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Image compression and reconstruction using improved Stockwell transform for quality enhancement

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ABSTRACT

Image compression is an important stage in picture processing since it reduces the data extent and promptness of image diffusion and storage, whereas image reconstruction helps to recover the original information that was communicated. Wavelets are commonly cited as a novel technique for image compression, although the production of waves proceeding smooth areas with the image remains unsatisfactory. Stockwell transformations have been recently entered the arena for image compression and reconstruction operations. As a result, a new technique for image compression based on the improved Stockwell transform is proposed. The discrete cosine transforms, which involves bandwidth partitioning is also investigated in this work to verify its experimental results. Wavelet-based techniques such as multilevel Haar wavelet, generic multiwavelet transform, Shearlet transform, and Stockwell transforms were examined in this paper. The MATLAB technical computing language is utilized in this work to implement the existing approaches as well as the suggested improved Stockwell transform. The standard images mostly used in digital image processing applications, such as Lena, Cameraman and Barbara are investigated in this work. To evaluate the approaches, quality constraints such as mean square error (MSE), normalized cross-correlation (NCC), structural content (SC), peak noise ratio, average difference (AD), normalized absolute error (NAE) and maximum difference are computed and provided in tabular and graphical representations.

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1. INTRODUCTION

The amount of visual data we generate in our daily lives is skyrocketing, making it increasingly difficult to store and transfer them [1]. When an image file is compressed, it takes up less space than the original file because of the encoding or conversion process. Reduces the size of a picture file while maintaining or improving its quality to the greatest extent possible. Image compression in digital picture processing is the most useful and commercially effective technology for minimizing the quantity of data desired for the image [2], while the image reconstruction helps to retrieve the original information that was transferred. They have employed wavelets since the late 1980s to handle a wide range of complex problems like fingerprint compression, signal denoising, and medical image processing [3]. The discrete wavelet transformation (DWT) of an image is made up of a summation of wavelet functions identified as wavelets, in addition to the size and station of the wavelets vary depending on the image. The DWT creates an image for each of the picture's 32×32 blocks by applying two filters, one on the high pass and one on the low pass, to each of the image's 32×32 blocks. Wavelet transformation techniques are frequently used in image compression and reconstruction applications, and they are usually recognized as one of the most effective methods of achieving these results. The use of a constant scale factor to a transformation matrix results in the compression of the transformation matrix. When the outcomes of this process are compared subjectively and objectively, they are found to be excellent and extremely precise. These algorithms are commonly used to reduce the size of an image. DWT output is not ideal for smooth image portions.

Additionally, a Shearlet transform is employed for image compression and reconstruction instead of just wavelets. Shearlets are mostly utilized in multivariate functions by proving a better context [4]. The Shearlet was originally developed for the analysis and sparse based type of approximation of functions in the year 2006. Usually, the Shearlets are considered as a valid extension of the standard form of wavelets since wavelets, as isotropic objects, are unable to capture multivariate functions that are often influenced by anisotropic features such as image edges. It was the primary goal of developing Shearlets to improve on wavelets as an extension strategy for attaining optimal outcomes even on multivariate functions. Wavelets were first designed to improve on this goal. The procedures involved in these approaches based on the Shearlet transform have typically been examined for edge-based features, as has been the case in the past.

The Stockwell transform has been used as an alternative to typical picture reduction and reconstruction methods. When it comes to classical compression, only statistical redundancy is taken into account. A significant portion of the redundancies is generated by the abrupt insertion of picture characteristics as a result of several errors. As a result of these redundancies, photographs may contain data that has been duplicated, leading in the superimposition of visual qualities and objects, resulting in the non-perception of information contained within images. Utilizing images' visual redundancy in order to increase coding efficiency has become widespread practice during the last few years [5]. In order to transmit and receive photos with the least amount of information duplication possible, numerous protocols must be followed. Current efforts, on the other hand, only produce unsatisfactory visual redundancy reduction solutions. Using both subjective and objective evaluations, this study compares the existing approaches with the suggested improved Stockwell transform method. The ability to lower the dimensionality of data and minimize the amount of inaccuracy between the extracted components and the original data is one of the primary benefits of using the improved Stockwell transform in a variety of scientific and engineering domains.

