industrial applications such as warning against danger, information dissemination, crime investigation, entertainment, diagnosis, phenomenon interpretation and illustration, education, Database management, transportation, aviation, production, remote sensing and mass communication.

A huge amount of digital images containing a huge amount of information are created and stored in Databases in educational institutions, hospitals, government ministries, businesses, industries, arts, sciences, and social sciences for specific purposes. There is a need for efficient browsing, searching, and retrieval of these images. Browsing is sufficient to identify the desired image from a small collection of images. Larger collections of thousands of images, however, require more effective image retrieval techniques. There is growing interest in image retrieval research in digital libraries, remote sensing, Database management applications, astronomy, and image processing [2, 3, 4].

In the 1970s, text and tags were associated with images for identification purposes. These text and tags are how images are searched and identified. This process is known as the Text-Based Image Retrieval System (TBIRS). TBIRS makes use of keywords as tags. TBIRS is efficient for small image Databases as few keywords are required. TBIRS has some limitations for large image Databases. The fact that several semantic keywords are required is a limitation of TBIRS. Furthermore, keywords are subjective as they depend on the different interests of the observers. It's not possible for captions to adequately describe images. TBIRS is time-consuming and inefficient [2, 4].

Content-Based Image Retrieval System (CBIRS) has been introduced to overcome the limitations of TBIRS. Image content is the basis of image searching and retrieval in CBIRS [5, 6]. A retrieval system with color and shape features as the basis for identifying images was presented in [5]. CBIRS has replaced TBIRS in domestic, medical, and industrial applications [7]. Image retrieval is the process of retrieving the most closely Matched Image to a given Query Image automatically by extracting the basic features such as edge, shape, color, and textures from the Query Image and comparing them with the similar features of all the images in the concerned Database.

A feature of an image describes a certain visual property of the image. Image features can be categorized as either global or local [8]. A local feature describes the visual content of a group of pixels while a global feature describes the visual content of the entire image. Global features based CBIRS is fast but has the disadvantage of failure to identify important visual characteristics [2]. Local features based CBIRS is better and more effective than global features based CBIRS [9]. This is because the former represents an image with multiple points in a feature space whereas the latter represents an image with a single point. Local features based CBIRS is, however, more expensive computationally and often require nearest neighbor approximation to perform points matching.

Different types of image features have been used and can be used in image retrieval [2, 4, 10, 11, 12, 13, 14, 15]. In [15], image retrieval based on histogram, color moment, Gray Level Co-occurrence Matrix (GLCM), and Tamura texture features were studied. The highest Recall ratio of 66% and the Highest Precision ratio of 33% were achieved with the color moment. Recall ratio of 36.2% and Precision ratio of 18.1% were achieved with GLCM. The authors concluded that retrieval methods based on a single feature cannot provide acceptable performance [15]. In [14], CBIRS based on certain features were studied. The Gray Level Co-occurrence Matrix is found to have a Precision ratio of 44% and is found to perform better compared with other features [14]. A Precision ratio of 81% was recorded with combinations of features [14]. The authors recommended the study and improvement of retrieval efficiency on a large-scale Database [14].

Content-Based Image Retrieval System (CBIRS) was developed in this work using image second-order statistics. The aim is to improve confidence in and sensitivity of CBIRS. The effectiveness of a combination of second-order statistics as a means of distinguishing one image from the other in a large Database was investigated.

2. CONTENT-BASED IMAGE RETRIEVAL SYSTEM (CBIRS) ALGORITHM

2.1 Basic Sub-Systems

There are three major stages in the Content-Based Image Retrieval System (CBIRS) as illustrated in Fig. 1. The first stage is Feature extraction from images in the Database and the Query Image. Feature Matching for the similarity between the Query Image and each of the images in the Database is the second stage. Finally, the Retrieved Image, the Best Match Image and similarity results are displayed. Fig. 1(a) is for loading or forming the Database while Fig. 1(b) is for querying the Database. During Database loading, features of all the images in a chosen Database of images are computed and stored in the Database. During Database querying, features of the Query Image are computed and compared with the features of all the images in that Database and similarity measures are evaluated.

2.2 Second-order statistics

First-order statistics of an image are descriptive statistics such as contrast, brightness, and histogram which are derived from the image itself [1, 11, 14, 16, 17, 18, 19]. Unlike second-order statistics, first-order statistics do not consider the relationship between neighboring pixels [14].

