Research Journal of Applied Sciences, Engineering and Technology 11(8): 885-897, 2015
DOI: 10.19026/rjaset.11.2100
ISSN: 2040-7459; e-ISSN: 2040-7467

Submitted: June 10, 2015 Accepted: July 8, 2015 Published: November 15, 2015

Research Article

Denoising using Non Local Linear Filtering and Quantization Matrix Estimation Using ANFIS Algorithm for JPEG Error Analysis to Digital Image Forensics

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Abstract: One of the most commonly used image format is Joint Photographic Experts Group (JPEG). The recognition of JPEG compression plays a significant part in digital forensics. In previous work, JPEG image can be compressed upto n times. However, in the compression techniques noise of the JPEG images and the error analysis in the JPEG images are not primarily concentrated. Hence, the recognition of the JPEG compression results will turn out to be complicated. With the intention of overcoming these concern and eliminate the noise from the image samples, in this study formulated a blend of non local-means filter and its method noise thresholding by means of wavelets. In order to diminish the size of the JPEG image, a Growcut based seam carving technique is employed in this study. Subsequently noises are added to image to carry out Non local Linear Filter (NLF) and its Method Noise Thresholding by means of wavelets (NLFMT) denoising framework. For the purpose of assessing the influence of image compression on the performance of JPEG, a sample Discrete Cosine Transform-Singular Value Decomposition (DCT-SVD) was computed for single and double image compression, images were quantized by means of numerous quantization matrices, quantization matrix results are assessed with the help of Adaptive Neuro Fuzzy Inference System (ANFIS). Based on ANFIS, the elevated frequency coefficients in quantization matrix are employed to make a distinction among singly and doubly compressed images. Extensive experiments and evaluations with previous techniques reveal that the proposed DCT-SVD-ANFIS scheme can discover the double JPEG compression efficiently and noise in the image samples are eliminated with the help of NLFMT methods; it outperforms the existing approaches considerably based on the parameters like Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE). The quantization matrix results were assessed using ANFIS; it has extremely much significance in the field of digital forensics.

Keywords: Adaptive Neuro Fuzzy Inference System (ANFIS) error analysis, Discrete Cosine Transform (DCT), filtering, Growcut Seam Carving (GCSC), image denoising, JPEG image compression, Singular Value Decomposition (SVD)

INTRODUCTION

Gradually more sophisticated and economical digital technologies, together with the open extension of Internet, have made it feasible to simply capture, reproduce, distribute and manipulate digital images with extremely modest effort. This has also paved way for challenging issues relating to multimedia authenticity and consistency. Digital image forensics has come forward as a new discipline to assist rescuing some trust in digital photographs, by discovering clues regarding the history of content (Delp *et al*., 2009). In the nonexistence of any form of digital watermarks or signatures, this department works on the assumption that most forms of tampering will upset certain features of the image. To the degree that these perturbations can be quantified and identified, they can be employed to validate a photo. Practices in digital forensics can be classified as:

- Pixel-based, discovering statistical patterns at the pixel level (Redi *et al*., 2011)
- Format-based, discovering statistical patterns particular to an image compression format (e.g., JPEG or GIF) (Neelamani *et al*., 2006)
- Camera-based, utilizing artifacts introduced by the camera lens, sensor or on-chip post-processing (Chen *et al*., 2008)
- Physically based, modeling and computing the contacts between physical objects, light and the camera (O'Brien and Farid, 2012)
- Geometry-based, utilizing the principles of image construction as governed by projective geometry (Conotter *et al*., 2012)

JPEG is the one of the most recent subject in the image compression technique that is employed today. The Joint Photographic Experts Group stands for JPEG, a standards committee that had its source within the

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International Standard Organization (ISO). The JPEG format is accepted in the majority of the digital cameras and image processing instruments; numerous forensic instruments have thus been investigated to notice the existence of tampering in this class of images. On the whole, the manipulation is noticed by examining appropriate artifacts introduced by JPEG recompression taking place when the forged image is generated; specifically, these artifacts can be classified into two classes, in accordance with whether the second JPEG compression implements a DCT grid aligned with the one employed by the first compression or not. The first scenario will be indicated as aligned double JPEG (A-DJPG) compression, at the same time the second scenario will be indicated as nonaligned sdouble JPEG (NA-DJPG) compression. Schemes come under the first category include (Feng and Doërr, 2010), while the existence of nonaligned double JPEG compression has been examined in (Bianchi and Piva, 2012).

Recognition of double compression of the JPEG images is extremely helpful for applications in steganography (Pevny and Fridrich, 2008). Primarily it is having two uses; first of all it portrays an efficient scheme for discovering double compression of the JPEG images with the assistance of Support Vector Machines. A vital characteristic of this scheme is that, it is capable of identifying double compression of the cover images as well as the images processed with steganographic approaches. Secondly, it assists in creating a highest probability estimator of the prime quality factor in double compressed JPEG images.