2. LITERATURE REVIEW

There is a lack of storage and bandwidth capacity, it has been difficult to send digital photographs over long distances. This problem is commonly solved by compressing the images before sending them over the internet, which is one of the most common remedies. Because digital images have become increasingly popular for communicating, distributing, storing, and visualizing information, high-speed compression solutions are required to keep up with demand. With transform techniques, the most important objective of the basic image compression systems is to store data efficiently while also achieving a reasonable balance between compression rates and noise reduction (or noise reduction and compression). The transform-based compression method can be used to a variety of different uses. When combined with other compression techniques, these and other techniques can efficiently transmit, save, and show images that would otherwise be impractical to send, save, and display [6]. Transformations require less bandwidth to be encoded than other types of data. In this coding approach, the digital parts of Fourier as well as the coding transform procedures are generally employed to convert the initial input into the required frequency domain coefficients, which are then converted back into images. The energy compression property of these coefficients is another desirable characteristic. In study [7], the operations are allocated for reconstructing the compressed image. The simulation results show that, even if the compression ratio parameter is raised due to the decrease of wavelet packet sub-bands, the quantity of the image is still good. Because discrete wavelet transformation (DWT) and discrete cosine transform (DCT) are considered to be lossy methods, they are discussed in [8]. Better peak signal to noise ratio (PSNR) results were obtained by using DCT and Wavelet change in this work, which takes pressure into account [9]. According to study [10], a DWT is used in conjunction with entropy coding and quantization as well as thresholding techniques to provide a lossless compression ratio of excellent quality and a high compression ratio for images.

Proposals were made in study [11] by Hasan. The Shearlet transform is used to develop a new coding method. Using an anisotropic Shearlet transform, notable features like the image's edges can be identified. Shearlets, on the other hand, are potentially better at representing images with geometrical features, such as edges, than traditional wavelets. In order to encode the threshold output, the set partitioning in hierarchical trees (SPIHT) method is utilized to apply the threshold method to the Shearlet transform coefficients before applying the threshold method to the Shearlet transform coefficients. When comparing Shearlet compression to wavelet compression, Shearlet compression is further effective for a broad variety of geometric features of the experimented images than that of a basic form of wavelet compression. The discrete orthogonal Stockwell transform (DOST) intended for image compression was described and studied by the authors in [12]. Multiresolution spatial-frequency representation, a greater PSNR value, and improved image quality are all benefits of this conversion. As seen in 2D image compression, this transforms approach outperforms wavelet compression in the smooth areas of 2D images. For transform-based approaches like wavelets, Shearlets, and Stockwell-based algorithms the whole literature review was conducted [13]. Transformation, quantization, and coding-based compression approaches have become more popular in recent years because the transform decomposes the spatially distributed energy into a smaller number of data points. As a result of all of these methods, an improved version of Stockwell's theorem has been proposed in this work, which will be described in detail with theoretical foundations of existing procedures.

3. IMAGE COMPRESSION AND RECONSTRUCTION METHODS

3.1. Shearlet transform

Shearlets were established with the stated goal of providing an extremely efficient representation for images having edges. Indeed, the Shearlet representation is composed of multiple locations, scales, and inclinations and exhibit extremely anisotropic morphologies. As a result, the Shearlet representation is particularly well-suited for displaying edges and other anisotropic objects that dominate conventional images. The representation components that we obtain are termed Shearlets. A single mother function is transformed via translations, dilations, and shear transformations. For two-dimensional functions with smooth curves, the Shearlets provide optimally sparse representations. Because these systems are based on a mathematical structure similar to that of conventional wavelets, they can enable multiresolution analysis in a way that aids in the development of fast algorithmic applications. Moreover, Fourier transformations is mostly used as pre-processing in these types of transforms to maintain the harmonics involved in their methods. This concept is explored in this article by applying rapid Fourier transformations as a foundation and employing shift-creating Shearlets for both image compression and reconstruction.

3.2. Multilevel wavelet transform (MWT)

Multiwavelets, like wavelets, were derived through multiresolution analysis (MRA). MRA with wavelets contains a single scaling function and a single wavelet function, whereas multiwavelets have a large number of scaling functions contained within a single vector. Multiwavelet transforms are a novel family of wavelet transforms that employ several prototype scaling functions and wavelets in multiresolution analysis and synthesis. As a result, they are particularly well suited for multiresolution analysis and synthesis. Ensure that the filter banks used to apply the wavelet transform satisfy orthogonality, symmetry, short support, and a higher approximation order all at the same time in order to achieve significant improvements in compression performance. The use of wavelets to satisfy all of these needs at the same time is unfortunately not possible due to technical limitations. This difficulty is solved by a new class of wavelets called multiwavelets [14].

This concept is revisited in this article by utilizing a multi-level wavelet transform to decompose the image depending on several filtering procedures. The image is wavelet decomposed using the Daubechies D4 filter as the initial low pass filter. The image is reconstructed using a multi-level inverse wavelet transform. This process is implemented by executing the inverse wavelet transform on the corresponding wavelet coefficients from a previous decomposition matrix.