Second-order statistics of an image are descriptive statistics derived from the Gray Level Co-occurrence Matrix (GLCM) of the image [11, 14, 15, 20, 21, 22, 23, 24]. The numbers of co-occurrences of pairs of gray values in an image are recorded in the GLCM. There are three distinct types of GLCM. These are Horizontal GLCM, Vertical GLCM and Diagonal GLCM [20, 21, 22, 23, 24]. P(i,j) is the normalized GLCM which is obtainable by dividing each element with the sum of all the elements as given by Eqn. (1). There are ten (10) second-order statistics. The computations of the three types of GLCM and their corresponding 10 second-order statistics are explained in [20, 22, 24]. Second-order statistics are also referred to as image texture measures or texture features. The texture is connected with changes in elevation between the high and the low points on a topographical surface. Image texture refers to changes in brightness values (Gray levels) and not changes in elevation [20, 21, 22, 23, 24].

$$P(i,j) = NGLCM(i,j) = \frac{GLCM(i,j)}{\sum_{i=0}^{255}\sum_{j=0}^{255} GLCM(i,j)} \tag{1}$$

Each of the Horizontal GLCM, Vertical GLCM, and Diagonal GLCM generates its own set of ten (10) second-order statistics. Five of these 10 second-order statistics have values that are usually greater than 1 [24]. These five (5) second-order statistics were selected as features for the Content-Based Image Retrieval System in this work. These are Contrast, Dissimilarity, Entropy, Mean (μ), and Standard Deviation (σ) which are given by Eqns. (2), (3), (4), (5) and (6) respectively [11, 14, 15, 20, 21, 22, 23, 24].

$$Contrast = \sum_{i=0}^{255}\sum_{j=0}^{255} (i-j)^2 P(i,j) \tag{2}$$

$$Dissimilarity = \sum_{i=0}^{255}\sum_{j=0}^{255} |i-j| P(i,j) \tag{3}$$

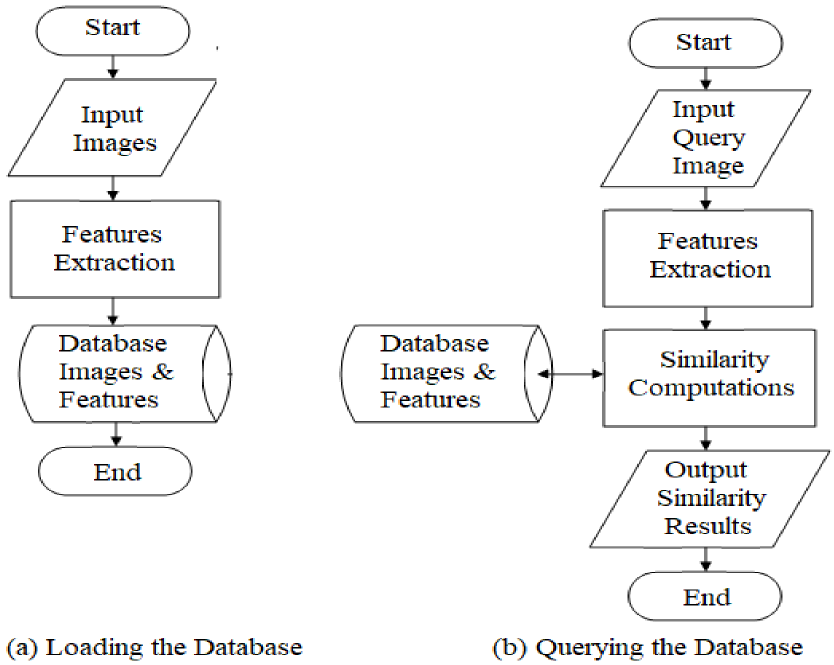

Fig 1: Content-Based Image Retrieval System (CBIRS)

$$Entropy = \sum_{i=0}^{255}\sum_{j=0}^{255} -P(i,j)Log_e[P(i,j)] \qquad (4)$$

$$\mu = \sum_{i=0}^{255}\sum_{j=0}^{255} iP(i,j) = \sum_{i=0}^{255}\sum_{j=0}^{255} jP(i,j) \qquad (5)$$

$$\sigma = \sqrt{\sum_{i=0}^{255}\sum_{j=0}^{255}(i-\mu)^2 P(i,j)} = \sqrt{\sum_{i=0}^{255}\sum_{j=0}^{255}(j-\mu)^2 P(i,j)} \qquad (6)$$

2.3 Test Image Database

An image collection of 7,200 images was selected as the test image Database [25, 26]. The Columbia Object Image Library (COIL-100) is a Database of color images of 100 objects as shown in Fig. 2 [25, 26]. There are 72 versions or poses of each of the 100 objects. Each of the images is a 128-by-128-by-3 matrix [25]. Each image in the Database has a unique name associated with it. For example, 'obj46__250.png' is the image of Object number 46 taken at 250^o pose [25]. In this work, each image in the Database is associated with a unique Serial Number (S/N). Serial Number (S/N) varies from 1 to 7200.