The majority of the previous approaches based on the hypothesis to know the exact spot of the possibly manipulated region, for instance, by implementing a segmentation of the image under test prior to the forensic analysis as done (Barni *et al*., 2010), or they are simply intended to examine the complete image, with the intention that the exact spot of the forgery in a tampered image is still an open concern, image resizing is not carried out, noises like the Gaussian noise, sharpening noise, salt and pepper noise and the speckle noise, in the images samples are not eliminated in the double compression scheme. With the intention of surpassing these concerns and eliminate noise in the image sample, carry out image denoising based on the filtering methods.

Image Denoising (Kumar, 2013) is a most widely used practice in digital image processing intended to the elimination of noise, which possibly will distort an image at some stage in its acquisition or transmission, at the same time preserving its quality. Although denoising has long been a focal point of research, there constantly remains space for enhancement, particularly in image denoising. For images, noise suppression/reduction is a delicate and a complicated process since there is a trade-off among noise reduction and preservation of actual image features. When high frequency noise is to be eliminated from the distorted image, the uncomplicated spatial filtering might be adequate, however at the cost of computational complexity concerned in carrying out the convolution.

With the aim of solving these filtering methods complications, Non Local Means Filtering and its method noise thresholding by means of wavelets have been formulated for image denoising. In this study consider JPEG double image compression, initially the image was transformed into resized image by means of Growcut based seam carving resizing scheme, subsequently noise in the images are eliminated with the help of NLFMT filtering methods, then it is quantized by means of DCT transformation matrix is called the primary quantization matrix, the quantization matrix employed in second compression is called the secondary quantization matrix. These quantization matrixes are examined using Adaptive Neuro Fuzzy Inference System (ANFIS). Several quality factors are employed to analyze quantization results of single and double compression quantization matrix.

LITERATURE REVIEW

JPEG can be regarded as an algorithm that can be handy for image compression and also that approach can be transformed to meet the different requirements of the users. By means of JPEG image compression, it can accomplish extremely high compression ratios. When the compression ratios increase, the quality of the image diminishes considerably. However, those images are still exceptionally helpful in several applications. For transferring extremely compressed image by means of internet, it will utilize incredibly small bandwidth.

JPEG standard portrays the image compression system that is at present most extensively utilized, this compression represents a forensically interesting operation to be investigated. Certainly, numerous forensic researches in the literature make use of the characteristic footprint left in the DCT coefficients distribution of an image at some stage in compression, aiming at determining traces of previous JPEG compression and approximating the employed quantization step (Luo *et al*., 2010). Current results demonstrate that even multiple instances of JPEG compression can be identified (Milani *et al*., 2012). Unfortunately, the above mentioned approaches have certain drawbacks in real life circumstances, where chains of operators might have been executed to the content.

In earlier works (Conotter *et al*., 2013), revealed that linear image processing, for instance, filtering, frequently executed to the whole image (full-frame) as post processing for image improvement, however probably also for forensic footprints elimination, might modify the characteristic artifacts introduced by the JPEG compression scheme. In (Conotter *et al*., 2013) a precise mathematical model was formulated to tentatively differentiate the probability distribution of the DCT coefficients of JPEG full-frame linearly filtered images. Considering the quantization phase to be known, such knowledge can be utilized with the intention of retrieving the applied filter kernel by measuring the difference among the derived models (each model based on the implemented filter kernel) and the real distribution of a to-be-tested image.

Two image features, the smoothness and the similarity, which furnish rise to local and global redundancy in image representation investigated in Kil *et al*. (2006), the smoothness indicates that the gray level values inside a specified block diverge gradually rather than abruptly. The JPEG compression will bring JPEG compression features to the DCT coefficients, these features are strongly associated with the quality factor. Concepts that optimize image compression ratio by making use of the information regarding a signal's features and their uses are introduced in (Golner *et al*., 2000). This supplementary information regarding the image is employed to accomplish advance gains in image compression.

A quick and efficient technique is given in (Fan and de Queiroz, 2003) to decide whether an image has been formerly JPEG compressed. Subsequent to noticing a compression signature, compression constraints are approximated. A technique for the maximum likelihood evaluation of JPEG quantization phases has been formulated. An adaptive regression scheme implemented to the standard JPEG compression for archiving elevated compression ratios presented in (Chang and Lai, 2009). However, the entire schemes don't carry out the image denoising and the image double compression quantization matrix results are not determined, noises in the image samples are not eliminated.

Seam carving is an efficient image processing operator for the purpose content-aware image resizing (Avidan and Shamir, 2007). It produces an energy map from gradient intensity of pixels and looks for seams, which are vertical or horizontal uninterrupted paths of pixels that run through local minimum energy regions. For the purpose of image resizing, user typically desires to defend or eliminate particular inappropriate pixels in the image. On the other hand, automatic image resizing by seam carving is complicated to meet this condition since the energy function by low-level characteristics is hard to separate different object with high-level semantics.

Constraints of the last JPEG compression from the file header and as a result, their schemes will not be appropriate for the forensic scenarios, with the intention of solving this complication and estimate the image quantization matrix results, eliminate noise from images, diminish the space of the image, proposed work carry out image resizing, image denoising framework, then execute image quantization matrix by means of the classification method.