3.3. Multilevel Haar wavelet transform (MHWT)

Any study of wavelets must begin with the simplest and first wavelet, the Haar wavelet. Haar wavelet is discontinuous and has a step function-like appearance [15]. The Haar transform reduces the area of the frame by a fourth at each level, allowing for an extremely simple mapping of the threshold for background foreground object distinction. However, with multilevel wavelets, we use the Haar transform for multiple levels to reduce the computation time of the corresponding frames (1, 2 and 3). Throughout this work, a signal thresholding for images is created using wavelet packet coefficients thresholding, and an extra output argument TREED is provided to show the decomposition of compressed images using wavelet packet trees in order to reconstruct the image.

3.4. Stockwell transform

The function wavelet transform (WT) is an efficient method for takeout time and incidence data fields in addition to is noise tolerant [16]. The short time Fourier transform (STFT) takes a stable resolution, and the WT does not incorporate phase information. This resulted in the creation of a new-fangled transform called the Stockwell transform, which is an addition of the WT or STFT adjustable window [17]. It is entirely predicated on a modular Gaussian localization window as well as provides frequency dependent resolution [18]. The S-transform is very well for the local spectral phase properties. The ability of the S-transformations to incorporate frequency-dependent time-frequency resolution to referenced local phase information distinguishes them [12]. The S-transform is a mathematical transformation that enables for frequency-based resolution via immediate supervision of a Fourier spectrum relationship. The wavelet transform is not considered a continuous wavelet transform because it does not satisfy the condition of zero mean [13]. The S-transform is especially robust in the face of noise, making it useful for characterizing and processing non-stable signals with high accuracy. S-transforms have a wide range of applications in a variety of sectors, including medical and non-medical [19]. This technology is utilized in non-medical applications like as geophysics, gravitational wave detection, picture transmission/compression, and other similar fields. The Stockwell transforms, primarily orthogonal versions of the Stockwell transform, are used in this work to compress and rebuild images.

4. IMPROVED STOCKWELL TRANSFORM

When applying the transform methods discussed in the preceding section based on available theoretical and practical concepts through simulation, it is discovered that Stockwell transforms can provide superior results in terms of both appearance and parametric properties when image reconstruction is performed. The orthogonal Stockwell transform, which has been previously investigated, is modified in such a way that it yields more favorable outcomes. Thus, the discrete cosine transforms, which employs bandwidth partitioning and is used in a wide variety of applications is combined with the currently available Stockwell transform to produce the proposed approach, dubbed improved Stockwell transform. The methodology is detailed in detail below, along with a proposed block design seen in Figure 1.

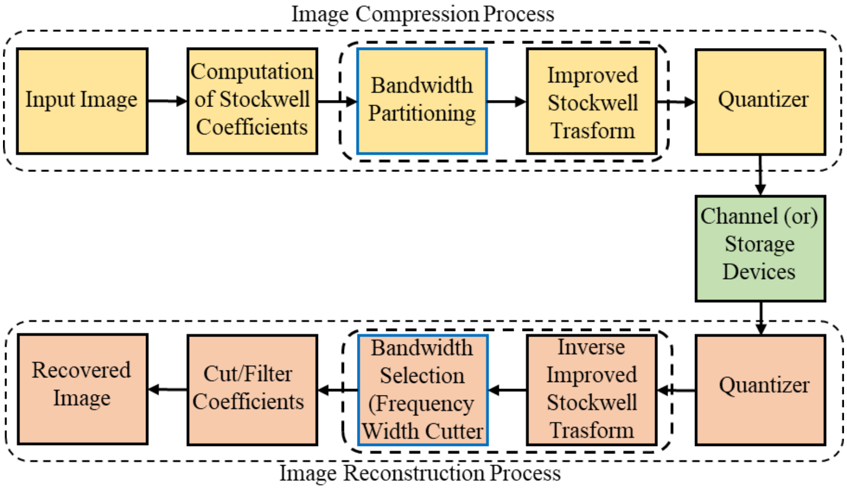


Figure 1. Image compression block diagram and reconstruction with improved Stockwell transform

4.1. Proposed methodology

The following is the proposed methodology of improved Stockwell transform:

a. The proposed method works rows and columns of the input image using the improved function created by involving discrete cosine transform along with Stockwell transform.
b. Later this improved function computes the DCT based discrete orthonormal Stockwell coefficients of a given input image.
c. Function takes a look at the number of rows of the input and initializes the output by keeping a condition that same output size as the input.
d. Further a partition of the frequency space carried out by DCT based band width partitioning of samples function depending on number of frequency bands and bandwidths.
   – Samples represent length of the image analyzed.
   – Here number of different frequency bands means on which partitioning the time-frequency space is required.