2.4 Feature Extraction

For each image in the Database, the values of the Contrast, Dissimilarity, Entropy, Mean (μ), and Standard Deviation (σ) are computed in the horizontal, vertical and diagonal directions. Thus, fifteen (15) features or parameters are stored for each image. A 7200-by-17 matrix **p** is used for the storage. The first column in **p** is reserved for the image Serial Number (S/N). A lookup table was developed to link the Serial Number and the unique name of each image in the Database. Columns 2 to 16 in matrix **p** are reserved for the fifteen features of each image in the Database. Similarly, the values of the Contrast, Dissimilarity, Entropy, Mean (μ), and Standard Deviation (σ) are computed in the horizontal, vertical and diagonal directions for the Query Image. A 1-by-16 matrix **q** is used for the storage. The first column in **q** is reserved for the Query Image's Serial Number which is 1 as there is only one Query Image at a time. Columns 2 to 16 of matrix **q** are reserved for the fifteen features of the Query Image.

2.5 Similarity Computations: Feature Matching

The similarity between the Query Image and each of the images in the Database is determined by evaluating the Euclidean distance between the fifteen texture features of the Query Image and those of each of the images in the Database [27]. Euclidean distance is selected because of its low complexity [15]. Euclidean distance or Euclidean metric is the distance of a straight line between two points in Euclidean space or Cartesian space. Euclidean distance is also referred to as Euclidean metric or Pythagorean metric [28, 29, 30, 31].

Fig. 2. 100 Objects in the Columbia Object Image Library [25, 26].

The Euclidean distance $E_d(k)$ between the Query Image and the k^{th} image in the Database is calculated using Eqn. (7) and is stored in the k^{th} row and 17^{th} column of Matrix **p**. Matrix **p** is sorted according to Euclidean distance values in column 17 from smallest to largest. The row with the lowest Euclidean distance becomes the 1^{st} row and the row with the largest Euclidean distance becomes the 7200^{th} row.

$$p(k,17) = E_d(k) = \sqrt{\sum_{n=2}^{16} [p(k,n) - q(1,n)]^2} \qquad (7)$$

2.6 Similarity Results

The image in the Database corresponding to the first row in Matrix p after sorting is picked as the Best Match Image. The images in the Database corresponding to the 2^{nd} to 9^{th} rows are picked as being close to the Query Image. The smaller the Euclidean distance value of an image in the Database, the more similar or the closer is it to the Query image. The Serial Numbers (column 1) of the first 9 rows of Matrix **p** are used as pointers to the lookup table to reference the unique names of the Best Match Image and the Next 8 Close Images.

The algorithm computes the features of the Query Image and the Euclidean distance of the Query Image from each of the images in the Database. The algorithm publishes the Best Match Image with the smallest Euclidean distance; it's the Exact Match Image or Retrieved Image if the Euclidean distance is zero. If the Euclidean distance of the Best Match Image is greater than 0.0001, the algorithm declares that the Query Image is not part of the Database and there is no Retrieved Image. The algorithm also publishes the Next Eight Close Images and their Euclidean distances from the Query Image.

2.7 System's Performance Measurement

To measure the performance of the developed Content-Based Image Retrieval System (CBIRS), the concepts of Recall, Precision, and F-Measure are adopted [32, 33, 34]. These concepts are based on the four-cell contingence table of Fig. 3 [32, 33, 34]. If a Query Image is part of the Database and is correctly retrieved by the CBIRS, the retrieval process is classified under true positive (**tp**). **tp** is marked with green color to indicate error free retrieval. If a Query Image is part of the Database but a different image is wrongfully retrieved from the Database or is wrongfully declared as not being part of the Database by the CBIRS, the retrieval process is classified under false negative (**fn**). **fn** is marked with red color to indicate erroneous retrieval.

If a Query Image is not part of the Database but a different image is wrongfully retrieved from the Database by the CBIRS, the retrieval process is classified under false positive (**fp**). **fp** is marked with red color to indicate erroneous retrieval. If a Query image which is not part of the Database and is correctly declared by the CBIRS as not belonging to the Database, the retrieval process is classified under true negative (**tn**). **tn** is marked with green color to indicate error free retrieval.

