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Design of a hybrid measure for image similarity: a statistical, algebraic, and information-theoretic approach

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ABSTRACT

Image similarity or distortion assessment is fundamental to a wide range of applications throughout the field of image processing and computer vision. Many image similarity measures have been proposed to treat specific types of image distortions. Most of these measures are based on statistical approaches, such as the classic SSIM. In this paper, we present a different approach by interpolating the information theory with the statistic, because the information theory has a high capability to predict the relationship among image intensity values. Our unique hybrid approach incorporates information theory (Shannon entropy) with a statistic (SSIM), as well as a distinctive structural feature provided by edge detection (Canny). Correlative and algebraic structures have also been utilized. This approach combines the best features of Shannon entropy and a joint histogram of the two images under test, and SSIM with edge detection as a structural feature. The proposed method (ISSM) has been tested versus SSIM and FSIM under Gaussian noise, where good results have been obtained even under a wide range of PSNR. Simulation results using the IVC and TID2008 image databases show that the proposed approach outperforms the SSIM and FSIM approaches in similarity and recognition of the image.

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Introduction

It is a well-known task in digital image analysis to compare the similarities of images. This comparison may be limited to a special area of any image. The measures of images similarity are methods that provide a quantitative evaluation of the similarity between two image regions or two images. These measures are used as a base for registration measures because they provide the information that indicates when the process of registration is going in the appropriate direction. Many of images similarity measures have been proposed in the medical image field and computer vision community. There is no right image similarity measure but a set of measures that are appropriate for particular applications (Qaid, 2015).

Image similarity involves retrieving similar-looking images given a reference image. The ability to find a similar set of images for a given image has multiple uses and multiple cases from visual search to duplicate product detection to domain-specific image clustering (Appalaraju & Chaoji, 2017).

The measurement of image similarity is a necessary issue in real-world applications. The measures of image similarity play a vital role in digital image processing. It can be applied to improve the quality of the image and

parameter optimization in many applications of digital image processing, such as image enhancement, image compression, and image restoration. The aim of image similarity is to produce methods for objective assessment of quality versus subjective human image-quality evaluation (Hassan Asmhan, Hussain Zahir, & Cailin, 2014). Image similarity compares two images to detect how visually similar they are; it is also possible to identify images that are identical, even if they are taken from different sides or a different angle of the same body or were under any distortion.

There are several challenges in the field of image similarity. Some of these challenges are fundamental, more application-specific, and actively being researched. Some are resolved relatively, and others remain largely unsolved. It is a real challenge when the researchers designing a model of human visual processing which can cope with natural images. There is a need for improved models of the primary visual cortex, more ground-truth data on natural images, and models that incorporate processing by higher-level visual areas. Researchers also face a problem when designing an algorithm that can cope with the diversity of distortions that image similarity algorithms can face. Distortion of the image's appearance is a particular challenge when

researchers want to design an algorithm for image similarity. In fact, there are differences between distortions perceived as additive and distortions that affect the image's objects. There is a need for adaptive visual approaches and other high-level effects that humans use when judging quality. Images that are simultaneously distorted by multiple types of distortions are an interesting challenge for researchers who design and improve image similarity approaches; where the effects of multiple distortions on image quality and the potential perceptual interactions between the distortions and their joint effects on images. Geometric changes to images are one of the challenges of image similarity algorithms faced by researchers (Chandler, 2013).

Related works

There are several mathematical concepts can have a positive effect on image processes such as image enhancement, image compression, image similarity, or image recognition. Finding and using these concepts represents the starting point for reaching the desired goal. There are many works that dealt with the approach of images similarity in different ways, but the most characteristic method was based on the information theory because information theory has a high capability to predict the relationship between image intensity values, especially when the use of this approach in the identification of images and find similarities between images for the purpose of recognition.

An image similarity measure (SEME) proposed by (Silva, Panetta, & Agaian, 2007) is based on the measure of enhancement by entropy. This measure is a modified version of the measurement of enhancement by entropy (EME). Similarity-EME can be used for image similarity and image quality because image similarity assessment is closely related to image quality assessment in that quality is based on the apparent differences between a degraded image and the original, unmodified image. SEME has been compared with and outperformed the existing measures (SSIM, PSNR, and MSE) by applying on the database of images compressed with JPEG.

The relationships among fuzzy logic entropy, similarity, and subethood measures are studied and calculated based on their definitions by (Li, Qin, & He, 2013). The transformation of these measures has been calculated by using new formulae.

(Hassan, Hussain, & Cai-Lin, 2014) proposed, analyzed, and tested HSSIM for image similarity using the information-theoretic approach. The method detects the similarity of images in the database under the conditions of noisy. HSSIM is proposed for general similarity testing between different kinds of database images.

The group theory and entropy function have been considered in the similarity index by (Suarez, Garcia, Barzaga, & Rodriguez Morales, 2015). The algebraic group of images has been introduced by an inner law for the subtraction of images which is proved that the existence of the quotient group.

(Palubinskas, 2017) proposed Composite Means, Standard deviations, and Correlation coefficient measure (CMSC), which based on the similar concepts in structural similarity (SSIM) and Mean Squared Error (MSE). CMSC is based on means, the square root of the variance, and correlation. Many challenges have been considered in CMSC measure such as mean shift, contrast stretching, additive noise, multiplicative noise, impulsive noise, and blurring.

(Aljanabi, Shnain, & Lu, 2017) introduced THS image similarity metric based on information theory. THS method based on Taneja entropy and the alternative of histogram; THS tested on the ORL and Brazilian datasets against structure similarity and feature similarity.

kurtosis and skewness measure (KSDM) is a measure for image similarity introduced by (Shnain, Hussain et al., 2017). KSM is based on high-order statistics (HOS). KSM focused on the statistical properties of the images. The performance of KSM applied versus SSIM and FSIM using AT&T database and FEI image database.

(Shnain et al., 2017) proposed FSM similarity approach which is based on the features of structure similarity measure and feature-based similarity. Canny edge detector has been used in the introduced approach as a distinctive structural feature. FSM has been tested under Gaussian noise and PSNR. The Brazilian and ORL databases are the test environment in the proposed approach.

In our recent paper (Aljanabi, Hussain, & Lu, 2018) we proposed two entropy measures SHS and RSM based on a joint histogram and entropies (Shannon and Renyi). These measures have high performance for the sake of image similarity and face recognition.

Similarity measures

Similarity measures are probably the most critical element of a registration problem. The measures define the goal of the process, and they measure how well the target object is matched by the reference object after the transformation has been applied. The measures should be selected in view of the types of objects to be registered and the expected kind of misalignment. Some measures have a rather large capture region, which means that the optimizer will be able to find his way to a maximum, even if the misalignment is high. Typically, large capture regions are associated with low precision for the maximum. Other metrics can provide high precision for the final

registration but usually need to be initialized quite close to the optimal value.

Unfortunately, there are no clear rules on how to select a measure, other than trying some of them in different conditions. In some cases, there could be an advantage to using a particular measure to get an initial approximation of the transformation and then switching to another, more sensitive measure to achieve better precision in the final result. Measures depend on the objects they compare. In general, image similarity measures can be classified into two main directions: statistical-based and information-theoretic-based quality measures. The proposed measure (ISSM) incorporates the two directions into one, and we utilized edge detection properties to provide a more reliable similarity measure.