- The bandwidths are ordered from zero to high frequencies.

e. Further computation of the DCT of the input using the fast Fourier transform (FFT) is carried out.
f. At the receiver Inverse DCT is carried out for the reconstruction process.
   - Here we have to choose the bandwidth interested in and call it as frequency width cutter
   - Later cut all the DCT coefficients of the function in the frequency band.
   - Finally perform the inverse discrete cosine transform (IDCT) just on the selected frequency band.

In this improved Stockwell transform, the standard inputs are treated to producing the coefficients based on the Stockwell transform, after which they are submitted to the bandwidth partitioning process as well. As a result of the deconstructing operation performed in the early stages, the obtained values are then fed into the proposed method for transformation, which results in the generation of the frequency components. Later on, the Quantizer is supposed to convert them into a format that can be communicated across a channel or media of choice. Inverse Quantizer has a tendency to turn these components into normal elements at the receiver side, which is ultimately a stage of image reconstruction after they have been received. These values are subjected to the inverse Stockwell transform in order to convert frequency components into observable coefficients, which are then subjected to the bandwidth selection process, which is primarily for the purpose of frequency width cutting, as well as to declutter the coefficients, in order to obtain the reconstructed image, which is then compared with the original input in order to determine whether the proposed method has produced optimal results in terms of various statistical parameters, as well as subjective comparison. After transforming the input using processes such as the Stockwell transform, the transformed coefficients, which represent different frequency components, are quantized in the proposed method. A quantizer performs this quantization, essentially mapping these coefficients to a set of specific values or levels. The goal is to reduce the precision of these coefficients so that they can be used more efficiently for communication or storage. Each coefficient is assigned to the quantization level closest to it, reducing the continuous range of values to a smaller set. The quantization error introduced by this mapping process represents the difference between the original and quantized coefficients. The primary advantage of quantization is that it significantly reduces the amount of data that must be transmitted or stored, resulting in compression. However, there is a trade-off: greater compression comes at the expense of some error or loss of information. The challenge is to strike the right balance between compression and detail preservation. The quantization process is critical in image compression because it influences how efficiently data is represented and the resulting image quality.

5. IMAGE QUALITY ASSESSMENT

A major improvement has been made in the image quality assessment parameters that are utilized to compare the proposed approach to existing methods in this section of the paper. The quality analysis of a picture is used to determine the substance and texture of the image. Image distortions can occur during the development, processing, compression, and storage of digital images. These distortions can occur throughout the creation, processing, compression, and storage procedures. Additionally, image quality-degrading distortions might arise throughout transmission in addition reconstruction [20]. Peak signal to noise ratio is one of the promising visual evaluation parameter [21]. The mean squared error (MSE) besides the PSNR remain two frequently considered as image quality parameters [22]. A remarkable performance clearly illustrated that the convolution neural networks-Slanlet transform (CNN-SLT) method worked well for three datasets [23]. MSE in addition to PSNR are straightforward to calculate and require a distinct denotation, which is illogical and unsuitable for pictorial quality [24]. Additionally, the following quality measurement metrics can be used to evaluate the reconstructed image's quality [25]. A system that uses low-level descriptors is introduced and shown a significance in image processing [26].

5.1. Mean squared error (MSE)

The mean squared error (MSE) is used to calculate the difference between the predicted and expected outcomes. This metric is called the dispersion metric, and it is used to assess the quality of the image enhancement technique used to remove noise and blur. Here (1) is considered as the mean square error aimed at a two-dimensional image of a measure (M×N)

$$\mathrm{MSE} = \frac{1}{\mathrm{MN}} \sum_{x=1}^{M} \sum_{y=1}^{N} [I(x,y) - I'(x,y)]^2 \quad (1)$$

In computing this parameter, the variables are $I'(x,y)$ which denotes the contribution image (or) novel Image whereas $I'(x,y)$ is considered as the production image or reconstructed image. Generally, if obtained MSE value is smaller, it indicates that the reconstructed image has fewer errors.

5.2. Peak signal to noise ratio (PSNR)

Peak signal to noise ratio (PSNR) is a critical parameter for determining the quality of a restored image that has been distorted by noise and blur. The PSNR value is determined by the MSE. PSNR is obtained when comparing two images by calculating the MSE between the pixel intensities and the ratio of the maximum possible intensity to the calculated value. The PSNR is a way of measuring of peak error inside the restored image that can be calculated using (2).

$$PSNR = 10 \log_{10}\left(\frac{255^2}{MSE}\right) \quad (2)$$

As shown in (1) and (2), there is an inverse relationship between PSNR and MSE. The smaller the MSE, the greater the PSNR. A greater PSNR number indicates a stronger signal-to-noise ratio.