Precision or Confidence is defined as the number of correct image retrievals divided by the number of image retrievals as described by Eqn. (8). Recall or Sensitivity is defined as the number of correct image retrievals divided by the number of possible image retrievals that could have been made as described by Eqn. (9). Inverse Recall or Specificity is defined as the number of correctly declined images not belonging to the Database divided by the number of Query images which do not belong to the Database as described by Eqn. (10). F-Measure combines Recall and Precision as given by Eqn. (11) [32, 33, 34].

tp	fp	Positive Prediction pp
fn	tn	Negative Prediction np
Positive Class pc	Negative Class nc	

Fig. 3. Four-cell contingence table [32, 33, 34].

$$Precision = Confidence = \frac{tp}{pp} = \frac{tp}{tp + fp} \qquad (8)$$

$$Recall = Sensitivity = \frac{tp}{pc} = \frac{tp}{tp + fn} \qquad (9)$$

$$Specificity = Inverse\ Recall = \frac{tn}{nc} = \frac{tn}{tn + fp} \qquad (10)$$

$$F\text{-}Measure = \frac{2(Precision)(Recall)}{(Precision + Recall)} \qquad (11)$$

3. RESULTS AND DISCUSSIONS

3.1 Sample CBIRS Tests

The CBIRS Algorithm was tested four times. For Tests 1 and 2, the Query Images were selected from the Database as shown in Fig. 4. The Query Image for Test 3 shown in Fig. 4 is not part of the Database. An image from the Database was corrupted to give the Query Image for Test 4 as shown in Fig. 4. The results of the Tests 1, 2, 3, and 4 are presented in Figs. 5, 6, 7, and 8 respectively. Tables 1 and 2 show the values of the fifteen (15) second-order statistics along the Vertical, Horizontal and Diagonal directions which were used to compute the Euclidean distance for the Best Match Image and the Next Eight Close Images for Tests 1 and 3 respectively.

The Query Images for Tests 1 and 2 were from the Database. The Euclidean distance of the Best Match Image was found to be zero for the two tests as shown in Table 1, Figs. 5 and 6. The Retrieved Image was the same as the Best Match Image in these two tests. Exact correct images were retrieved. These results are classified as true positive (**tp**). The result would have been classified as false negative (**fn**) if no or incorrect image is retrieved. The Next Eight Close Images in Figs. 5 and 6 are considered close to the Query Image because they have smaller Euclidean distances from the Query Image. Close Images may or may not visually appear to be similar to the Query Image but have shorter Euclidean distances from the Query Image.

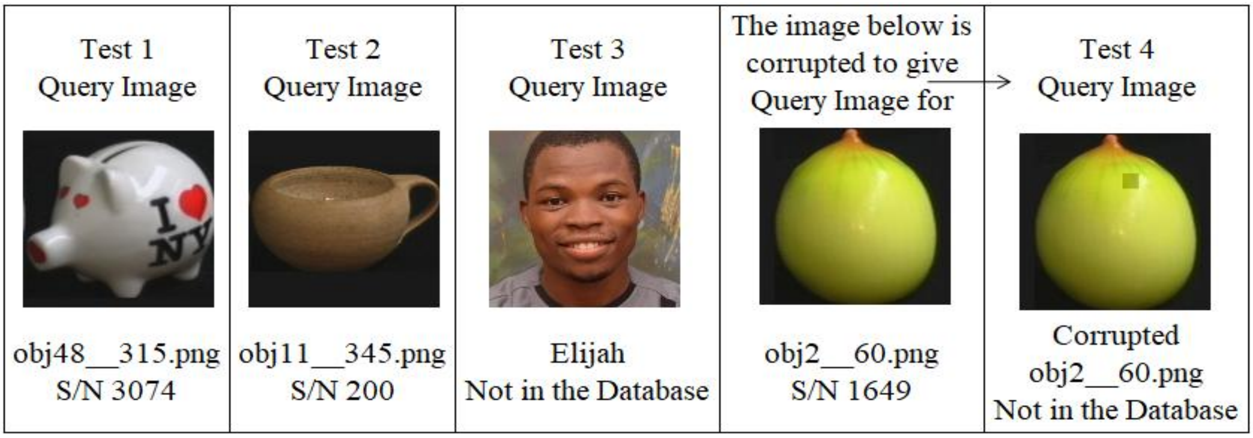

Fig. 4. Four Query Images for Sample Image Retrieval Tests.