Structural similarity index measure (SSIM)

One of the most dependent measure for image similarity is SSIM (structural similarity index measure). The structural similarity measure is introduced by (Wang, Bovik, Sheikh, & Simoncelli, 2004). A structural similarity measure is based on the statistical measurements such as the standard deviation (σ) and mean (μ) to extract the statistical image features for image similarity purpose. To get the similarity between the reference image and a test image by a definition of a distance function between the two images by using the SSIM by this formula:

$$S(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}, \quad (1)$$

where $S(x, y)$ is a structural similarity measure of a statistical similarity between the test image (x) and training image (y). The quantity μ_x is the statistical mean of pixels in the image x , σ_x^2 is the statistical variance of pixels in the image x , μ_y is the statistical mean of pixels in the image y , and σ_y^2 is the statistical variance of pixels in the image y . The quantities c_1 and c_2 are constants: $c_1 = (k_1L)^2$ where k is a small constant and L is a maximum value of pixels; $c_2 = (k_2L)^2$ where $L = 255$.

Feature-Based Similarity Index (FSIM)

A Feature-based Similarity Index Measure (FSIM) is a measure can be used to find the similarity in images. FSIM has been proposed by (Zhang, Zhang, Mou, & Zhang, 2011). FSIM is mainly based on two basic features which are: the Phase Congruency (PC) as a primary feature and the Gradient Magnitude (GM) as a secondary feature. These features have

been passed in multi-stages to calculate the similarity between images by using the final definition of FSIM:

$$FSIM = \frac{\sum_{x \in \Omega} S_L(x) \cdot PC_m(x)}{\sum_{x \in \Omega} PC_m(x)} \quad (2)$$

where Ω means the whole image spatial domain, PC is a phase congruency and S_L is a similarity resulting from the combined similarity measure for phase congruency $S_{PC}(x)$ and similarity measure for gradient $S_G(x)$, as given by the formulas:

$$S_L(x) = [S_{PC}(x)]^\alpha \cdot [S_G(x)]^\beta \quad (3)$$

where α and β are parameters used to adjust the relative importance of phase congruency(PC) and gradient magnitude(GM) features.

$$S_{PC}(x) = \frac{2PC_1(x) \cdot PC_2(x) + T1}{PC_1^2(x) \cdot PC_2^2(x) + T1} \quad (4)$$

where $T1$ is a positive constant, inserted to raise the stability of S_{PC} (it was also included in SSIM), The period notation is the form of multiplication for two real numbers (similarity and Phase Congruency) in Equation (2) and Phase Congruency (PC) in Equation (4). The mathematical operation of period notation is defined in the context as a dot (.) multiplication of two real numbers.

$$S_G(x) = \frac{2G_1(x) \cdot G_2(x) + T2}{G_1^2(x) \cdot G_2^2(x) + T2} \quad (5)$$

is the gradient similarity, where $G = \sqrt{G_x^2(x) + G_y^2(x)}$ is the gradient magnitude; G_x and G_y are partial derivatives of image $f(x)$. The phase congruency PC is given by the equation:

$$PC(x) = \frac{E(x)}{\epsilon + \sum_n A_n(x)} \quad (6)$$

where ϵ is a small positive constant, and

$$E(x) = \sqrt{K^2(x) + H^2(x)} \quad (7)$$

where $H(x) = \sum_n o_n(x)$ and $K(x) = \sum_n e_n(x)$, $o_n(x) = \xi(x) * M_n^e$; $e_n(x) = \xi(x) * M_n^o$, noting that M_n^e and M_n^o are even and odd symmetric filters on scale n , and “*” denotes convolution. The function $\xi(x)$ is a 1D signal obtained after arranging pixels in different orientations. The local amplitudes $A_n(x)$ are defined as:

$$A_n(x) = \sqrt{e_n^2(x) + o_n^2(x)} \quad (8)$$

where x is the position on scale n .

Joint histogram

The traditional way to compare two images to find the similarity between these images based on the histogram intensity is applicable in case if we have some images in the database because if there are

many images in the database for instance image similarity datasets there might be identical histograms for very different images. So to avoid getting this situation (Pass & Zabih, 1999) proposed a joint histogram to be alternative to the histogram and includes additional information without losing the features of the histogram. The joint histogram selects the features of the local pixel to construct a multidimensional histogram. Let $H_{ij}(x, y)$ is a 2D joint histogram entry for image x and image y represents the probability that a pixel intensity value i from image x co-occurs with pixel intensity value j from image y . The normalized joint histogram for two images x and y of size $M \times N$ is defined here as follows:

$$H(x, y) = [H_{ij}] \quad (9)$$

where:

$$H_{ij} = \frac{\text{Number of joint events } (x = i, y = j)}{M \times N} \quad (10)$$

or:

$$H_{ij} = \frac{|\{x = i\} \cap \{y = j\}|}{M \times N} \quad (11)$$

We used a Joint Histogram (JH) as a basic element in this work and combine it with the entropy element and the structural measure (SSIM) to get the proposed measure (ISSIM).

The proposed measure (ISSM)

Image similarity belongs to a more general category known as image quality assessment. Although there are many measures that have tried to reduce the challenges faced by the approach of image similarity or object recognition within the images, the challenges and problems still exist so far, so requires more effort and work in this direction to get the reliable algorithms and its role to increase the rate of success in testing the similarity of images for the sake of identifying or searching for. The most disturbing problem in image similarity is the confusing high similarity given by a specific measure between the reference image and other images in the database. Therefore, we proposed a novel and unique image similarity measure based on the combined of the statistical and information theory approach for image similarity. In information theory, the main domains of interest in this paper are Shannon entropy theory and joint histogram. In the statistic, the main domain of interest in image similarity is SSIM. The foundations for entropy are in information theory, which is the mathematical theory for communication developed in the seminal work of Shannon (Cover & Thomas, 1991). Central to the theory is the concept of entropy (Shannon) and how lossless images similarity-recognition measure

can be constructed efficiently. Entropy is the expected value of the information. Entropy has several applications in statistical mechanics, coding theory, statistics, and related areas. Emerging fields have also used entropy, such as image similarity (Golshani, Pasha, & Yari, 2009). The most significant entropy in applications is Shannon entropy, whose mathematical formula is given by:

$$E_s(x) = - \sum_{i=1}^n p(x_i) \log_2 [p(x_i)] \quad (12)$$

where E_s represents the entropy, x is a discrete random variable $x = \{x_1, x_2, \dots, x_n\}$ and $p(x_i)$ is a probability of event x_i , $p \in [0, 1]$. Here the probabilistic events are the elements of the 2D joint histogram between two images (test image and reference image).