5.3. Normalized cross-correlation (NCC)

The NCC is a metric for comparing two sets of images. In image processing applications where the image's brightness can change due to lighting and exposure circumstances, the images can first be normalized. It is used to determine the number of instances of a pattern or object in a picture. A frequently used parameter that aids in determining the grade of resemblance or dissimilarity among the input image and its corresponding reconstructed image. Normally, the NCC value ranges between -1 and 1. If the NCC value is '1', the time series image alignment is precise, but the magnitude can differ and is symbolized in (3).

$$\text{NCC}=\sum_{x=1}^{M}\sum_{y=1}^{N} I(x,y).I'(x,y) \quad (3)$$

5.4. Average difference (AD)

The average difference (AD) as provided in (4) is the difference in pixels between the filtered and degraded images. This quantitative measure is utilized exclusively in object detection and recognition applications, but it can also be used in any image processing application where the average difference between two images is determined.

$$AD = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}[I(x,y) - I'(x,y)] \quad (4)$$

5.5. Structural content (SC)

The structural content of an image is concerned with the spatial organization of its pixels. It determines the proximity of two digital images, which may alternatively be expressed as a correlation function. This metric is used to determine the degree of resemblance between two photographs. It eliminates the intimate relationship between two images and says that the human eye is incapable of distinguishing the two images. The degree of correspondence between images is determined by their structural contents. The more similar the sections of together the original in addition to restored images are, the added analogous they are. The structural content equation is specified by (5).

$$SC = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N}[I(x,y)]^2}{\sum_{x=1}^{M}\sum_{y=1}^{N}[I'(x,y)]^2} \quad (5)$$

5.6. Maximum difference (MD)

It is proportional to contrast and so determines the dynamic range of a picture. It is accomplished by sending a picture through a low pass filter, as sharp edges correlate to the image's higher frequency parts, which the low pass filter suppresses. It illustrates a variation on the balancing comparisons method. The situation is denoted by an expression (6).

$$MD = Max(|I(x,y) - I'(x,y)|) \quad (6)$$

5.7. Normalized absolute error (NAE)

Normalized absolute error is the standard measure used to detect blurring in any real-time image. This calculates the numerical transformation among the original image and the rebuilt image. This is specified in expression (7).

$$NAE = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N}|I(x,y) - I'(x,y)|}{\sum_{x=1}^{M}\sum_{y=1}^{N} I(x,y)} \quad (7)$$

6. RESULTS ANALYSIS AND DISCUSSION

Typically, the reconstruction procedure is designed to recover as much of the original image as possible while maintaining extremely low deviations from several image quality assessment factors. The basic images Lena, Cameraman, and Barbara are investigated experimentally using current methods such as the Shearlet transform, MWT, MHWT, orthogonal Stockwell transform, and the suggested approach improved Stockwell transforms. These techniques assist in compressing the image using the conforming algorithms and producing the restored image at the receiver.

Shearlet transforms were applied to standard images such as Lena, Cameraman, and Barbara, and their corresponding Shearlets and reconstructed images are displayed in Figure 2. The primary advantage of Shearlet transforms is that they maintain more texture and edge information. Multilevel wavelets compress energy substantially more efficiently than some scalar wavelets. Thus, multiwavelets may be able to provide a higher-quality reconstruction at the same bit rate. Multilevel wavelet transforms were applied to standard images such as Lena, Cameraman, and Barbara, and the resulting reconstructions are presented in Figure 3.

The MHWT was applied to standard images such as Lena, Cameraman, and Barbara, and the resulting reconstructions are presented in Figure 3. Haar wavelets are easy to implement and compute quickly because to their small size. In comparison to wavelet transforms, the advantage of multilevel wavelets is that it has an uncommon representation, a speedy transformation, and a tiny memory footprint. The Haar transform is used in this piece to reduce the size of the frame by a factor of four at each degree of complexity.