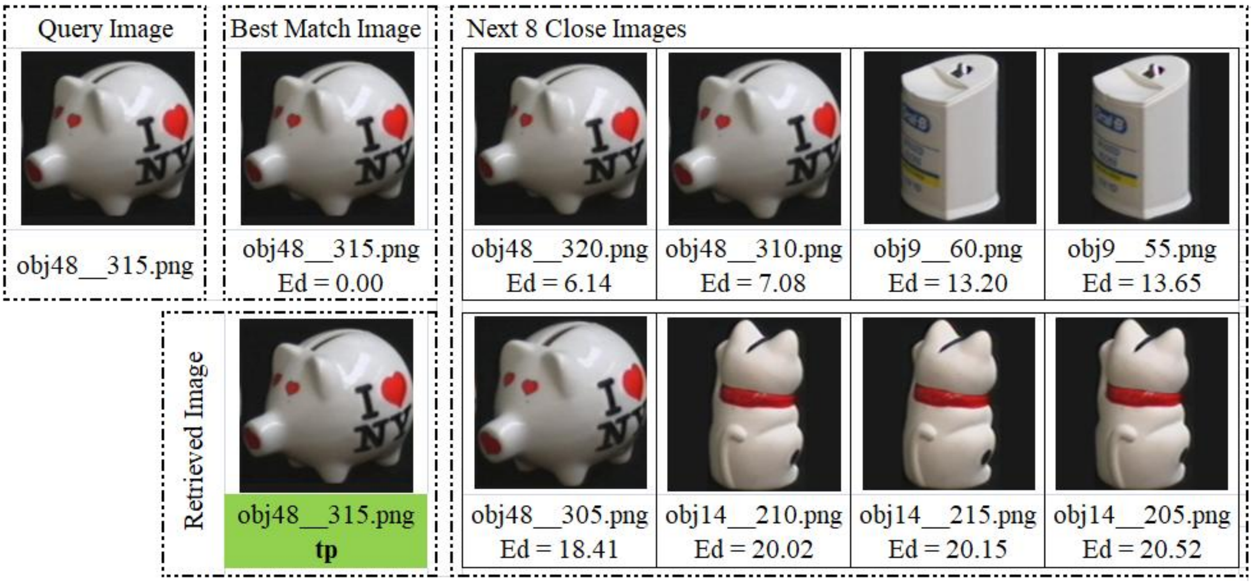

Fig. 5. True positive (tp) result of Sample Test 1: The Query Image, Retrieved Image, Best Match Image, Next Eight Close Images, and Euclidean distances.

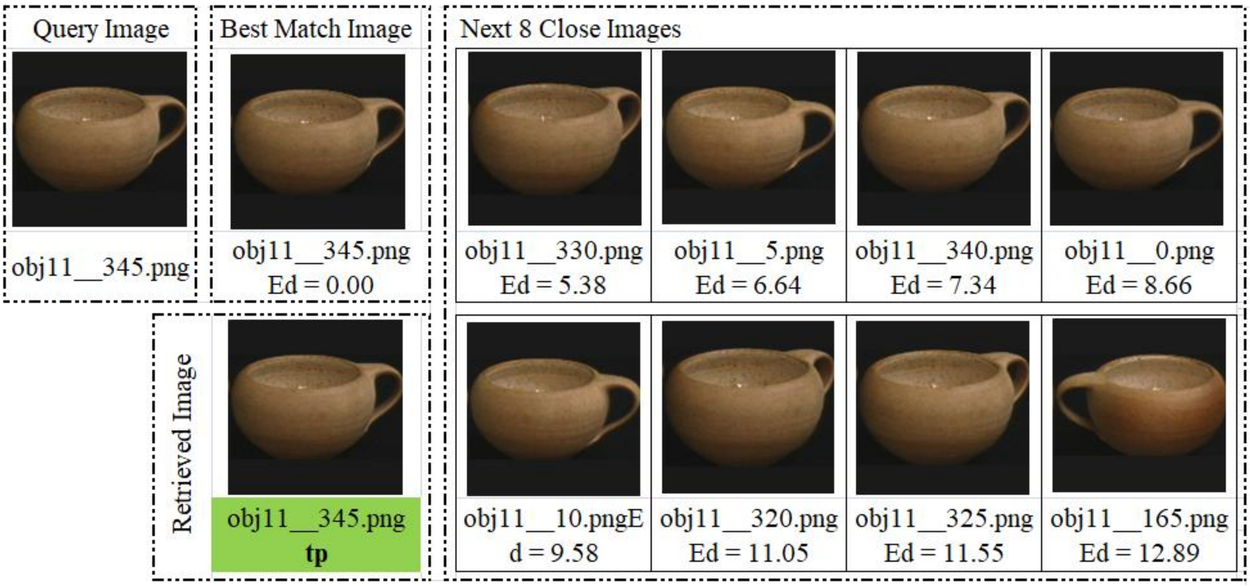

Fig. 6. True positive (tp) result of Sample Test 2: The Query Image, Retrieved Image, Best Match Image, Next Eight Close Images, and Euclidean distances.