PROPOSED METHODOLOGY

In this study, a well-organized double compression schema is formulated for JPEG images by improved DCT-SVD Methods. In order to diminish the size of the images following JPEG compression of images are resized by means of improved seam carving schemes. Following the image are resized, still certain amount of noises exist in the JPEG image sample, with the purpose of eliminating noises from the resized JPEG image sample, in this study presented a non local-means filter methods, prior to that some of the noises are appended to resized image. Subsequently execute Non Local-means Filter and its Method noise Thresholding by means of wavelets (NLFMT) to eliminate noise for resized JPEG image sample. Executed quantization step from (Chang and Lai, 2009) to examine the error of compression techniques with the help of Adaptive Neuro Fuzzy Inference System (ANFIS), it precisely carried out assessment of error results from quantization matrix in both single and double compression techniques. The proposed double compression scheme have lower error rate results when comparing to previous double compression schemes, in view of the fact that it exploits ANFIS for quantization matrix estimation in compressed images and carry out image denoising. Ahead of proceeding modified DCT decompression schemes, initially required to resize the compressed images by means of resizing techniques, it reduce size of JPEG compressed image, carry out image denoising and subsequently it sends into input to quantization process shown in Fig. 1.

Images resizing using Growcut based Seam Carving (GCSC): In this study, initially the JPEG images in the DCT compression image samples are resized with improved seam carving techniques. This resizing technique primarily choose anyone of the pixel value in the JPEG images pairs and then fragment the most significant substance of the JPEG Images. Let original JPEG images as $J = \{J_1, J_2, \ldots, J_n\}$ where $j \in n$ represents the number of JPEG image samples in the training phase. Improved Seam Carving approach is proposed for the purpose of image resizing. Image segmentation GrowCut (Vezhnevets and Konouchine, 2005) is integrated with the original Seam Carving approach to automatically choose the region of significance by draw one line inside the object and one line exterior to the object. The concept behind the seam carving approach is to eliminate unnoticeable pixels that merge in with their surroundings. An energy function is employed to calculate the energy of each pixel. It is utilized to discover and eliminate the seam of lowest significance of the pixels for JPEG image

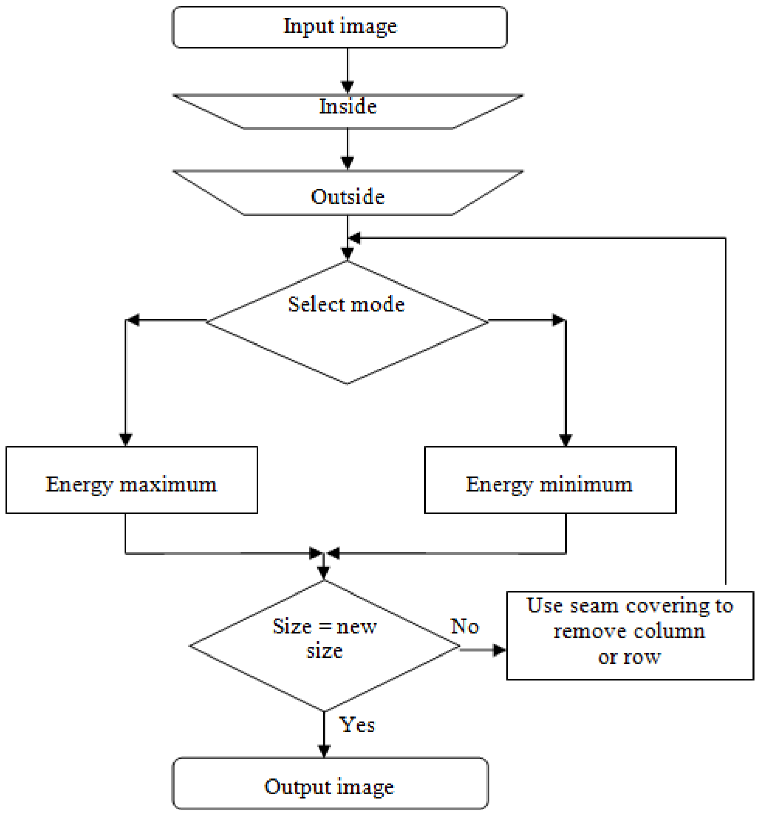

Fig. 1: Growcut based image seam carving

compression. In case of the original seam carving by Avidan and Shamir (2007), the energy functions are described by gradient magnitude as given below:

$$e(JIP) = \left|\frac{\partial}{\partial x}(JIP)\right| + \left|\frac{\partial}{\partial y}(JIP)\right| \tag{1}$$

where, *JIP* represent the pixel value of JPEG image. A seam is discovered by tracing the pathway from one edge of the JPEG image to the contradictory edge through the path with the smallest amount of energy given by the equation below:

$$S^{*} = \min_{s} E(s) = \min_{s} E(s) \sum_{i=1} e(JIP(s_i)) \tag{2}$$

The second process is to transform JPEG image energy. It is indeed a selection of pixel elimination or pixel protection for JPEG images. When it is to be protected, the energy of the pixel by GrowCut is fixed high. If not, when the pixel chosen by GrowCut is to be eliminated, its energy is fixed low. The third process is JPEG image resizes by using Seam Carving. Subsequent to successively eliminating seams, the output JPEG image will accomplish the preferred resized resolution.