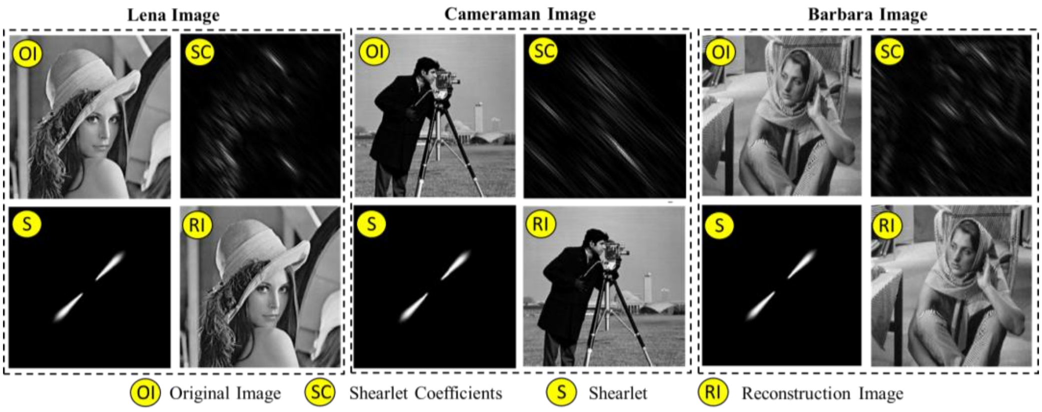


Figure 2. Lena image reconstruction, Cameraman image reconstruction and Barbara image reconstruction using Shearlet transform

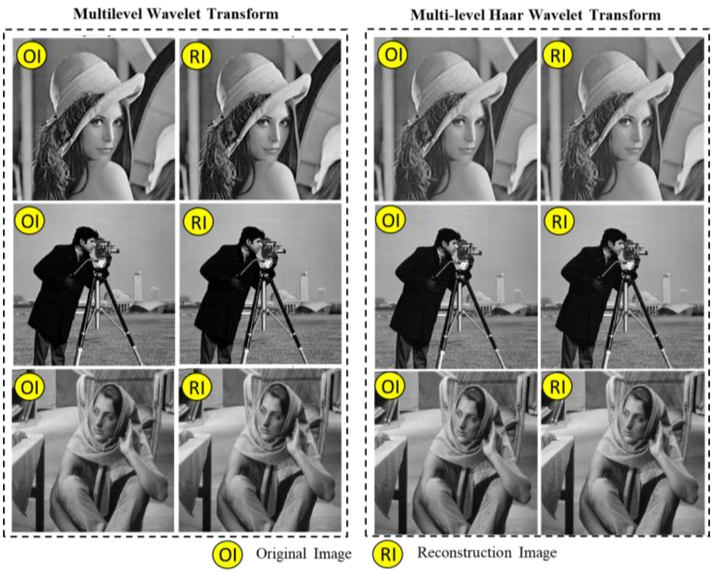


Figure 3. Lena image reconstruction, Cameraman image reconstruction and Barbara image reconstruction using MWT and MHWT

The Stockwell transform, in this case the DOST, was applied to standard images such as Lena, Cameraman, and Barbara, and their corresponding Stockwell transforms and reconstructed images are displayed in Figure 4. The zero-frequency components are found in the center of the figure, corresponding to the Stockwell transform of the image, with frequency increasing to the right and down as the figure progresses.

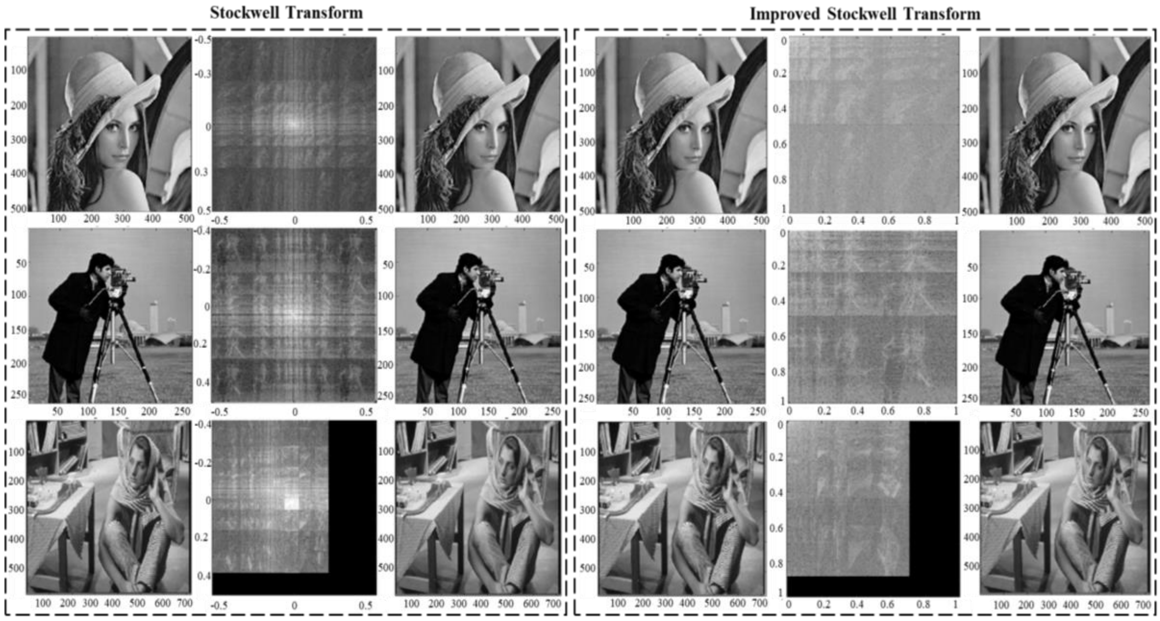


Figure 4. Lena, Cameraman and Barbara images reconstruction using Stockwell transform and improved Stockwell transform