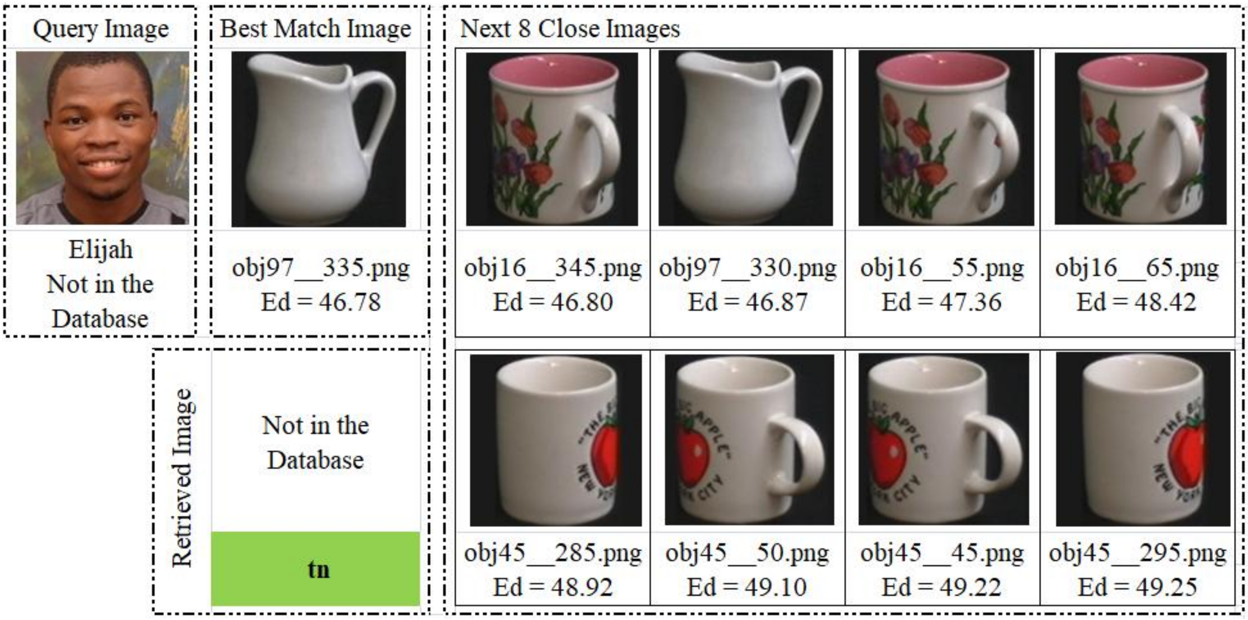

Fig. 7. True negative (tn) result of Sample Test 3: The Query Image, Best Match Image, Next Eight Close Images, and Euclidean distances.

