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New Distance Measurements for Image Similarity

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Abstract:
New measures have been proposed for assessing the similarity of gray-level images. The famous structural similarity index measurement (SSIM) has been designed using statistical approach that fails with high noise (lowPSNR). The two proposed measures have been suggested, the first one depend on Manhattan distance and standard division, this measure combined from two parts: the first part depend on the Manhattan distance which is used in geometric features the second part is based on statistical feature. The second measure utilized the modification of Euclidian distant. The two proposed similarity measures are outcome for human face. The new measures outperform the classical SSIM in detecting image similarity at low PSNR, with significant difference in performance. The results were (95.3% for the first measurement) and (99.2% for the second measurement). We used database Face94

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Keywords: image structural similarity, image similarity, Manhattan distance, Standard Deviation, Gaussian noise, Euclidian distance.

1-Introduction:

In image processing, applications that require comparing two images according to their content, image matching is an essential component in this process. One of the most important examples is the image database retrieval systems [1]. Image similarity has become in the recent years a basic point in image processing applications like monitoring, image compression, restoration, and many other applications. Various image similarity assessment techniques can be used to detect differences between two images.
Image similarity can be well-defined as the differece between tow images, and image match measure is a numerical difference between two different images under comparison.

Similarity techniques can be classified according to the methods they use in deriving or defining the difference. The first kind of techniques is the statistical – based methods, and the second important type is the information - theoretical techniques [2].

An old statistical measure that has been widely used to detect image similarity is the mean squared error

(MSE) [3- 5]. Recently, light has been shed on a new measure that coincides with the Human Visual System (HSV): Structural Similarity Index Measure (SSIM) is proposed in 2004 by Wangand Bovik. SSIM proved to be distinguished due to its notable performance as compared to the previous metrics [1] [6].

In 2013, D. Mistry, etal. Tatu proposed a new similarity measure that base on joint entropy (joint histogram). The proposed measure is based on the fact of the joint entropy is the measure of uncertainty between two images, so if the joint entropy is low then the similarity between two images are high, and vice-versa. The joint entropy was first applied on two compared images using joint histogram as in [9].

In 2014, A. F. Hassan, etal. Hussein proposed a new measure called HSSIM that based on joint histogram. HSSIM outperforms statistical similarity of SSIM; it has the ability to detect similarity under significant noise (low PSNR), with an average difference of nearly 20 dB with SSIM [2].

H. R. Mohammed and Z.M. Hussaing. (2017), the researcher proposed a new similarity measure that is called SjhCorr2 (Symmetric Joint Histogram— 2-D correlation) is a hybrid measure based on both: information-theoretic and statistical based. The proposed measures tested under different noise type such as Gaussian noise and impulsive noise [10].

S. K. Ali and Z.M. Aydam 2019, the researcher proposed a new similarity measure that is called modify Standardize Euclidian distance. [11]

In this work two similarity measures were proposed. The geometric and statistic features are combined to produce the measure similarity. The first similarity measure depends on Manhattan Distance and standard deviation. The second measure depend on Euclidean Distance.

2-Methodology:

There are two major approaches for image similarity: statistical approaches or called photometric that distills an image into values and compares the values with templates to eliminate variances. [8] and geometric approaches. which looks to distinguishing features.

2.1 Statistical methods:

Mean-squared error (MSE) is a well-known statistical measure. However, MSE is too weak for modern applications of image processing like face recognition. The first significant structural similarity measure, called Structural Similarity Index Measure (SSIM), which has been proposed in 2004 [1]. SSIM used statistical image parameters such as mean, variance, co-variance, and standard deviation as follows [1, 8]:

$$\mathbf{SSIM}=\frac{(2\mu x\mu y+C_1)(2\sigma_{xy}+C_2)}{(\mu_x^2+\mu_y^2+C_1)(\sigma_x^2+\sigma_y^2+C_1)} \qquad (1)$$

Where SSIM metric between images x and y, while μ_x , μ_y, and σ_x^2 , σ_y^2 are the statistical means and variances of x and y, respectively; σ_{xy} is the covariance of x and y, and finally the constants C_1 and C_2 are inserted to avoid unstable results that maybe reached due to division by zero, and are defined as C_1= $(K_1L)^2$ and C_2= $(K_2L)^2$,with K_1 andK_2 are small constants and L = 255 (maximum pixel value).