Image denoising using Non Local-Means Filter and its method noise Thresholding using wavelets (NLFMT):

Salt and pepper noise: Pepper-Salt noise causes on and off pixels. These noises are appended to resized images and their intensity values are also computed and filtered by means of NLFMT.

Speckle noise: Speckle Noise is the multiplicative noise; it appends multiplicative noise to resized image RSJI, with consistently distributed random noise with mean 0 and variance v.

Gaussian noise: Gaussian noise is a white noise with stable mean and variance and to filter by means of NLFMT. Additive White Gaussian Noise (AWGN) is a fundamental noise model employed in information theory to mimic the consequence of several random processes that take place in nature. The modifiers signify precise features:

- 'Additive' because it is appended to any noise that possibly is intrinsic to the information system.
- 'White' indicates to idea that it has consistent power across the frequency band for the information system. It is a similarity to the color white which has consistent discharges at all frequencies in the visible spectrum.

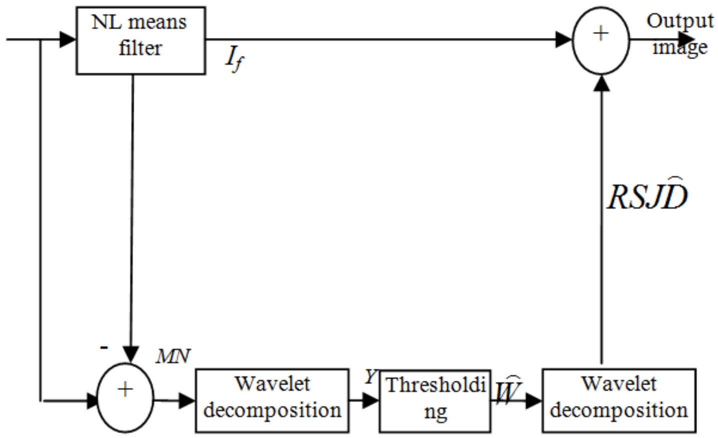

Fig. 2: Proposed image denoising framework

- 'Gaussian' because it has a regular distribution in the time domain with a mean time domain value of 0.

Sharpening: The sharpening of an image is also regarded as a kind of attack. It is a kind of alteration to reveal the image aspects. The edges are highlighted, with the intention that the eye can notice the image extremely quick. Blurriness of the image is diminished.

The objective of image denoising is to eliminate the noise at the same time preserving the significant resized JPEG image elements like edges, aspects as much as possible. Linear filter convolves the resized JPEG image with a constant matrix to get hold of a linear combination of neighborhood values and has been extensively employed for noise removal in the existence of additive noise. This constructs a blurred and smoothed resized JPEG image with reduced feature localization and imperfect noise suppression. The image denoising framework by means of the blend of Non-local Linear Filter and its Method noise Thresholding by means of wavelets (NLFMT) is shown in Fig. 2. A distinction among the original resized JPEG image and its denoised JPEG image demonstrates the noise eliminated by the algorithm, which is known as Method Noise (MN). In standard, the method noise is supposed to appear like a noise. In view of the fact that even good quality JPEG images have certain amount noise, it makes sense to assess any denoising method in that manner, without the conventional "add noise and then eliminate it" trick. Mathematically, it is given as follows:

$$MN = RSJI - I_F \tag{3}$$

where, RSJI represents the original resized image and, I_F indicates the output of denoising operator for a input resized JPEG image *RSJI*.

Non local means filter on the noisy resized JPEG image eliminates the noise and cleans the edges without losing several fine structures and features. Although the Non local-means filter is extremely effective in eliminating the noise at high Signal to Noise Ratio (SNR) (with a smaller amount noise) however as the noise raises, its performance worsens. In order to capture what kind of the noises is eliminated from the noisy resized JPEG image by the Non local means filter, the characterization of the method noise is redefined as the distinction among the noisy resized JPEG image and its denoised original JPEG image with reduced size. Consequently, Eq. (3) is rewritten as below:

$$MN = RJI - I_F \tag{4}$$

where, $RJI = RSJI+Z$ represents a noisy resized image acquired by distorting the original resized JPEG image RSJI by a noise Z and, I_F indicates the output of Non Local means filter for a resized input image. Denoising is subsequently carried out by computing the average gray value of these most similar pixels. Because the resized JPEG image pixels are extremely correlated with noise is characteristically independent and identically distributed averaging of these pixels results in noise elimination and yields a pixel that is comparable to its original value. Provided a discrete resized JPEG noisy image $RSJNI = \{rsjni(i) \mid i \in I\}$ the estimated value NL (i) for pixel i is worked out as a weighted average of all the pixel intensities rsjni (j) in the resized JPEG image *RSJI*:

$$NL(i) = \sum_{j \in RSJI} w(i, j)\, rsjni(j) \tag{5}$$

where, w (i, j) represents the weight assigned to value $rsjni$ (j) for restoring the pixel i. Although the conventional definition of the NL-means filter considers the intensity of each pixel can be connected to pixel intensities of the complete resized JPEG image, the amount of pixels for resized JPEG images considered in the weighted average is limited to a neighborhood search window S_i (4 centered at the pixel i. More specifically, the weight w (i, j) estimates the resemblance among the intensities of the local neighborhoods (patches) RSJNI (N_i) and RSJNI (N_j). Centered on pixels i and j such that 0≤w (I, j) ≤1 and $\sum_j w\ (i,j) = 1$ where N_k indicates a square neighborhood of predetermined size centered at a pixel k and is inside the search window S_i centered at the pixel i. This similarity is determined as a declining function of the weighted Euclidean distance, $\| rsjni\ (N_i) - rsjni\ (N_j) \|_{2,\sigma}^2$ in which $\sigma > 0$ denotes the standard deviation of the Gaussian kernel. This distance is the conventional L_2-norm convolved with a Gaussian kernel of standard deviation σ. The weights w (i, j) are calculated as follows:

$$w(i, j) = \frac{1}{z(i)} e^{\frac{\| rsjni\ (N_i) - rsjni\ (N_j) \|_{2,\sigma}^2}{h^2}} \tag{6}$$

$$Z(i) = \sum_j e^{\frac{\| rsjni\ (N_i) - rsjni\ (N_j) \|_{2,\sigma}^2}{h^2}} \tag{7}$$

At low SNR, the Non local means filter not only eliminates the noise however it also distorts the JPEG resized image in that way removing much of the image information. As a result, the method noise will include noise in addition to image information together with some edges. Therefore, the method noise MN can be regarded as a combination of image information RSJID and a noises N is given as (Kumar, 2012):

$$MN = RSJID + N \tag{8}$$

Now the complication is to approximate the feature of the resized JPEG image *RSJID*, which has only the original resized JPEG image characteristics and edges/sharp boundaries that are eliminated by Non Local Means Filtered image, I_F to obtain better denoised image with features. In wavelet domain, Eq. (9) can be represented as:

$$Y = W + N_w \tag{9}$$

where, Y is the noisy wavelet coefficient, W is the true wavelet coefficient and N_w is independent of noises. In wavelet domain, the objective is to estimate the true wavelet coefficient W from Y by means of thresholding Y with a proper value of threshold which reduces Mean Square Error (MSE), in order that it can maintain the original resized JPEG image characteristics and edges/sharp boundaries extremely well in the last denoised image. The estimate of the true wavelet coefficient is indicated as $\widehat{W}$ and its wavelet reconstruction provides an estimate of feature image $\widehat{RSJID}$ The summation of this feature resized JPEG image with the NL-means filtered image I_F will provide the denoised image B, indeed have more JPEG resized image characteristics and edges as compared with NL-means filtered image I_F Appends more power to the existing denoising framework Bayes Shrink system, which derives a wavelet threshold in a Bayesian framework by assuming a generalized Gaussian distribution for the wavelet coefficients (Hashemi and Beheshti, 2011). Bayes Shrink is moreover an adaptive, data-driven thresholding approach by means of soft-thresholding which derives the threshold in a Bayesian framework, assuming a generalized Gaussian distribution. This technique is adaptive to every sub-band since it based on data-driven estimates of the parameters. The threshold for a specified sub-band derived by minimizing Bayesian risk, given as follows:

$$T = \frac{\sigma_n^2}{\sigma_w} \tag{10}$$

where σ_n^2 represents the noise variance estimated from sub-band HH_1 by a robust median estimator given as follows:

$$\hat{\sigma}_n = \frac{Median\ (| Y_{i,j} |)}{0.6745}, Y_{i,j} \in \{HH_1\} \tag{11}$$

And σ_w^2 represents the variance of the wavelet coefficient in the subband whose estimation is calculated with the help of following equation:

$$\hat{\sigma}_w^2 = \max(\hat{\sigma}_y^2 - \hat{\sigma}_n^2, 0) \tag{12}$$

Image compression and decompression process with DCT-SVD: Figure 3a and b demonstrates the representation of DCT-SVD-ANFIS based single and double compressed images samples. At first, take LENA images as input image I, subsequently execute DCT-SVD transform function to input image. The transformed frequency coefficient Id_1 results from DCT is resized with the help of the GCSC, subsequently execute Non local Linear Filter and its Method noise Thresholding using wavelets (NLFMT) filtering technique to eliminate noise from resized JPEG image samples lastly quantization tables. In order to analysis the results of DCT compression techniques, an error value is introduced in this phase, is regarded as quantization and the quantization coefficient values of DCT compression results is examined with the help of