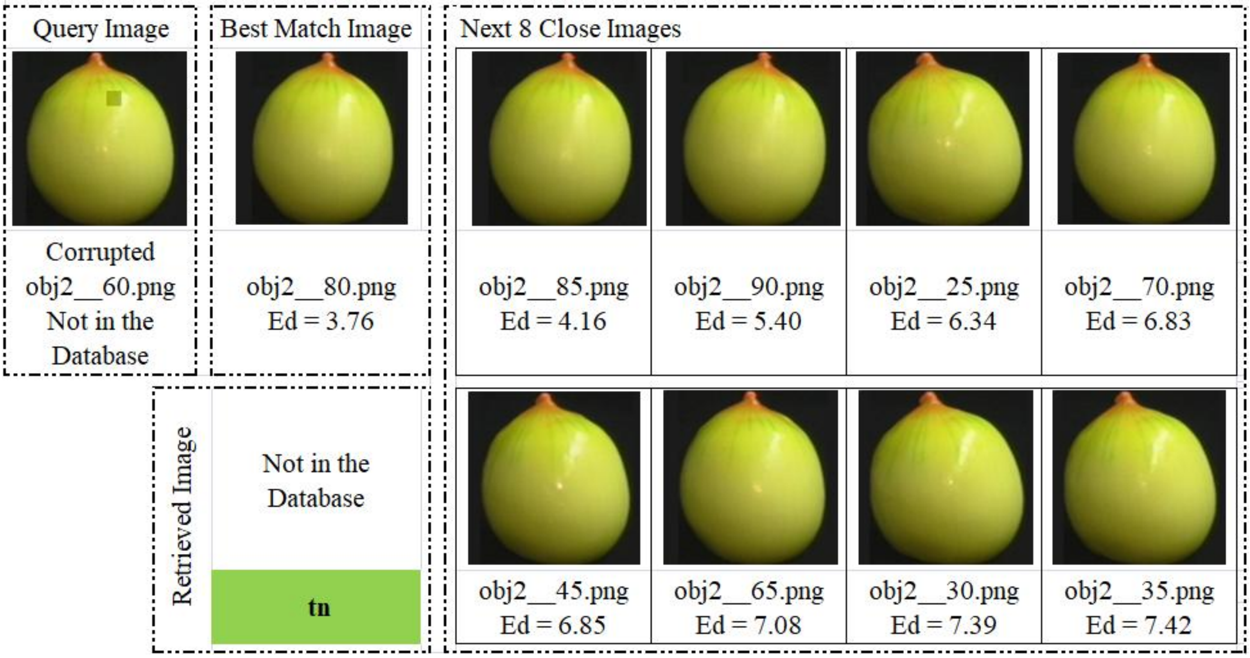

Fig. 8. True negative (tn) result of Sample Test 4: The Query Image, Best Match Image, Next Eight Close Images, and Euclidean distances.

The Query Images for Tests 3 and 4 were not from the Database. The Euclidean distance of the Best Match Image was found to be greater than zero for the two tests as shown in Table 2, Figs. 7 and 8. The Euclidean distance of the Best Match Image was found to be 46.78 and 3.76 for Tests 3 and 4 respectively. Therefore, there is no Retrieved image for Tests 3 and 4. The Query images were declared as not being part of the Database. These results are classified as true negative (**tn**). The result would have been classified as false positive (**fp**) if a wrong image is erroneously retrieved. The Next Eight Close Images in Figs. 7 and 8 are considered close to the Query Image because they have smaller Euclidean distances from the Query Image. Close Images may or may not visually appear to be similar to the Query Image but have shorter Euclidean distances from the Query Image.

3.2 CBIRS Performance Evaluation

In order to evaluate the performance of the developed CBIRS algorithm, the algorithm was tested with 7,600 Query Images one after the other. 7,200 of the Query Images were Database Images. The remaining 400 Query Images were not part of the Database. The Query Image was correctly retrieved with Euclidean distance of zero for each of the 7,200 Database images. Therefore, true positive (**tp**) results were recorded 7,200 times. The Query Image was correctly declared as not being part of the Database for each of the 400 external images. Therefore, true negative (**tn**) results were recorded 400 times. No false positive (**fp**) and no false negative (**fn**) results were recorded.

Table 1. True positive (tp) result of Sample Test 1: Features of the Best Match Image and Eight Close Images; The Best Match Image with Ed = 0 is the Retrieved Image.

	Column No	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
			Vertical					Horizontal					Diagonal					
Row No	Corresponding Image Name	Image S/N	Contrast	Dissimilarity	Entropy	Mean (μ)	Standard Deviation (σ)	Contrast	Dissimilarity	Entropy	Mean (μ)	Standard Deviation (σ)	Contrast	Dissimilarity	Entropy	Mean (μ)	Standard Deviation (σ)	Euclidean Distance
1	obj48_315.png'	3074	137.20	5.43	7.60	91.51	69.84	121.74	5.02	7.43	91.35	69.88	246.16	7.41	7.80	91.87	69.91	0.00
2	'obj48_320.png'	3075	140.69	5.39	7.48	88.97	69.72	122.39	4.96	7.31	88.76	69.74	248.41	7.32	7.67	89.26	69.79	6.14
3	'obj48_310.png'	3073	136.73	5.54	7.77	95.26	70.01	124.41	5.14	7.60	95.10	70.06	246.30	7.53	7.97	95.65	70.06	7.08
4	'obj9_60.png'	7193	137.70	3.76	5.47	89.98	72.80	115.58	3.93	5.49	90.01	72.77	255.33	5.57	5.69	90.49	72.85	13.20
5	'obj9_55.png'	7192	141.12	3.94	5.63	89.23	72.17	116.82	3.97	5.63	89.26	72.15	256.14	5.67	5.85	89.74	72.23	13.65
6	'obj48_305.png'	3072	130.89	5.54	7.99	99.23	69.05	116.92	5.14	7.82	99.11	69.10	236.54	7.54	8.20	99.69	69.06	18.41
7	'obj14_210.png'	387	130.33	3.94	5.37	81.65	71.23	125.89	3.89	5.38	81.66	71.22	251.01	5.77	5.59	82.09	71.33	20.02
8	'obj14_215.png'	388	132.46	3.99	5.40	80.85	70.73	124.59	3.86	5.40	80.86	70.72	250.36	5.75	5.61	81.29	70.84	20.15
9	'obj14_205.png'	386	126.46	3.90	5.47	83.41	71.79	128.84	4.00	5.51	83.44	71.77	251.95	5.82	5.72	83.87	71.88	20.52
		← First 9 rows of Matrix p at the end of Image Retrival Test 1. →																

Table 2. True negative (tn) result of Sample Test 3: Features of the Best Match Image and Eight Close Images; No Retrieved Image as Ed > 0 for the Best Match Image (Ed = 46.78).