2.2Geometric methods:

In geometric approach, the similarity between *x* and *y* (where *x* and *y* are images) can be defined as the corresponding differences between geometric features of the two images. The more differences between two images refer to that the images are not similar [9].

2-3 Pre-processing:

The input images were processing to have same conditions. It is usually done to change the acquired image size to a specific size such as 180x180 pixels, (depend on the system operates).

2-4 Feature extraction:

The main features are extracted from input human face images. These features are powerful against illumination, pose, aging differences and expression. [12].

2-4-1 Geometric features:

Geometric features are the features of the objects that have been created by a group of geometric elements like lines, points, curves or surfaces. There are a set of geometric measurements (Euclidean distance, Angle, Slope, Perimeter, Area, Rotation Centroid and Extreme Points) to extract the features of the human face as better than the others; the mathematical description of these measurements is given below.[13].

2-4-1. a Euclidean distance:

The Euclidean distance is one of the most important measuring ways used to find the similarity between two vectors (observed vector with saved vector) [1٤]. The formula of the Euclidean distance is in equation.2. Take the square root of the sum of the squares of the differences of the coordinates.

For example, if xx= (aa, bb) and yy= (cc, dd) the Euclidean distance between xx and yy is

$$EUD=\sqrt{(aa-cc)^2+(bb-dd)^2} \qquad \textbf{(2)}$$

2-4-1.b Angle:

Is the separation or break between the two straight lines merging with one another, where the crossing point of the two lines and their intersection are known as the angle head (Vertex), and the two line the two parts of the angle they know two ribs of the angle, the angle comprises of two bars going from a similar beginning stage. The angle is determined any between the two intersectional lines According to the accompanying equation .3 [1٥]

$$Angle = tan^{-1}((S_1-S_2)/(1+S_1*S_2)) \qquad (3)$$

$\boldsymbol{S_1}$: The slope between (Y) and (X).

S_2 : The slope between (Y) and (Z**).**

2-4-2 Statistical features:

Singular value decomposition (SVD) is a decent strategy to extricate image features. Since it has invariance for the turn and reflecting change, and furthermore has better heartiness for clamor and light force change [15]. SVD is a result of direct polynomial math. It plays an intriguing, key job in a wide range of uses that is, face recognition, image compression, watermarking, object detection, scientific computing, signal processing, texture classification and so on [1٧]. The singular value decomposition of a matrix is one of the most elegant the richest and amazing calculations in straight polynomial math, and it has been widely utilized for rank and measurement decrease in example pattern recognition and information retrieval applications [1٨].

3. 1 The First New Measurements:

This measument is based on two basic principles, Manhattan distance and standard division. The measurement was modified and was used as being based on the geometric features of the object and was incorporated with standard division to give better results and closer to reality.

3.1.a Manhattan distance:

Definition: The distance between two points measured along axes at right angles [1٩]. In a plane with vector u and vector v

$$D_{Ctb} = \sum_{i=1}^{N} |u_i - v_i| \qquad (4)$$

For example, if xx= (aa, bb) and yy = (cc, dd) the Manhattan distance between xx and yy is

D_{cti} = abs ((aa−cc) + (bb−dd)).

For your vectors, it's the same thing except you have more coordinates.

A taxicab geometry is a form of geometry in which the usual distance function or metric of Euclidean geometry is replaced by a new metric in which the distance between two points is the sum of the absolute differences of their Cartesian coordinates. The taxicab metric is also known as rectilinear distance snake distance, city block distance, Manhattan distance or Manhattan length, with corresponding variations in the name of the geometry. [٢٠] The latter names allude to the grid layout of most streets on the island of Manhattan, which causes the shortest path a car could take between two intersections in the borough to have length equal to the intersections' distance in taxicab geometry.