The proposed algorithm was tested on standard images such as Lena, Cameraman, and Barbara, and the corresponding Stockwell transform and reconstructed images are displayed in Figure 4. Each sub-band of the image's improved Stockwell transform contains a smaller version of the image. This is due to the fact that the fundamental functions have a stronger relationship with the edges, especially at higher frequencies. Because the order of the coefficients has been flipped in order to ensure conjugate-symmetry, the picture in bands with negative frequencies is mirrored in the resulting image.

Image quality evaluation is a critical component of a large number of picture and signal processing applications, as it verifies the quality of any image reconstruction algorithm. To conduct the objective study, image quality evaluation parameters for all approaches, including the proposed methods, were explored. Each metric contributes to the regulation of image quality. The correctness of the corresponding reconstructed image in this experimental process will be generally assessed utilizing industry-standard measurement criteria such as MSE, PSNR, NCC, AD, SC, MD, and NAE. MSE, for instance, is a simple and direct and widely used distortion measure. The disparity between both the produced and reference images is represented by the MSE value. The lesser the MSE, the better the outcome of the reconstructed image. In general, standard assessments PSNR is another popular metric for evaluating reconstruction efficiency of an algorithm or method. A greater PSNR value indicates a higher quality of reconstruction. MSE and PSNR comparisons, respectively, demonstrating that MSE is less and PSNR is greater for each given image simulated using the proposed improved Stockwell transform method. The relevant graphical representations of MSE and PSNR are shown in Figures 5(a) and 5(b), respectively, to illustrate how values are distributed and to support the proposed method's performance.

The NCC is the original image's similarity to the decoded image. The NCC is a metric for comparing two sets of photographs. NCC has standard values ranging from –1 to 1. A correlation coefficient of –1 shows complete correlation, while a correlation coefficient of 1 indicates perfect anti-correlation. The AD is the difference in pixels between the original image and its matching reconstructed image. A higher AD value indicates that the image is of poor quality. The corresponding graphical representations of NCC and AD are shown in Figures 5(c) and 5(d), respectively, to illustrate how values are distributed and to support the proposed method's performance.

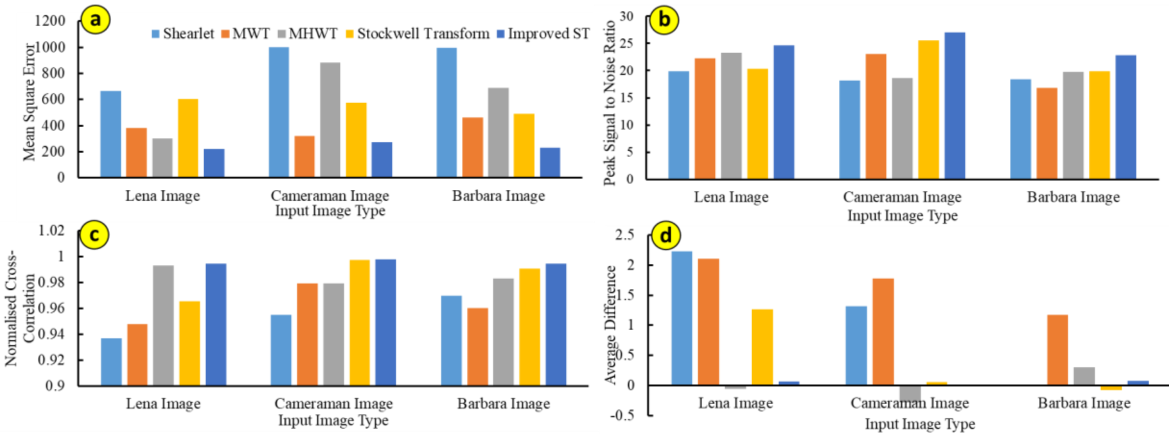


Figure 5. Graphical representation (a) mean square error, (b) peak signal to noise ratio, (c) normalized cross correlation, and (d) average difference for original and reconstructed image using different techniques

The comparison of the SC parameters eliminates the tight relationship of two images and implies that the human eye cannot separate the two images, as illustrated graphically in Figure 6(a). The considered structural excellence metric is a universal metric that associates the total weightiness of the compacted image to the inventive image's entire weight. The structural content with a weight of one provides a higher-quality image than the rest of the stuff. A little average value discrepancy implies that the image quality is excellent. This parameter must be very close to 1, or unity, and so the proposed technique has shown promise. MD values greater than zero indicate that the image is of poor quality, while values less than zero indicate that the image reconstruction is of high quality, depicted graphically in Figure 6(b). As with AD, the MD metric can be useful in object identification and recognition applications.