Now we apply the entropy to measure the information held in the joint histogram that represents the joint probability of pixel co-occurrence. Note that both i and j range from 0 to $L = 255$. Shannon entropy measure is applied to get Entropy-Histogram Similarity Measure (EHS) as follows:

$$EHS(x, y) = - \sum_{k=1}^{M \times N} T(k) \cdot \log_2 [T(k)] \quad (13)$$

where $T = H(\cdot)$ reshapes the 2D joint histogram H into a one-dimensional column vector T via the colon operator, as defined in MATLAB, with a new dimension $1 \times (M \cdot N)$. After getting the EHS, the inclusion of edge effects using Canny's method (Canny, 1987) into ISSM to give more reliable similarity measure. The Canny edge detector is the effective edge detection algorithms because it is based on three criteria in estimating the efficiency of the algorithm. The first criterion is to achieve the lowest percentage of error in the number of edges to be detected and this is reflected in not ignoring the real edges as much as possible and not detect the false edges as much as possible. The second criterion is that adopted by the Canny algorithm is accuracy in edge detection which means achieving the least possible distance between the location of the specified edge and its real location in the image. The third criterion is to make the algorithm one response to the same edge as this criterion is a complement to the first and second criteria because the repetition of the edge means the addition of false edges (shadow edges) and therefore difficult to detect the precise location of the edge. These features, as well as the other features contributed by the other concepts in the proposed algorithm, lead us to say that the introduced measure is unique because it depends on the operation of more than one scale in the process of finding similarities or identifying images and that is actually why we used Canny; noting that $C(x, y)$ is the 2D edge correlation coefficient defined as:

$$C(x, y) = \left| \frac{\sum_i \sum_j (g_{ij} - g_0)(h_{ij} - h_0)}{\sqrt{\left[\sum_i \sum_j (g_{ij} - g_0)^2 \right] \left[\sum_i \sum_j (h_{ij} - h_0)^2 \right]}} \right| \quad (14)$$

where g and h are the new images resulting from applying an edge detection technique to the test images x and y , respectively, while g_0 and h_0 are their global means. Peak Signal to Noise Ratio (PSNR) was used in this test as follows:

$$PSNR = \frac{L^2}{P_n} \quad (15)$$

where $L = 255$ is the maximum value of illumination and P_n is the power of the Gaussian noise. Now we have four robust basic concepts have been used together for the first time in this paper: Information theory (Shannon entropy), Joint Histogram (JH), Statistic (SSIM), and edge detection (Canny). The main principles of information theory, which provides a framework for efficient images similarity from a statistical perspective. One of the fundamental theories is Shannon entropy. In this paper, the widely used and examined Shannon entropy is introduced and its application to image similarity and image recognition due to its speed and good compaction performance. We applied Shannon entropy to the joint histogram as a probabilistic distribution to get Shannon–Histogram Similarity (EHS) as one measure; next we will use it in Equation (16) with SSIM and edge detection, hence we propose the following image similarity measure equation:

$$I(x, y) = \frac{C(x, y) \cdot EHS(x, y) \cdot (a + b) + e}{a \cdot C(x, y) \cdot EHS(x, y) + b \cdot EHS(x, y) + c \cdot S(x, y) + e} \quad (16)$$

where $I(x, y)$ represents the proposed ISSM similarity between two images x and y ; usually, x represents the reference image and y represents a corrupted version of x . EHS is the Entropy-Histogram Similarity as defined in Equation (13) and S represents SSIM as defined in Equation (1). The constants are chosen as $a = 0.3$, $b = 0.5$, and $c = 0.7$ are added to balance the quotient and avoid division by zero and inserted to raise the stability. Chosen any other constants give similar results approximately in the distance function between the highest match and the second-best match. In fact, what distinguishes this proposed measure and makes it unique is when it is implemented to find similarities between images or identify images as in the faces, all these elements are used simultaneously. We have combined all four concepts in one algorithm that can run all these tools and to find the similarities between the images or to recognize the images and thus the results are very accurate and reliable in security and other purposes and the most characteristic feature of the ISSM measure and that makes it unique

is the great combination between two basic approaches in image similarity which are statistical approach and information theoretic approach while the previous measures were based on either statistic direction such as the well-known SSIM or based on information theory such as (Aljanabi et al., 2017, 2018), and (Aljanabi et al.,). ISSM chose the features of the structural similarity index measure due to its performance in such image processing field and entropy as an information theory measure. The main properties of the proposed algorithm are mainly all the properties of the main components of the $I(x, y)$, which are the extraction of the statistical properties of the image by the statistical method (SSIM) and theoretical properties of the image using the theoretical approach (Shannon entropy and joint histogram), hence to sum up the properties of Equation 16 is the combination of the components properties. The proposed measure, namely ISSM, reduces confusion by giving a very small similarity (near zero) between unrelated images; ISSM has been tested under the condition of Gaussian noise and a wide range of PSNR. In particular, the discussion examines how information theory and statistic theory are used to establish performance bounds for images similarity and recognition. The proposed methodology was applied to actual data under several situations which include pure and contaminated data.

Motivation

A high level of uncertainty about the similarity of two images, for example, the reference image and test image in the same database is one of the most difficult challenges faced by researchers in measuring similarities between images, especially when the image has low resolution, distorted, different lighting and background changes. In this work, we have contributed to reducing these challenges regarding the similarity of images. We proposed new image similarity measures, these measures are built using an information-theory approach combined with statistics; they proved to be very accurate in finding similarity between images with more confidence than existing images similarity and image recognition measures. Our method is motivated by the problem of finding image similarity in large databases, where reduced confidence may open the door for big confusion. The aim of this work is to provide metrics to find the similarity between images, this can be used in case of nonface images. High performance and accuracy are the main features of proposed measures as compared to existing measures. Although other measures may have the ability to find the similarity between images (even for image recognition), the proposed measures have high confidence by giving almost a near-zero value in case of different images, while other measures

give a nontrivial amount of similarity when comparing different images.

Experimental results and performance

We have implemented the proposed measures on MATLAB and tested their performance against other measures as follows.

Test environment: image databases

There are several publicly available image databases in the image similarity community, including TID2008 as shown in [figure 1](#) and image and video-communication (IVC) as shown in [figure 2](#). Both are used here for algorithm validation and comparison. TID2008 contains 25 reference images and 1,700 distorted images (25 reference images \times 17 types of distortions \times 4 levels of distortions) (Ponomarenko et al., 2009). The IVC database has 10 original images and 235 distorted images generated from four different processes: JPEG, JPEG2000, LAR coding, and blurring (Ninassi, Callet, & Atrousseau, 2005). In this paper, we use part of each of the TID2008 and IVC databases for implementation and we use six complex-distorted versions as image poses to test, compare, and prove that the proposed ISSM outperforms the well-known SSIM and feature similarity index measure (FSIM) in a recognition test.

Performance criterion

Performance of the proposed ISSM measure has been tested against other efficient image similarity measures: SSIM and FSIM. The criterion for good performance is the amount of confusion in deciding how similar the reference image with the noise version of it is. This confusion is measured by the difference in similarity produced (by a specific measure) between the reference image and the database images. If a measure gives little difference in similarity between unrelated images, that means the confusion is high and the performance is low.

The difference in the values of the peaks of each measure is a new feature showing the high performance of the proposed measure (ISSM). If the distance between the highest match and the second-best match is higher, that means the measure has better performance; and vice versa, i.e., if the distance is less, that means the measure has been confused in deciding the best match by giving a non-trivial similarity between the different images. The new feature of recognition confidence can be very useful in security systems of big databases.

Results and discussion

Performance Comparison with Image Similarity Metrics

The performance of the proposed ISSM indices will be evaluated and compared with two representative



Figure 1. Eight TID2008 reference images used for the test and comparison image similarity measures.



Figure 2. Ten IVC reference images used for the test and comparison image similarity measures.

similarity metrics: SSIM and FSIM. In this work, we have two kinds of tests – one is for similarity and the other for recognition – to evaluate and test the proposed ISSM versus the well-known SSIM and FSIM. In the first test, we used some images from the environment of the two databases (TID2008 and IVC, respectively) randomly; note that other images also achieve good results with high performance. Figures 3–6 have three images: (a) is the original reference image from databases, (b) is the noise version of the reference image, and (c) represents the performance of our proposed similarity measure compared with the SSIM and FSIM, where the proposed ISSM gives more confidence in the similarity decision between the reference image and the noise image under the Gaussian noise condition and a wide range of PSNR.