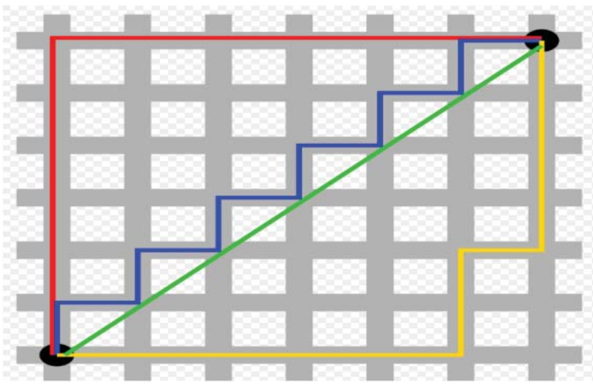

Figure (١) display Graphical comparison between Manhattan and Euclidean distance

In figure (١) Taxicab geometry versus Euclidean distance: In taxicab geometry, the red, yellow, and blue paths all have the same shortest path length of 12. In Euclidean geometry, the green line has length and is the unique shortest path.

3.1.b Standard Deviation:

The standard deviation is a numerical value used to indicate how widely individuals in a group vary. If individual observations vary greatly from the group mean, the standard deviation is big; and vice versa. [20] It is important to distinguish between the standard deviation of a population and the standard deviation of a sample. They have different notation, and they are computed differently. The standard deviation of a population is denoted by σ and the standard deviation of a sample, by ***s***.

The standard deviation of a population is defined in equation.5:

$$\sigma = \sqrt[2]{[\Sigma\,(Xi - X)2\,/\,N\,]} \quad (5)$$

Where σ is the population standard deviation, X is the population mean, X_i is the *i*th element from the population, and N is the number of elements in the population. [19]

The standard deviation of a sample is defined by slightly different formula:

$$s = \sqrt[2]{[\Sigma\,(xi - x)2\,/\,(n - 1)\,]} \quad (6)$$

where *s* is the sample standard deviation, x is the sample mean, x_i is the *i*th element from the sample, and n is the number of elements in the sample.

The new measure is

$$M(x, y) = (\sum|x-y|/\ \mathrm{STD}\ y)^2$$

The value of proposed measure will ensure that:

$$0 \le v(x, y) \le 1$$

The final version of the first part can be stated as follows:

$$q(x, y) = 1 - v(x, y)$$

The second part of the measure is standard deviation to the internal image(observed) images follows:

$$\sigma = \sqrt[2]{[\Sigma\,(Xi - X)2\,/\,N\,]} \quad (7)$$

where xi and *are* the mean values of *x*.

Note that 0 ≤ new measure≤ 1; giving 1 for completely similar images and 0 for completely different images.

The above new measure can be calculated according to the following algorithm

Algorithm:

Input: Images *x* and *y*, which are the observed image (with noise) and saved image respectively.

Output: Similarity, a number ranging between 0 and 1.

Step 1: Convert color image into gray scale.

Step 2: Convert image values into double type.

Step 3: Set feature vector (Geometry and statistical) of observed (noisy image) and saved image that is represent x and y.

Step 4: Set(Q)= Manhattan distance (X, Y)

Step 5: Set *S*= Standard deviation (y)

Step 6: compute Z

$$Z = (Q/S) \wedge 2.$$

Step 7: Set q *(x, y)* = 1 –*Z*.

End.

3.2The second new measurement:

Modify Euclidean distance for being new measurement for similarity between images because it dependent on geometric features of object to give better results and closer to reality. Details as below.

