Modify Manhattan Distance For Image Similarity

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Abstract

A New measure is proposed for assessing the similarity among gray-scale images. The well-known Structural Similarity Index Measure (SSIM) has been designed using a statistical approach that fails under significant noise (low PSNR). The proposed measure, denoted by Manhattan distance and STD, uses a combination of two parts: the first part is Geometric method, while the second part is based on statistical feature. The concept of Manhattan distance is used in the geometric part. The new measure shows the advantages of statistical approaches and geometric approaches. The proposed similarity method is outcome for human face. The novel measure outperforms the classical SSIM in detecting image similarity at low PSNR, with significant difference in performance.

Keywords: Image Structural Similarity, Image Similarity, Mahattan distance, Standard deviation, Gaussian Noise

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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. In recent years, image similarity measure has become an essential aspect in real world applications. It can be used for various image processing applications such as dynamic monitoring, adjusting image quality, image enhancement, compression, restoration, and other applications.

Image similarity can be defined as the difference between two images, and image similarity 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, 4, 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 Wang and Bovik. SSIM proved to be distinguished due to its notable performance as compared to the previous metrics [1, 6].

Image recognition has become an interesting subject for researchers over the past two decades because of its potential applications in many important fields like character recognition, human computer interfaces, identity authentication and video surveillance.

Different methods for image recognition, mostly for face image recognition, have been proposed [7]. Many algorithms of face and

object recognition systems have recently been designed based on image similarity measure like SSIM [1]

In this work we propose a similarity measure that combines features of Statistical approach and geometry features as represented by (distance, angle) a new formula for measure similarity by used Manhattan Distance and standard deviation.

The paper is organized as follows: Section 2 deals with SSIM, which is the well-known structural similarity, Section 3. In Section 4, experimental results are presented; along with performance measures. The conclusions of this study are given in Section 5

METHODOLOGY

There have been 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 look at distinguishing features.

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), has been proposed in 2004 [1]. SSIM used statistical image parameters such as mean, variance, co-variance, and standard deviation as follows [1, 8]:

$$P(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_1)} \quad (1)$$

where $\rho(x, y)$ is the SSIM metric between images x and y , while μ_x , μ_y , σ_x^2 and 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 may be reached due to

division by zero, and are defined as $C_1 = (K_1 L)^2$ and $C_2 = (K_2 L)^2$, with K_1 and K_2 are small constants and $L = 255$ (maximum pixel value).

Geometric 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 they have, the less similar they are [9].

In 2013, D. Mistry, A. Banerjee and A. Tatu proposed a new similarity measure that based on joint entropy (joint histogram). The proposed measure is based on the fact of the joint entropy is the measure of uncertainty among 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, D. Cai-lin and Z. M. Hussain 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. Hussain (2017), in this paper, 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, in this paper, the researcher proposed a new similarity measure that is called modify Standardize Euclidean distance. [11]

FEATURE EXTRACTION

At this stage and after the implementation of appropriate pre-processing, the main features are extracted. These features are powerful against pose, illumination, expression and aging differences. [12]

Geometric features

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

EUCLIDEAN 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) [13]. The formula of the Euclidean distance is shown below

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

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

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 (2.24) [14]

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

S_1 : The slope between (Y) and (X).

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

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 [16]. The singular value decomposition of a matrix is one of the most elegant the most rich 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 [17].

See Appendix- A

A NEW MEASUREMENT

A Modify MahattanDistance measure is utilized here to create a new measure, designed to be a hybrid measure combining statistical features (represented by Standard Deviation) with geometrical features. The new measure is a combination of two parts as follows. The first part of the proposed measure is the geometry - theoretic part that uses the concept of MahattanDistance, defined as follows:

Manhattan distance

Definition: The distance between two points measured along axes at right angles [18]. In a plane with p_1 at (x_1, y_1) and p_2 at (x_2, y_2) , it is $|x_1 - x_2| + |y_1 - y_2|$.

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. [19]

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 by the following formula:

$$\sigma = \sqrt{\sum (X_i - X)^2 / N}$$

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:

$$s = \sqrt{\sum (x_i - x)^2 / (n - 1)}$$

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.

And finally, the standard deviation is equal to the square root of the variance.

The new measure is

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

The value of proposed measure will ensure that:

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

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(tested) images as follows:

$$\sigma = \sqrt{\sum (X_i - X)^2 / N} \quad (5)$$

where X and σ are the mean values of x .

Note that $0 \leq$ 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

$$Z = (Q/S)^2$$

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

End of Algorithm.

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 have

been considered: a human face (face 94 database, [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 the 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]:

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

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.

RESULTS AND DISCUSSION

The proposed measure has been tested and simulated using MATLAB.

Performance under Gaussian Noise:

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 vs. SSIM for three human face

Human image	MMD	ssim
image1	0.9484	0.7188
Image2	0.9046	0.8143
Image3	0.9387	0.6558

(a) input image (noisy)

(b) saved image (D.B.)

Performance comparison off SSIM and MDD

Fig 1: Performance comparison of SSIM and MDD using similar images (human image1)

(a)input image

(b) saved image

Performance comparison off SSIM and MDD

Fig 2: Performance comparison of SSIM and MDD using similar images (human image)

(a)Input Image

(b) saved image

In figure 3 show the Images: Observed(noisy) and Saved (D.B) and their Performance comparison off SSIM and MDD

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 measure gave better result than using statistical measure and geometrical theoretic measure individually.