As shown in the figures above, the ISSM is superior in the similarity between the original image and the noise of the same image under the condition of Gaussian noise and PSNR. Now, we have to evaluate the proposed ISSM against SSIM and FSIM to find the similarity by using the

noise image of the original image and compare with the different image in the database. In this test, the work of all measures (SSIM, FSIM, and ISSM) is to decide how they are similar between the noise image and the different image, whether these two images are highly similar or highly dissimilar. The proposed measure gives (near zero) similarity between unrelated images, while the other measures give a non-trivial amount of similarity between different images. Figures 7–10 have four images: (a) is the original image, (b) is the noise of the original image, (c) is the different image in the databases (TID2008 and IVC, respectively), and (d) is the performance comparison among SSIM, FSIM, and the proposed ISSM under Gaussian noise and a wide range of PSNR.

On the other hand, the three measures (SSIM, FSIM, and the proposed ISSM) were tested in their ability to recognize the reference images with destructive images. The following results show that the proposed ISSM is still superior to the other measures. However, there is another challenge to test measures in image recognition.

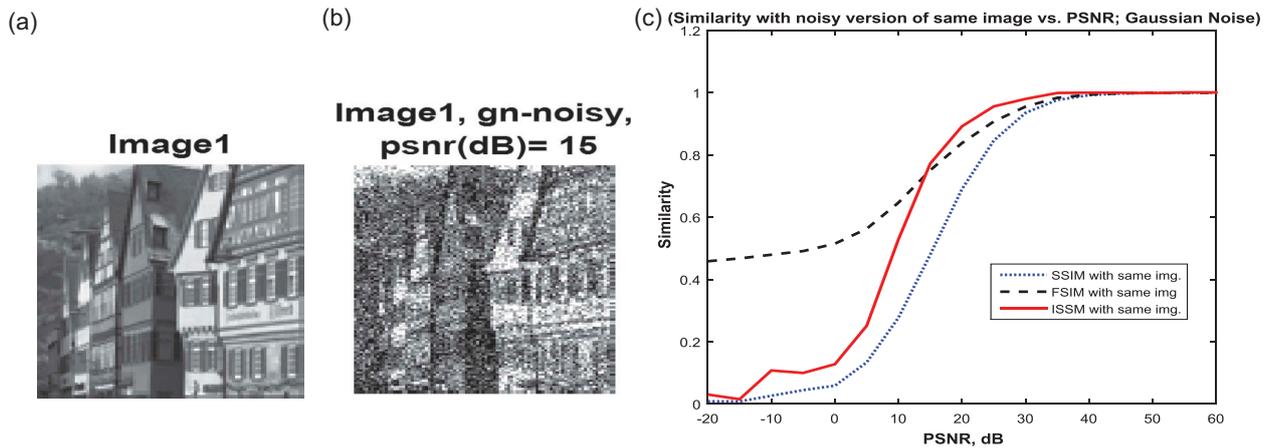


Figure 3. Performance of similarity measures using similar images from TID2008 database under Gaussian noise and wide range of PSNR; (a) The test image; (b) The noise version of reference image; (c) Performance comparison among (SSIM, FSIM and ISSM) under Gaussian noise using.

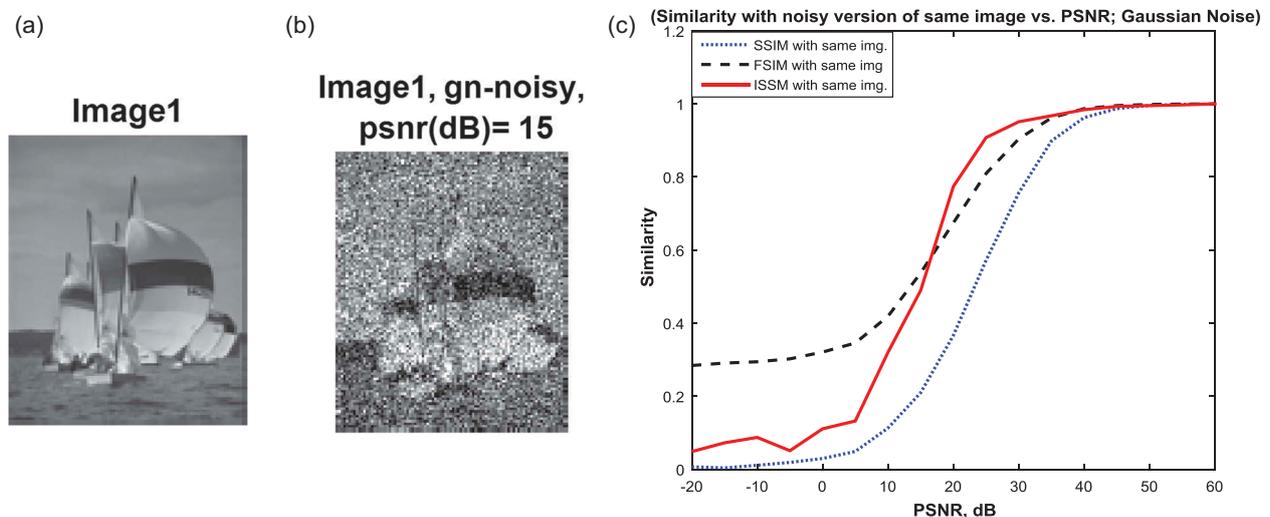


Figure 4. Performance of similarity measures using similar images from TID2008 database under Gaussian noise and wide range of PSNR; (a) The test image; (b) The noise version of reference image; (c) Performance comparison among (SSIM, FSIM and ISSM) under Gaussian noise using.

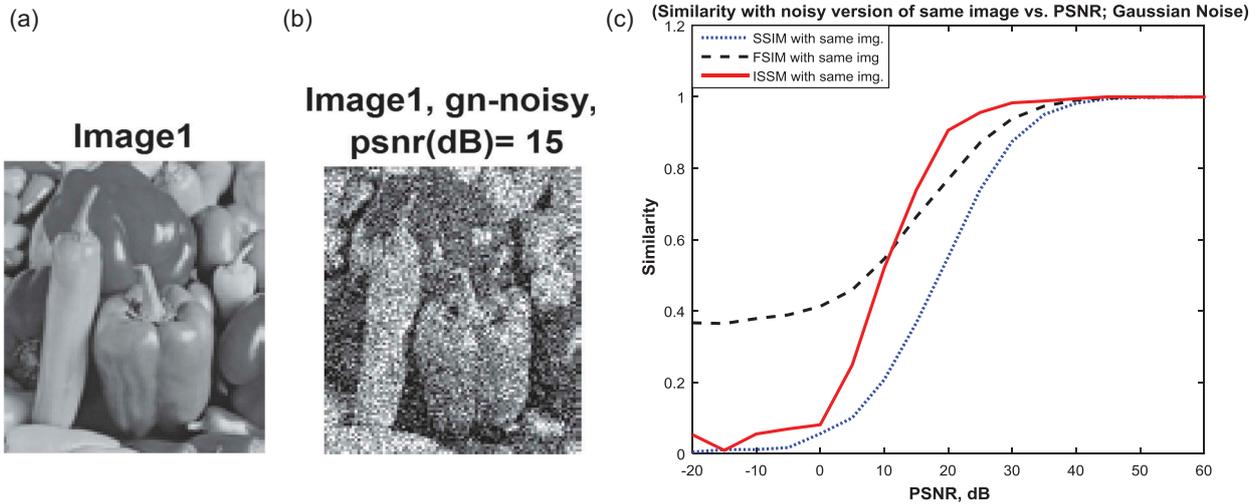


Figure 5. Performance of similarity measures using similar images from IVC database under Gaussian noise and wide range of PSNR; (a) The test image; (b) The noise version of reference image; (c) Performance comparison among (SSIM, FSIM and ISSM) under Gaussian noise.