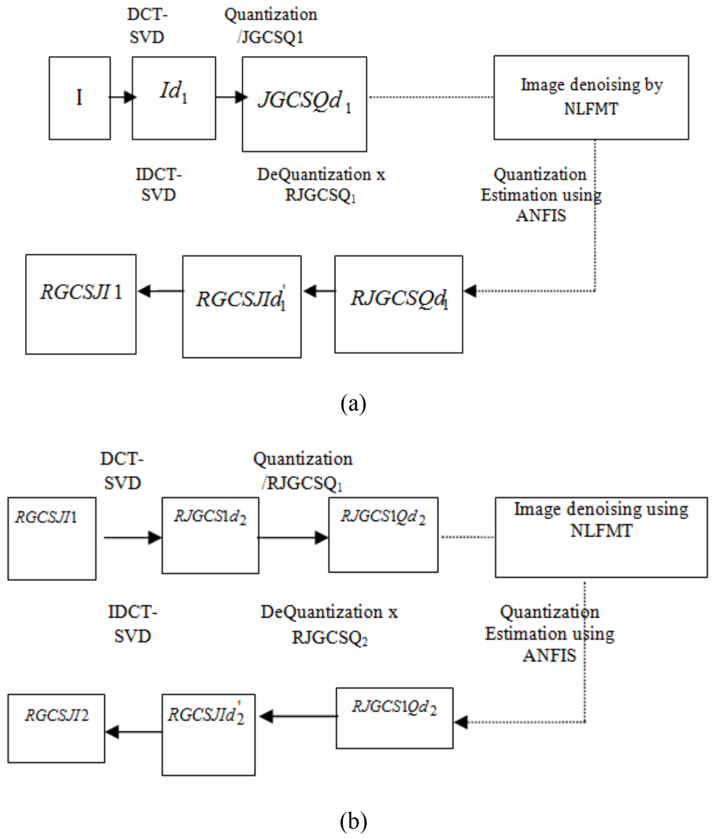

Fig. 3: (a): Single image compression for resized images resized JPEG image one RSJI1; (b): Double image compression for resized images resized JPEG image two RSJI2

ANFIS. In last stage, the resultant bit from ANFIS is integrated to header file to generate specific JPEG file. In JPEG image decompression stage, the compressed JPEG file turned out to be one of significant entropy measures to decode and recover the quantization coefficient $JSQd_l$ results precisely from FNN and it is multiplied by quantization table $JGSQ_l$ is denoted as the JPEG image from GCSC quantization to acquire the dequantized coefficient JSd'_1. DCT-FNN inverse transformation function is employed to dequantized outcome. Subsequently dequantized images samples results from DCT-FNN is given as input to second compression technique, it carries out the similar procedure from single DCT-FNN compression process, until the entire images are compressed and decompressed again.

With the aim of reducing the complexity in the DCT transformation technique, employ the singular value decomposition technique for resized JPEG image compression phase. The SVD approach is implemented to DCT compression matrix DCTC (k) is defined as given below:

$$DCTC(0) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} f(JGCS) \tag{13}$$

$$DCTC(k) = \sqrt{\frac{2}{N}} \sum_{n=0}^{N-1} f(RJGCS)COS \frac{(2rjcgs+1)k\pi}{2N}, k = 1,..N-1 \tag{14}$$

The above *DCTC* (*k*) is transformed into four quadrants by means of Zig-Zag mapping. Size of each quadrant is 8×8. The SVD is employed to every quadrant and subsequently can obtain a diagonal matrix S with 8×8. The Singular Value Decomposition (SVD) is one of the most useful tools of linear algebra with several applications to multimedia. Applications including Image compression, Watermarking and other Signal Processing. Given a real image matrix from DCT methods is decomposed into a product of three matrices given by Eq. (3). The SVD of a m×n matrix $JGCS_A$ from DCT is characterized by the operation:

$$RJGCS_{DCTC(k)} = U \times S \times V^T \tag{15}$$

where, $U \in R^{m \times m}$ $V \in R^{n \times m}$ are unitary and $S = diag(\sigma_1, ...\sigma_r)$ represents a diagonal matrix. The diagonal matrix S are called as singular value of $JGCS_{DCTC(K)}$ and are considered to be organized in descending order $\sigma_i > \sigma_{i+1}$. The columns of the U matrix are taken as the left singular vectors at the same time the columns of the V matrix are taken as the right singular vectors of A. Each singular value σ_i indicates the luminance of a data layer at the same time the equivalent pair of singular vectors indicates the geometry of the data layer. Subsequently, inverse discrete cosine transform is given as follows:

$$f(RJGCS_{DCTC(k)}) = \frac{1}{\sqrt{N}} DCTC(0) + \sqrt{\frac{2}{N}} \sum_{n=0}^{N-1} DCTC(k) COS \frac{(2RJGCS_{DCTC(k)}+1)k\pi}{2N}, k = 0,...N-1 \quad (16)$$