The NAE, which stands an extent of the guesstimate excellence of determined value images, graphical display in Figure 6(c) for simple comprehension. It is obvious that the statistical measures of the improved Stockwell transform approach the ideal values and produce much better outcomes. Figure 7, which plots PSNR versus bit rate, provides a more detailed picture of the proposed compression algorithm's performance. PSNR initially rises as bit rate increases, reflecting the algorithm's ability to faithfully represent transformed coefficients during quantization and encoding. This initial improvement plateaus, indicating diminishing returns in perceptual image quality above a certain bit rate. Convergence to a stable PSNR level denotes an optimal trade-off between compression efficiency and image fidelity, emphasizing the importance of striking the right balance in bit allocation for representation.

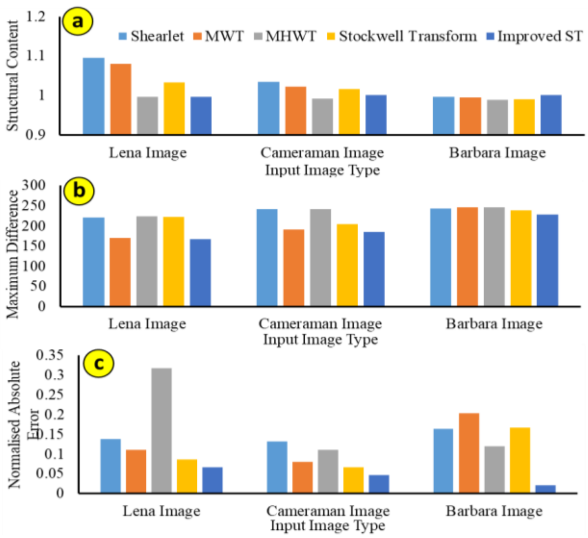
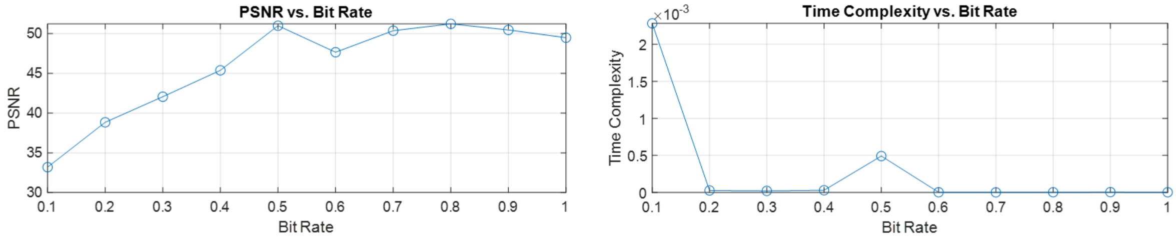


Figure 6. Graphical representation (a) structural content, (b) maximum difference and (c) normalized absolute error for original and reconstructed images using different techniques

The correlation between PSNR vs bit rate in Figure 7(a), time complexity and bit rate in Figure 7(b) sheds light on the algorithm's computational efficiency. Time complexity is particularly high at the beginning of the bit rate range due to intensive processes such as the Stockwell transform and transformation methods. However, as the bit rate increases, so does the time complexity, implying algorithmic optimizations. The algorithm's ability to streamline operations and converge towards an efficiently optimized state is reflected in the decreasing time complexity. Beyond the point where time complexity minimizes, further increases in bit rate have a diminishing impact on computational requirements, confirming the algorithm's refined and well-optimized compression process. These figures show the delicate balance between image quality, compression efficiency, and computational resources.



(a) (b)

Figure 7. Correlation between (a) PSNR vs bit rate and (b) time complexity vs bit rate

7. CONCLUSION

It is consequently critical to return the damaged image to its original state. As a result, the approaches mentioned in the study were analyzed subjectively in order to extract the main changes between the original image and the reconstructed image. Quality assessment of metrics was also investigated. Each statistic has a role to play in monitoring the image's quality, and these were thoroughly explored to determine the outcomes. The above-mentioned statistic evaluates the image's quality objectively. A comparison of four methods, including the proposed method, was conducted using various quality assessment parameters such as peak noise ratio, MSE, AD, NCC, SC, NAE and MD and it was concluded that the proposed improved Stockwell transform provides better image quality of reconstructed images than other existing techniques.

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