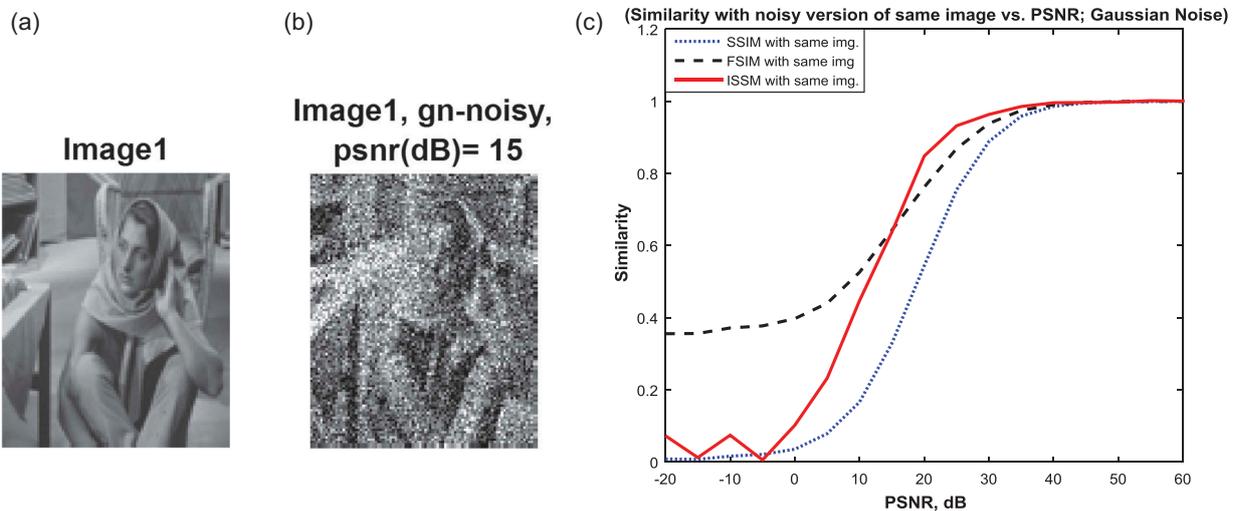


Figure 6. Performance of similarity measures using similar images from IVC database under Gaussian noise and wide range of PSNR; (a) The test image; (b) The noise version of reference image; (c) Performance comparison among (SSIM, FSIM and ISSM) under Gaussian noise.

Note that incorporation of the statistical characteristics of the image with the information theory in the proposed ISSM gives robust and reliable results in the testing of image recognition of all images in the databases used. Figures 11–14 have three images: (a) is the original reference image from databases, (b) is the distorted version of the reference image, and (c) represents the performance of our proposed similarity measure compared with the existing measures. The proposed ISSM demonstrates better performance in terms of recognition confidence. Although the other measures (SSIM and FSIM) correctly decide the proper image with maximum similarity, they give low confidence in their decision because there are many cases of distrust (big similarities with wrong images) in their decisions (similarities). This is a big challenge when we employ these measures in security recognition tasks. ISSM gives more confidence to decide the proper image from a database.

The difference in the values of the peaks of each measure is a new feature showing the high performance of the proposed measure (ISSM). If the distance between the highest match and the second-best match is higher, that means the measure has better performance and vice versa; i.e. if the distance is less, that means the measure has been confused in deciding the best match by giving a non-trivial similarity between the different images. The new feature of recognition confidence can be very useful in security systems of big databases. The scores of various measures (proposed and existing) for the shown images and other images in the database has been shown in Table 1 and the confidence in recognition for SSIM, FSIM and ISSM by using part of each of the TID2008 and IVC databases for implementation and we use six complex-distorted versions as image poses to test, compare, and prove that the proposed ISSM outperforms the well-known SSIM and feature similarity index measure

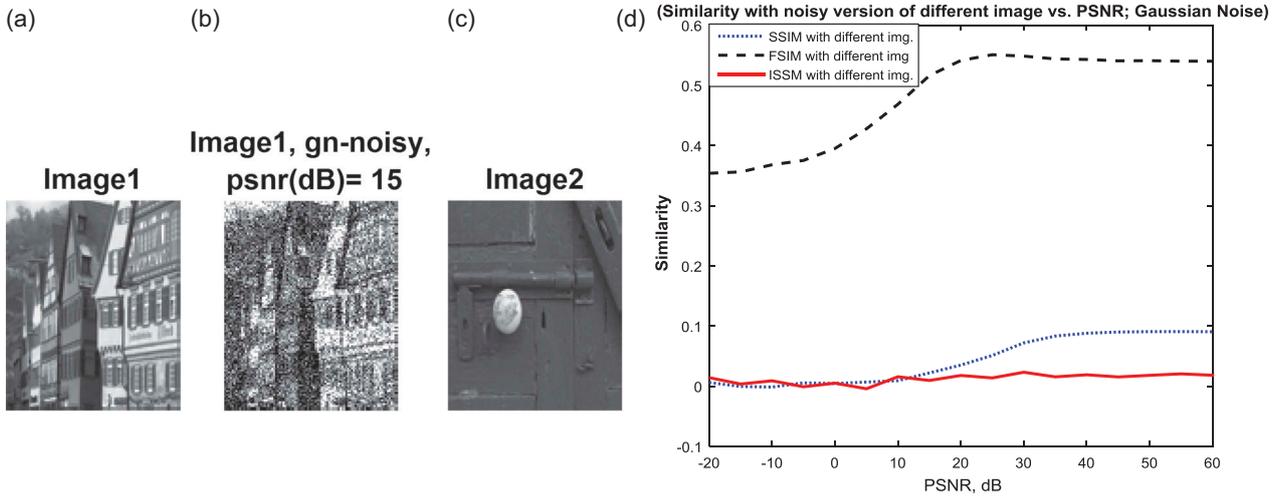


Figure 7. Performance of similarity measures using dissimilar images under Gaussian noise; (a) The original image; (b) The noise image; (c) Dissimilar image and (d) Performance of SSIM, FSIM and ISSM under Gaussian noise using TID2008 database.