	Column No	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
			Vertical					Horizontal					Diagonal					
Row No	Corresponding Image Name	Image S/N	Contrast	Dissimilarity	Entropy	Mean (μ)	Standard Deviation (σ)	Contrast	Dissimilarity	Entropy	Mean (μ)	Standard Deviation (σ)	Contrast	Dissimilarity	Entropy	Mean (μ)	Standard Deviation (σ)	Euclidean Distance
1	'obj97_335.png'	6966	132.79	4.47	7.10	94.57	62.78	105.83	4.09	7.02	94.57	62.78	217.48	6.31	7.38	95.10	62.74	46.78
2	'obj16_60.png'	569	128.61	5.31	7.10	80.44	53.73	123.46	5.34	7.16	80.45	53.72	253.27	8.01	7.48	80.87	53.72	46.80
3	'obj97_330.png'	6965	126.79	4.38	7.08	94.49	62.33	106.81	4.08	7.01	94.50	62.32	215.29	6.27	7.36	95.03	62.27	46.87
4	'obj16_55.png'	568	131.71	5.56	7.42	82.03	53.52	130.75	5.63	7.48	82.06	53.49	258.74	8.30	7.80	82.48	53.48	47.36
5	'obj16_65.png'	570	129.46	5.26	7.04	80.29	53.63	120.19	5.29	7.11	80.31	53.60	255.26	7.98	7.41	80.72	53.61	48.42
6	'obj45_285.png'	2851	145.04	4.36	6.51	92.18	59.35	96.21	3.93	6.48	92.22	59.31	228.67	5.97	6.75	92.70	59.29	48.92
7	'obj45_50.png'	2871	147.72	5.12	7.59	99.91	62.65	104.97	4.67	7.53	99.94	62.61	213.99	6.75	7.86	100.49	62.55	49.10
8	'obj45_45.png'	2869	151.48	5.33	7.72	96.88	61.65	104.40	4.77	7.64	96.90	61.63	213.96	6.90	7.98	97.44	61.56	49.22
9	'obj45_295.png'	2853	150.11	4.61	6.53	87.59	58.82	103.28	4.18	6.50	87.62	58.79	240.43	6.31	6.77	88.08	58.78	49.25
		← First 9 rows of Matrix p at the end of Image Retrival Test 3. →																

The Precision, the Recall, the Inverse Recall and the F-Measure are calculated to be 1 (100%) as shown in Eqn. (12) to (16). These levels of Recall ratio and Precision ratio are higher than those recorded in [14] and [15].

$$tp = 7200, tn = 400, fp = 0, fn = 0 \tag{12}$$

$$Precision = Convidence = \frac{tp}{pp} = \frac{tp}{tp + fp} = \frac{7200}{7200} = 1 \tag{13}$$

$$Recall = Sensitivity = \frac{tp}{pc} = \frac{tp}{tp + fn} = \frac{7200}{7200} = 1 \tag{14}$$

$$Specificity = Inverse\ Recall = \frac{tn}{nc} = \frac{tn}{tn + fp} = \frac{400}{400} = 1 \tag{15}$$

$$F\text{-}Measure = \frac{2(Precision)(Recall)}{(Precision + Recall)} = 1 \tag{16}$$

4. CONCLUSIONS

A Content-Based Image Retrieval System (CBIRS) has been developed. The system is based on fifteen second-order statistics which are descriptive statistics derived from the Horizontal, Vertical and Diagonal versions of the Gray Level Co-occurrence Matrix (GLCM) of the concerned images. Euclidean distance has been employed as the similarity measure for matching the fifteen features of the Query Image with those of the Database images. The CBIRS has been extensively tested on a Database of seven thousand and two hundred images. The system accurately retrieves images from the Database. The system also accurately identifies Query Images which are not in the Database with Euclidean distance of the Best Match Image being greater than zero. The combination of fifteen selected features which are Contrast, Dissimilarity, Entropy, Mean (μ), and Standard Deviation (σ) in the Horizontal, Vertical and Diagonal versions of GLCM are therefore sufficient and adequate in detecting similarities and or differences between a large number of images in a Database. The system recorded 100% Recall ratio and 100% Precision ratio.

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