REFERENCES

1. Z. Wang, A. Bovik, H. Sheikh, E. Simoncelli, Image quality assessment: From error visibility to structural similarity, *IEEE Trans. Image Process.* 13 (4) (2004).
2. F. Hassan, D. Cai-lin, Z. M. Hussain, An information-theoretic image quality measure: comparison with statistical similarity, *Journal of Computer Science* 10 (11) (2014).
3. P. Premaratne, M. Premaratne, New structural similarity measure for image comparison, *Proceedings of the International Conference on Emerging Intelligent Computing Technology and Applications, ICIC 2012, Huangshan, China* (2012).
4. M. Eskicioglu, Quality measurement for monochrome compressed images in the past 25 years, *IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP2000)* (2000).
5. Girod, Psychovisual aspects of image processing: What's wrong with mean squared error?, *Proceedings of the Seventh Workshop on Multidimensional Signal Processing* (1991).
6. J. Goldberger, S. Gordon, H. Greenspan, An efficient image similarity measure based on approximations of kl-divergence between two gaussian mixtures, *IEEE International Conference on Computer Vision (ICCV)* (2003).
7. W. Zhao, R. Chellappa, P. J. Phillips, A. Rosenfeld, Face recognition: a literature survey, *ACM Computing Surveys* (2003).
8. Zhang, David; Jain, Anil (2006). *Advances in Biometrics: International Conference, ICB 2006, Hong Kong, China, January 5-7, 2006, Proceedings*. Berlin: Springer Science+Business Media.
9. Z.Wang, A. Bovik, *Modren Image Quality Assessment*, Morgan & Claypool Publishers, 2006 (2006).
10. D. Lin, An information-theoretic definition of similarity, *Proceedings of the Fifteenth International Conference on Machine Learning (ICML'98)* (1998).
11. H. R. Mohammed and Z.M. Hussainga, acoorlative information theoritice measure for image similarity.(2017)
12. S.K.Ali and Z.M.Aydam, Gestures conversion to Arabic letters(2019)
13. J. L. Rodgers, W.A. Nicewander, Thirteen ways to look at the correlation coefficient, *The American Statistician* 42 (1) (1988).
14. Mahmoud A Muhsan Al-Dulami, "Feature-Based Face Recognition System Using Gabor Filter", M.Sc. Thesis, University Of Technology, Informatics Institute For Postgraduate Studies, Iraq, 2005.
15. Michel Marie Deza and Elena Deza, "Encyclopedia of Distances", Springer, p. 94, 2009.
16. Hermann K. , "Real-Time Systems Design Principles for Distributed Embedded Applications", Second edition, Springer, 2011.
17. Zhang, David; Jain, Anil (2006). *Advances in Biometrics: International Conference, ICB 2006, Hong Kong, China, January 5-7, 2006, Proceedings*. Berlin: Springer Science+Business Media.
18. V.Vijayakumari, "Face Recognition Techniques: A Survey", *World Journal of Computer Application and Technology*, vol. 1, no. 2, pp. 41-50, 2013.
19. Sergios Theodoridis And Konstantinos Koutroumbas, "Pattern Recognition", Book, Elsevier Inc, 2009.
20. Face94 Laboratories Cambridge, face94 face database <http://www.cl.cam.ac.uk/research/dtg/attarchive/facedatabase.html> (2002).
21. The Directed Distance" (PDF). Information and Telecommunication Technology Center. University of Kansas. Archived from the original (PDF) on 10 November 2016. Retrieved 18 September 2018.
22. 2008 الاحصاء والاحتمالات، الجزائر
23. R. Verma and J. Ali, "A comparative study of various types of image noise and efficient noise removal techniques," *International Journal of advanced research in computer science and software engineering*, vol. 3, no. 11, pp. 617-622, 2013.
24. L. Spacek, University of essex, department of computer science, <http://cswww>.

25. essex.ac.uk/mv/allfaces/faces94.html.
26. M. A. Farooque and J. S.Rohankar, "Survey on various noises and techniques for denoising the color image," International Journal of Application or Innovation in Engineering & Management (IAIEM), vol. 2, no. 11, pp. 217-221, 2013.
27. C. Saxena and P. D. Kourav, "Noises and Image Denoising Techniques: A Brief Survey," International Journal of Emerging Technology and Advanced Engineering, vol. 4, no. 3, pp. 878-885, 2014.3

APPENDIX – A

image	distances		angle s	svd
image1	image2			
27.771	24.186	25.495		
14.318	13.647	13.086		
32.33	28.57	28.901		
53.339	45.136	25.495		
32.33	28.57	36.335		
39.513	36.401	44.071		
27.771	24.187	44.071		
37.911	34.34	28.901		
53.339	45.136	36.173		
37.911	34.34	36.335		
14.318	13.647	13.086		
39.513	36.401	36.173		
36.721	35.053	24.214		
1.963	-3.085	-2.748		
-3.109	2.401	-9.437		
-3.109	1.707	-7.652		
9.619	10.696	10.892		
6.953	-2.234	-1.147		
5.829	8.347	6.939		
1.561	-8.035	2.869		
7.237	7.01	4.611		
-5.048	-3.161	3.572		
1.639	-8.708	3.180		
2.322	9.246	-3.608		
4.559	-2.685	-4.108		
3.293	-1.422	-3.507		
2.456	1.145	-3.608		
1.693	-3.764	1.124		
7.373	2.054	-3.209		
4.666	-1.605	-9.159		
6.072	-1.346	-3.088		
1.867	5.412	9.539		
4.961	3.574	2.429		
1.52	1.383	1.307		
2.181	2.049	1.886		