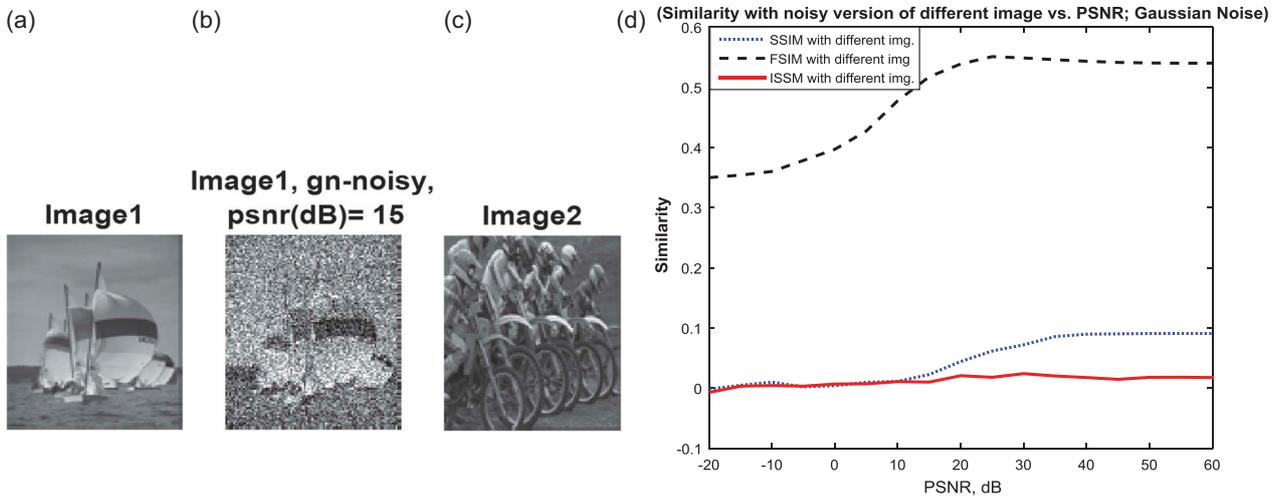


Figure 8. Performance of similarity measures using dissimilar images under Gaussian noise; (a) The original image; (b) The noise image; (c) Dissimilar image and (d) Performance of SSIM, FSIM and ISSM under Gaussian noise using TID2008 database.

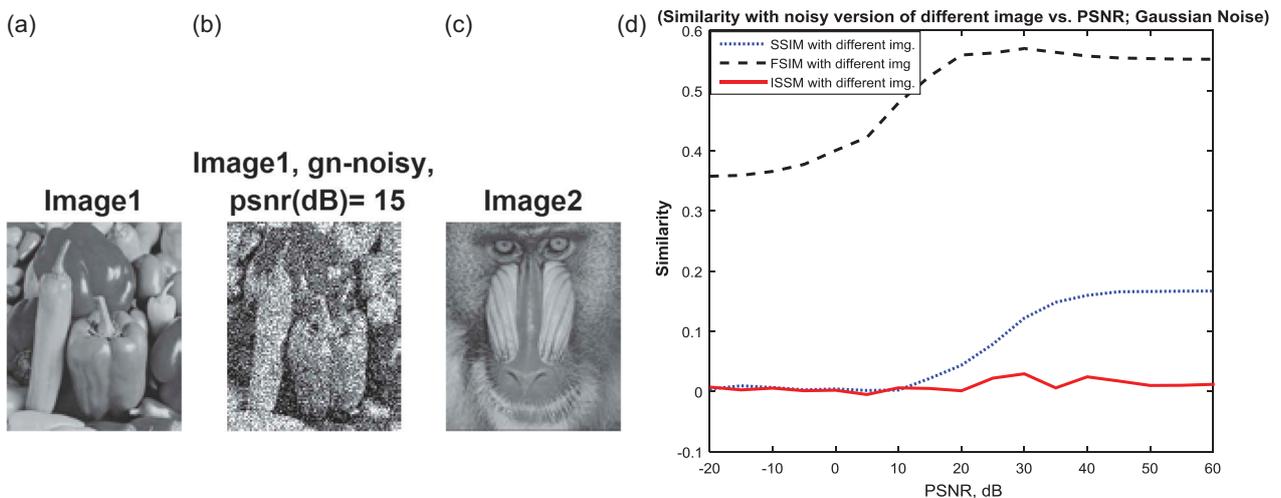


Figure 9. Performance of similarity measures using dissimilar images under Gaussian noise; (a) The original image; (b) The noise image; (c) Dissimilar image and (d) Performance of SSIM, FSIM and ISSM under Gaussian noise using IVC database.

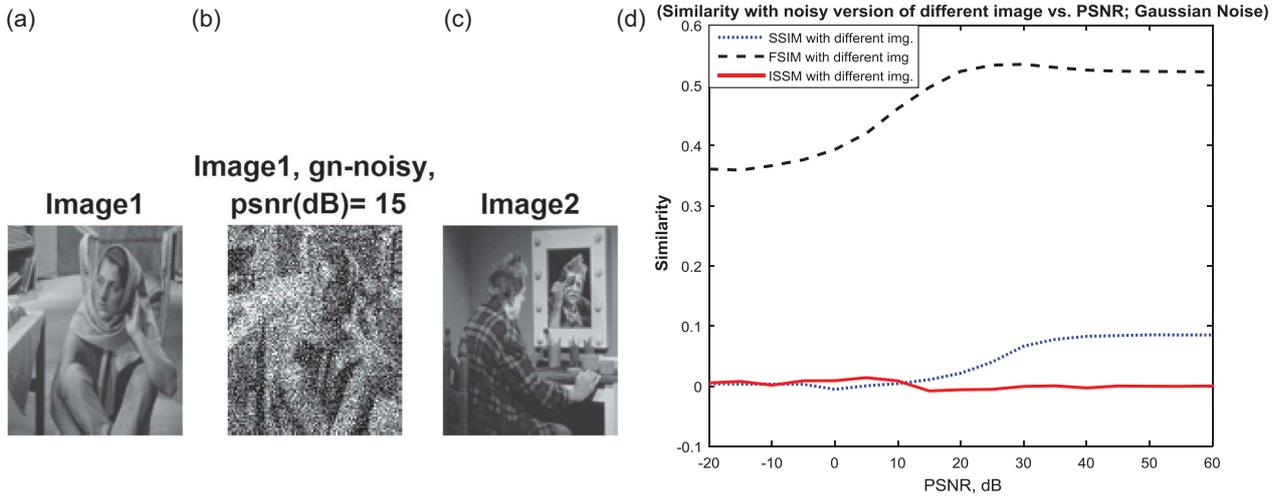


Figure 10. Performance of similarity measures using dissimilar images under Gaussian noise; (a) The original image; (b) The noise image; (c) Dissimilar image and (d) Performance of SSIM, FSIM and ISSM under Gaussian noise using IVC database.