3.2. aEuclidean distance:
The Euclidean distance is one of the most important measuring ways used to draw the similarity between two vectors (testing vector with dataset vector). The formula of the Euclidean distance is shown below. Take the square root of the sum of the squares of the differences of the voters.

$$D_{Euc}(u,v) = \sqrt{\sum_{i=1}^{N}(u_i - v_i)^2}$$

The result of the Euclidian distance between the vector of observed and stored images divided by the vector of observed image and finally, the value of the process multiple in C that is small constant The new measure is

$$E(x, y) = (\sqrt[2]{(a-c)^2 + (b-d)^2}/y) * C$$

The value of proposed measure will ensure that:

$$0 \leq E(x, y) \leq 1$$

The final version can be stated as follows:

$$q(x, y) = 1 - E(x, y).$$

Note that 0 ≤ new measure ≤ 1; giving 1 for completely similar images and 0 for completely different images. The above new measure can be calculated according to the following algorithm.

Algorithm:
Input: Images *x* and *y*, which are the observed image (with noise) and saved image respectively.
Output: Similarity, a number ranging between 0 and 1.
Step 1: Convert color image into gray scale.
Step 2: Convert image values into double type.
Step 3: Set feature vector (Geometry and statistical) of observed and stored image that is represent x and y.
Step 4: Set(Q)= Euclidian distance (X, Y) by Eq.2
Step 5: Set *S*= *y*
Step 6: compute Z

$$Z = (Q/S) * C.$$

Step 7: Set q $(x, y) = 1 - Z$.
End.

4.Test Environment:
In common noise is representing the unwanted things produced in the image [21]. Image noise is random difference of brightness or color information in images. Noise can be created from dissimilar sources such as the sensor and circuit board of a scanner or digital camera. Image noise can also create in film grain and in the necessary shot noise of an ideal photon detector. Image noise is an unwanted by- product of image capture that increases false and minor information to test the performance of the proposed measure, type of images has been considered: a human face (face 94database, [22]), [23] Type of noise have been considered in simulation and testing: Gaussian noise, Gaussian noise is squarely distributed above the signal. Generally, each pixel in the noisy image is values of the sum of a random Gaussian distributed noise and true pixel. Gaussian distribution of this type of noise.
The probability distribution function takes the shape of the bell as such [24]:

$$PG(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu_x)^2}{2\sigma^2}} \qquad (8)$$

where x signifies the grey level, σ the standard deviation and.
μ_x the mean value which is one of the most popular noise types that are encountered in signal processing systems; which is common in image processing. To test the performance of the proposed measure, a human face (face94 database,) images have been considered.

5.The Results and The Discussion:

The proposed measure has been tested and simulated using MATLAB.
The proposed measure has been tested with Gaussian noise, which is the most popular noise that attacks images and systems. Results are shown in Figures 1-3. Table 1 shows a comparison between the SSIM and MMD for different types of images. The proposed measure gives larger similarity than SSIM with Gaussian noise.

Table 1: The proposed measure MMD, MED vs. SSIM for three human face

Human image	MMD	MED	SSIM
image1	0.9484	0.9997	0.7188
Image2	0.9046	0.9999	0.8143
Image3	0.9387	0.9998	0.6558

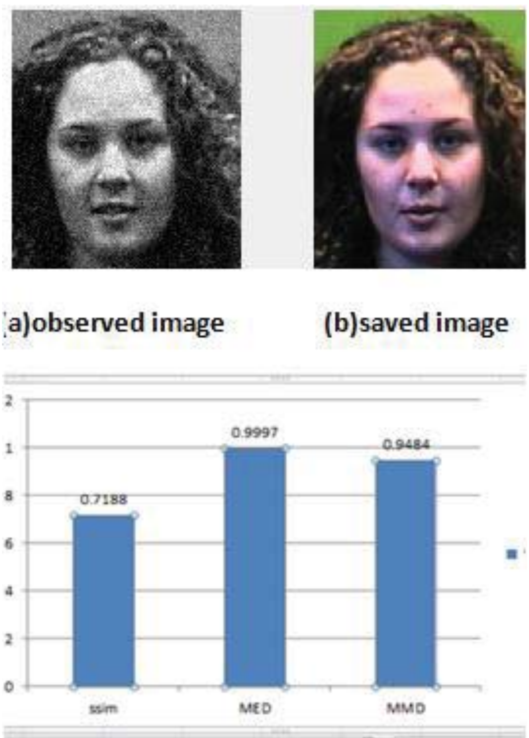

Figure 2: Performance comparison of SSIM and MDD using similar images (human image1)