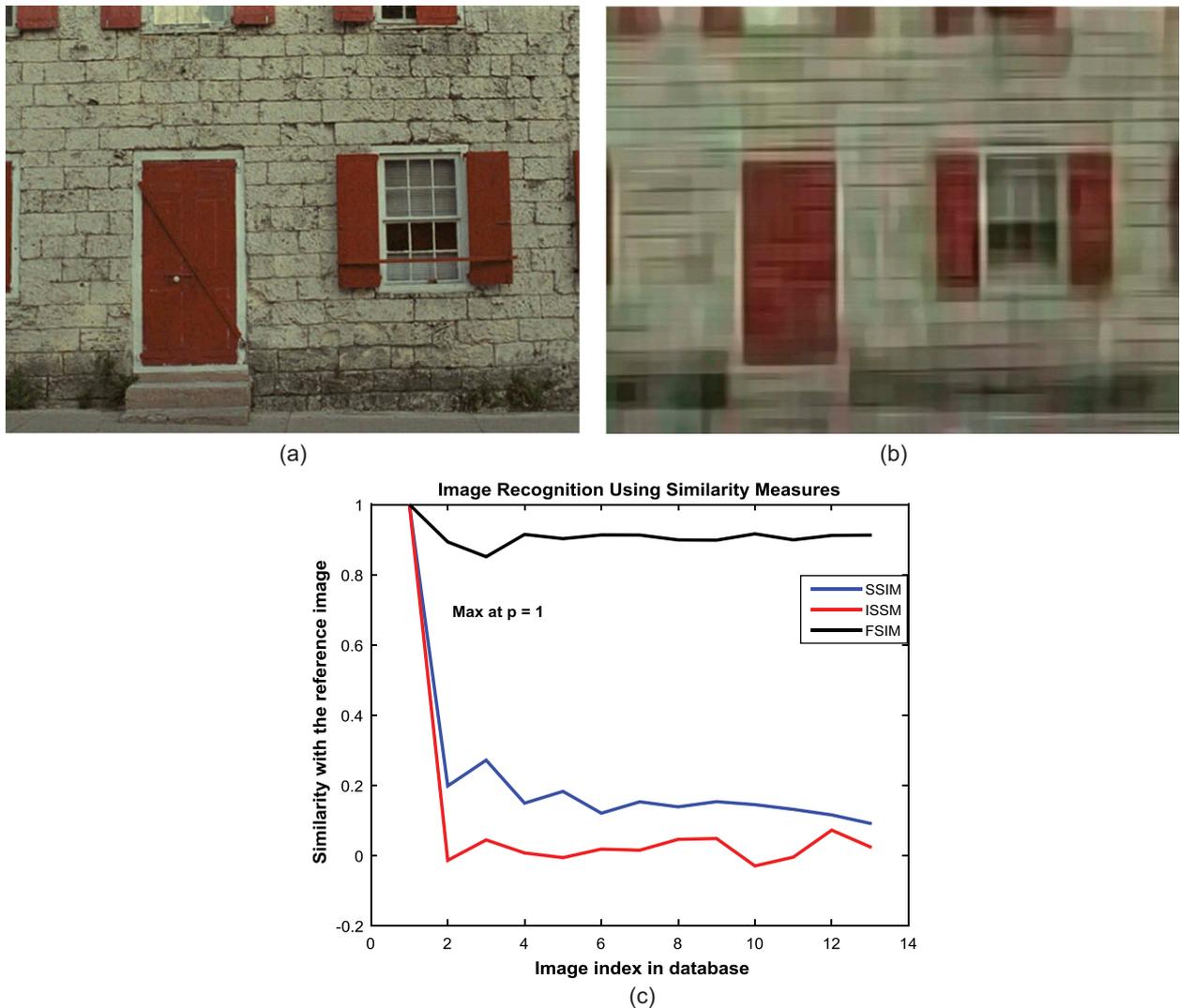


Figure 11. Performance of recognition measures using original image from TID2008 database and distort of the original image; (a) The reference image; (b) The distorted version of it; (c) Performance of SSIM, FSIM and ISSM. Confidence in recognition for SSIM, FSIM and ISSM is 0.7285, 0.0837 and 0.9279 respectively.

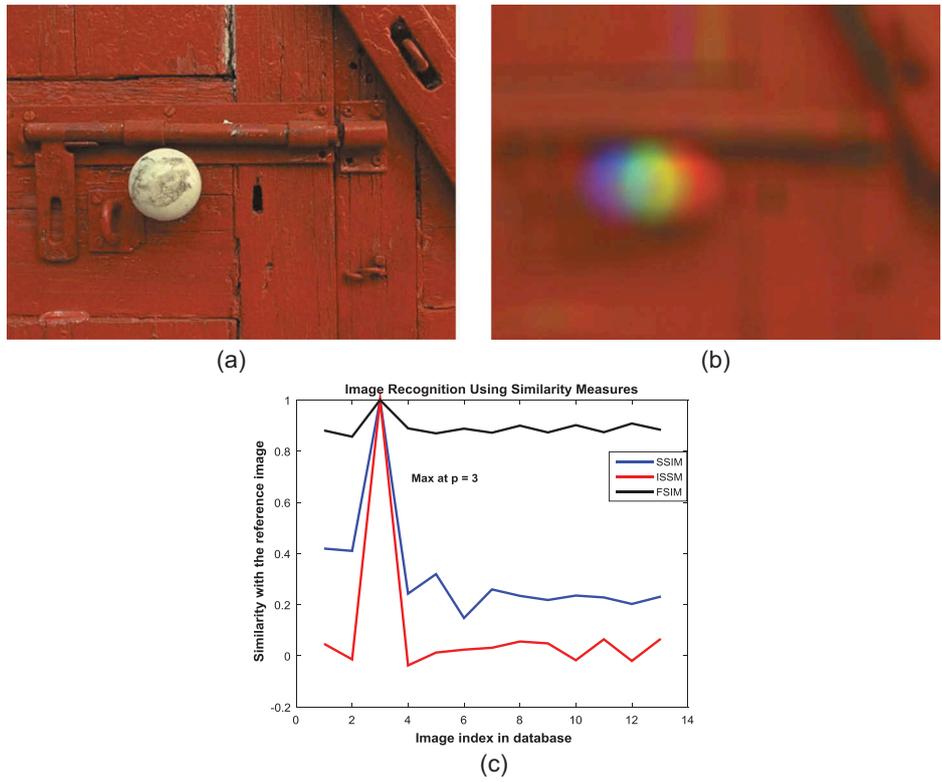


Figure 12. Performance of recognition measures using original image and distort of the original image from TID2008 database; (a) The reference image; (b) The distorted version of it; (c) Performance of SSIM, FSIM and ISSM. Confidence in recognition for SSIM, FSIM and ISSM is 0.5808, 0.0918 and 0.9356 respectively.

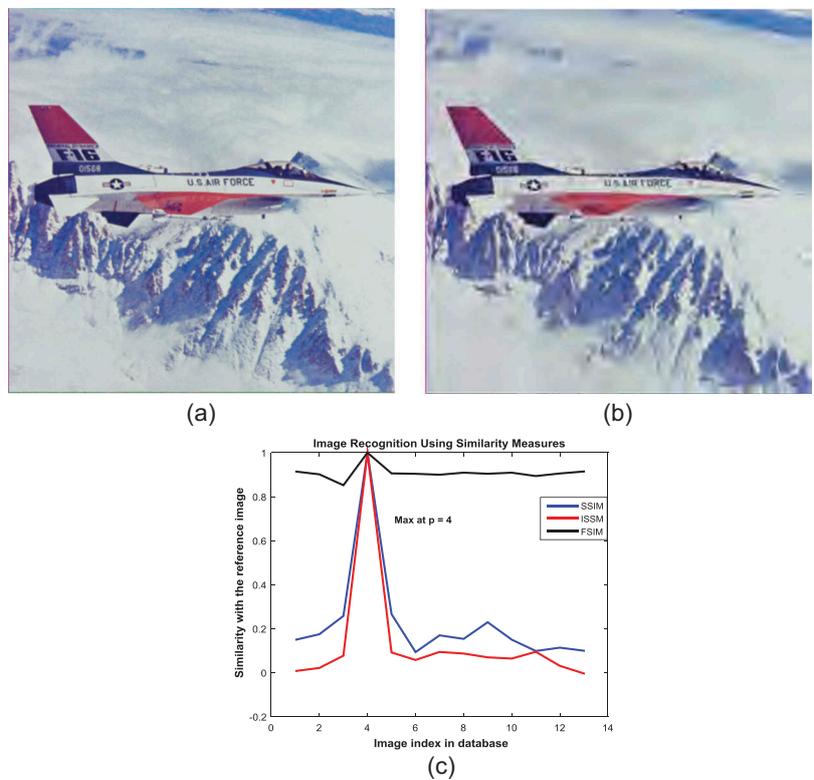


Figure 13. Performance of recognition measures using original image and distort of the original image from IVC database; (a) The reference image; (b) The distorted version of it; (c) Performance of SSIM, FSIM and ISSM. Confidence in recognition for SSIM, FSIM and ISSM is 0.7339, 0.0854 and 0.9053 respectively.