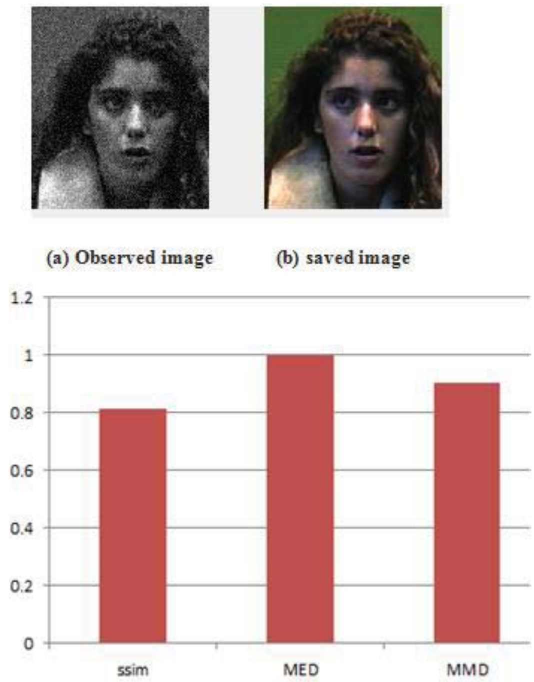

Figure 3: Performance comparison of SSIM and MDD using similar images (human image)

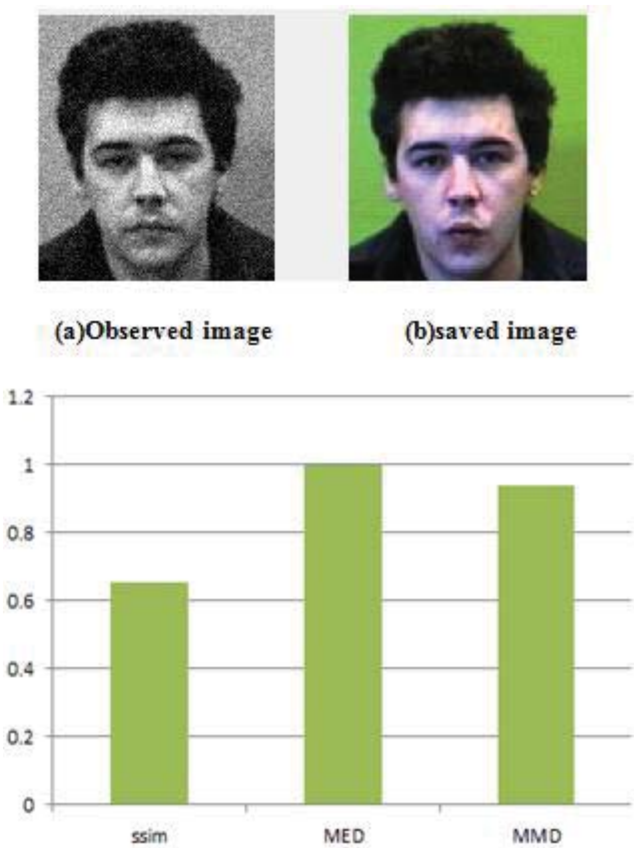

Figure 4: Performance comparison off SSIM and MDD

6- CONCLUSION:

Results show that the proposed quality measure (by Manhattan distance and STD) provides results that are more consistent with human perception of color image quality assessment and also greatly improves the performance of SSIM at low PSNR on many distortion types. In this paper, we present an improvement to the well-known Multi-Scale Structural Similarity index (SSIM) by adding a gray comparison to the criteria of the gray scale SSIM. The new image quality measure fully uses the geometry and statistical information of the image for the assessment of color distortions that are difficult to be noticed using the luminance channel only or gray scale conversion of the color image at low PSNR. The proposed measures gave better result than using statistical measure and geometrical theoretic measure individually.

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