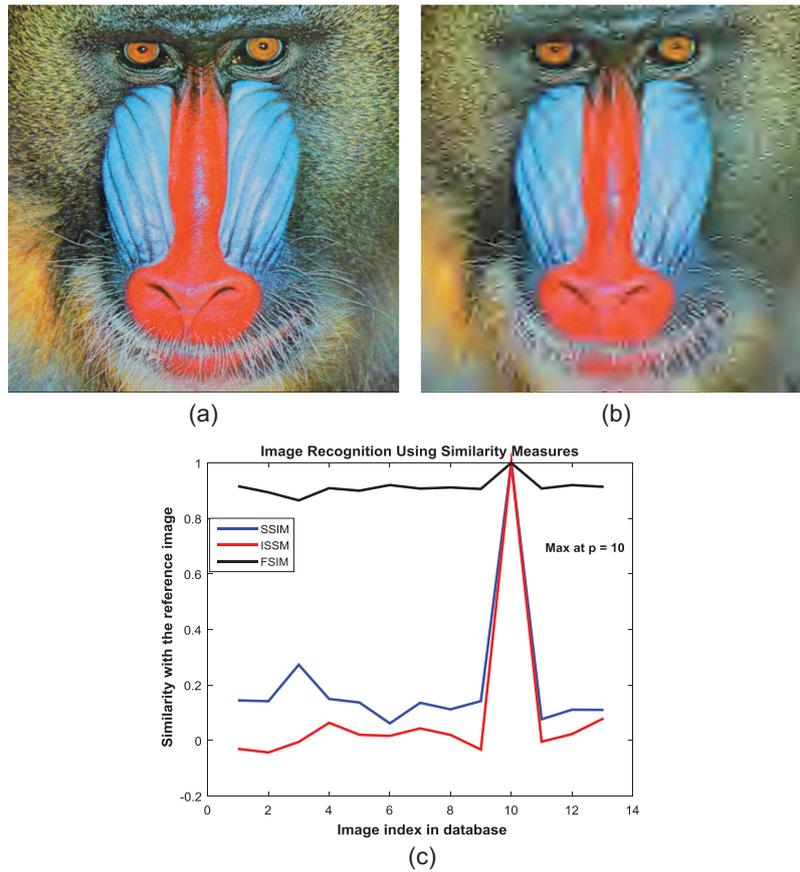


Figure 14. Performance of recognition measures using original image and distort of the original image from IVC database; (a) The reference image; (b) The distorted version of it (c) Performance of SSIM, FSIM and ISSM. Confidence in recognition for SSIM, FSIM and ISSM is 0.7269, 0.0797 and 0.9225 respectively.

Table 1. Results of applying the proposed algorithm to part of each of the TID2008 and IVC datasets.

Images	SSIM	FSIM	ISSM
1	0.8316	0.0862	0.9408
2	0.6965	0.0864	0.8919
3	0.6965	0.1025	0.9271
4	0.7596	0.0855	0.9136
5	0.7596	0.0929	0.8678
6	0.8665	0.0752	0.9263
7	0.8114	0.0798	0.9002
8	0.8225	0.0828	0.8994
9	0.7715	0.0915	0.8678
10	0.8201	0.0798	0.9405
11	0.8282	0.0906	0.8848
12	0.8543	0.0752	0.9123
13	0.8439	0.0828	0.9314

(FSIM) in a recognition test. Implementation should be done in the least time and hence ISSM is better than others as shown in Table 2 and computational time analysis proves to be the fastest amongst all.

To show the real performance of the proposed measure, we provided an average similarity difference using

Table 2. Computational time analysis of the ISSM, SSIM, and FSIM.

Measures	Computational Time Analysis
ISSM	0.016s
SSIM	0.667s
FSIM	0.031s

all images as a reference image and all images as test images. In this case, similarity difference is (best match of reference image) - (second best match within any other images). In this paper, we did an average of the similarity as a confidence measure for all images in the TID2008 and IVC datasets. The global average can be obtained as the mean of all these sub averages. Let s_{ij} denote the similarity confidence when the image (i) with the distorted version of it (j) is the reference image while recognizing image (i) among all images under distorted (j), and let N refers to the number of all images (original images and distorted images) and M denote the number of original images. Then, the global confidence average is taken as $S_{av} = (\frac{1}{N}) \sum_{j=1}^6 \sum_{i=1}^M S_{ij}$. Table 3 shows the performance of the proposed ISSM versus other methods. The preparation of the database that is more suitable for this approach (e.g., in security applications) should take into consideration some important factors like lighting, expression, and viewpoint, while the reference image should consider the same factors.

Table 3. The global average similarity difference of best match and second-best match within all images.

Measures	ISSM	SSIM	FSIM
All persons			
Average	0.0704	0.0625	0.0279

Future Directions. The Authors may extend their testing the performance of similarity measures to modern engineering systems, especially long-range wireless channels as in (Mahmoud, Hussain, & O’Shea, 2002, 2006); and short-range communication systems as in (Lau & Hussain, 2005).

Conclusion

This paper presented an efficient and unique approach to image similarity. The proposed Information theoretic-based Statistic Similarity Measure (ISSM) is based on information theory and statistic. The incorporation of Shannon entropy and joint histogram gives high performance in image similarity. This merger is represented in an EHS measure in Equation (13), which considers an information theory direction. SSIM was used as a statistical direction with Canny edge detection in the proposed ISSM in Equation (16). A wide range of peak signal to raise ratios was used in this paper. The performance of ISSM was tested against efficient existing similarity metrics: FSIM and structural similarity SSIM. ISSM outperforms conventional SSIM and FSIM. ISSM resolves the shortcomings of the existing measures of FSIM and SSIM. Experimental results showed the superior performance of the proposed ISSM in terms of correct decisions with minimal confusion in image similarity and image recognition using the TID2008 and IVC image databases.

In this work, we treat the whole image at once as global image analysis. Also, the local analysis of images can improve image similarity and image recognition. Therefore, in the future work, we will combine modern measures based on statistics and others based on information theory to get better results to find similarities between images or identify images by finding similarities between them.

Authors contributions

All Authors extensively discussed the contents of this paper and contributed to its preparation. Mohammed Abdulameer Aljanabi and Zahir M. Hussain have proposed and developed the model, performed experiments, and drafted the manuscript. Results analysis, mathematics check-up, and simulation revision of this manuscript were done by Noor Abd Alrazak Shnain and Songfeng Lu. All of the Authors have contributed to the literature overview and modeling discussions.

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No potential conflict of interest was reported by the authors.

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Ethical issues

The Authors declare that there are no ethical issues regarding this work.

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