Prior to estimating the results of the quantization matrix from both single and double compressed images, initially required to compute the association of frequency coefficient among the first image and second images are taken as:

$$\begin{aligned} RJGCSd_2 &= DCT-SVD(I_1) = DCT-SVD([IDCT-SVD(RJGCSd_1^{'})]) \\ &= DCT-SVD(IDCT-SVD(RJGCSd_1^{'}) + RE) \\ &= DCT-SVD(IDCT-SVD(RJGCSd_1^{'}) + DCT-SVD(RE)) \\ &= RJGCSd_1^{'} + \varepsilon = \left[\frac{RJGCSd_1}{RJGCSQ_1}\right] \times RJGCSQ_1 \end{aligned} \quad (17)$$

where, RE represents the rounding error from previous DCT-SVD compression stages. Considering that $\varepsilon(i,j)$ is approximated Gaussian distribution through zero mean and their variance is 1/12. In DCT-SVD compression techniques, the transformed frequency coefficient location values are taken as $(i,j) \in (0,7)$ correspondingly and their quantization matrixes is given as RJGCSQ = $RJGCSQ_1$ (i, j). The outcome of quantization matrix is assessed in accordance with the rounding error function. The rounding error function is not simple to accomplish results for various sizes of images. With the aim of overcoming this complication, in this study an Adaptive Neuro Fuzzy Inference System (ANFIS) algorithm is employed to estimate quantization of single and double compressed image samples.

Adaptive Neuro Fuzzy Inference System (ANFIS) to estimate quantization matrix: ANFIS classification method is employed in this study to estimate the quantization results of $JGCSQ_1(i,j) \& JGCSQ_2(i,j)$ through the association amongst two compression images. The proposed system primarily obtains histogram based features from resized images to approximate quantization results into two different classes, for instance, single quantization and double quantization result. The proposed ANFIS (Adaptive Neuro Fuzzy System) as it is a integration of the quantitative fuzzy logic approach and adaptive ANN. It builds the fuzzy inference progression by the use of known quantization matrix from DCT-SVD and their corresponding fuzzy membership values for histogram features of the JPEG resized image are fine-tuned automatically with the help of well-known back propagation approach. The Adaptive Neuro-Fuzzy Inference System (ANFIS) is employed for estimation of quantization matrix results by permitting for only two most important classes rd_1&rd_2. With the intention of representing the ANFIS framework, it is considered in the form of fuzzy-if then rules. The generalized form of fuzzy-if then rules is characterized in the following method:

Rule 1: If:

$$(RJGCSh_{DCT-SVDc(k)} x_1(i,j) is A_1)$$

and:

$$(RJGCSh_{DCT-SVDc(k)} y_1(i,j) is B_1)$$

then:

$$(f_1 = p_1 RJGCSh_{DCT-SVDC(k)} x_1 + q_1 RJGCSh_{DCT-SVDC(k)} y_1 + r_1)$$

Rule 2: If:

$$(RJGCSh_{DCT-SVDc(k)} x_2(i,j) is A_2)$$

and:

$$(RJGCSh_{DCT-SVDc(k)} y_2(i,j) is B_2)$$

then:

$$(f_2 = p_2 RJGCSh_{DCT-SVDC(k)} x_2 + q_2 RJGCSh_{DCT-SVDC(k)} y_2 + r_2)$$

where inputs that are histogram dependent features from the DCT-SVD technique is characterized as variables RJGCShx and RJGCShy, A_1 and B_1 are the fuzzy sets for estimation of the quantization matrix from the DCT-SVD with obtained histogram features, f_i represent the outputs of quantization estimation matrix results within the fuzzy region indicated by the fuzzy rule p_i, q_i, r_i, are the design parameters that are established at some stage in the training process. The ANFIS construction for development of fuzzy-if then rules is illustrated in Fig. 4, in which fixed node of the structure is indicated by circle, where adaptive node of the structure is indicated by square.

In ANFIS framework, the input nodes are regarded as adaptive nodes where input of these nodes takes histogram dependent features from the DCT-SVD

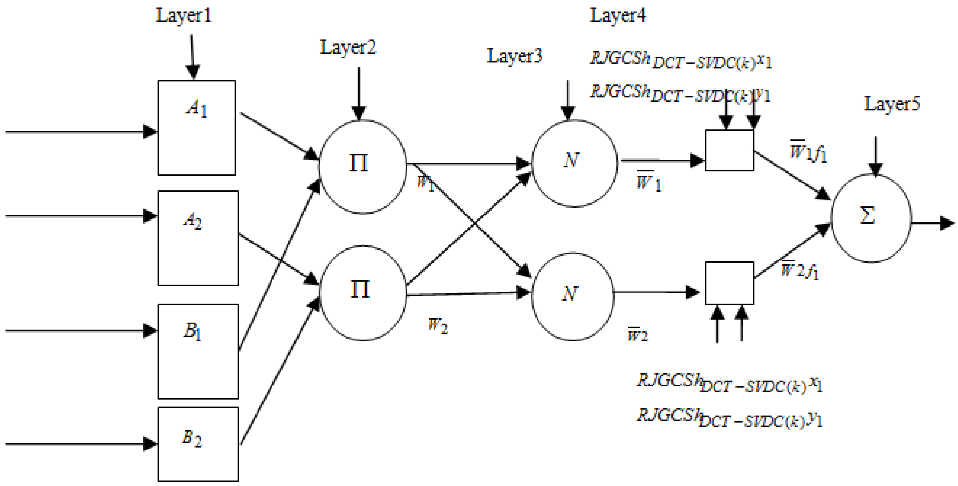

Fig. 4: ANFIS architecture for quantization matrix estimation

matrix. The output result of layer 1 indicates the fuzzy membership ranking of the quantization matrix results, which are denoted by:

$$O_i^1 = \mu_{A_i}(RJGCSh_{DCT-SVDc(k)}x), i = 1,2 \tag{18}$$

$$O_i^1 = \mu_{B_{i-2}}(RJGCSh_{DCT-SVDc(k)}y), i = 3,4 \tag{19}$$

Where fuzzy membership function of the layer 1 is:

$$\mu_{A_i}(RJGCSh_{DCT-SVDc(k)}x),$$
$$\mu_{B_{i-2}}(RJGCSh_{DCT-SVDc(k)}y)$$

Required to compute membership functions to estimate the layer 1 results are $\mu_{A_i}(x)$ is given as:

$$\mu_{A_i}(RJGCSh_{DCT-SVDc(k)}x) = \frac{1}{1+\left\{\left(\frac{RJGCSh_{DCT-SVDc(k)}x - c_i}{a_i}\right)^2\right\}^{b_i}} \tag{20}$$

where a_i, b_i, c_i represents the parameters of fuzzy membership function for quantization matrix results from DCT-SVD, foremost the bell shaped functions accordingly. In case of the first layer, the nodes are fixed nodes. They are indicated with M, envoy that they complete as a simple multiplier. The outputs of the second layer can be indicated as:

$$O_i^2 = w_i = \mu_{A_i}(RJGCSh_{DCT-SVDc(k)}x)\,\mu_{B_i}(RJGCSh_{DCT-SVDc(k)}y) \tag{21}$$

This is also regarded as the evident strengths of the fuzzy-if then rules. In case of the third layer; the nodes are also fixed nodes. These nodes are indicated with a parameter N that designates the normalization to the evident strengths of the fuzzy-if then rules from the second layer. The outputs of third layer can be indicated as:

$$o_i^3 = \overline{w_l} = \frac{w_i}{w_1 + w_2} \tag{22}$$

which are the presumed normalized evident strengths. In case of the fourth layer, the nodes are adaptive nodes. The output of each node in fourth layer is predominantly the multiplication of the normalized evident strength and a first order polynomial. Accordingly, the outputs of fourth layer are indicated as:

$$o_i^4 = \overline{w_l} f_i = \overline{w_l}(p_i RJGCSh_{DCT-SVDC(k)}x_1 + q_i RJGCSh_{DCT-SVDC(k)}y_1 + r_i), i = 1,2 \tag{23}$$

In the fifth or concluding layer, there is only one fixed node indicated with S This node carries out the summing up of the entire received eye movement signals. As a result, the complete output of the representation is indicated as:

$$o_i^4 = \sum_{i=1}^{2} \overline{w_i} f_i = \frac{\sum_{i=1}^{2} w_i f_i}{w_1 + w_2} \tag{24}$$

In ANFIS architecture, there are two adaptive layers exist in the structure, there are first and fifth layer. In the first layer, there are 3 fuzzy membership function associated adjustable parameters a_i, b_i, c_i represents the parameters of fuzzy membership function for quantization matrix results with histogram feature obtained, it is regarded as basis parameters. With the intention of influencing the first order polynomial function in fourth layer with the help of three adjustable parameters p_i, q_i, r_i, If the adjustable parameters a_i, b_i, c_i for fuzzy membership function are fixed, the result of the ANFIS representation can be given as:

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 \tag{25}$$

Subsequently, the equation is transformed into:

$$f = \overline{w_1} f_1 + \overline{w_2} f_2 \tag{26}$$

Replacement of fuzzy if then rules above equation, it transformed as:

$$\begin{aligned} f = {} & \overline{w_1}(p_1 RJGCSh_{DCT-SVDC(k)} x_1 + q_1 RJGCSh_{DCT-SVDC(k)} y_1 + r_1) \\ & + \overline{w_2}(p_2 RJGCSh_{DCT-SVDC(k)} x_2 + q_2 RJGCSh_{DCT-SVDC(k)} y_2 + r_2) \end{aligned} \tag{27}$$

Which is a linear grouping of the adjustable resultant parameters from f. The least squares technique is employed to categorize the optimal quantization matrix results of the single and double compression image values of these resulting parameters merely. At last, completion of the previously mentioned steps quantization matrix result is found. A model is allocated to single quantization and double quantization class $(rd_1 \,\&\, rd_2)$ with the maximum class membership value with less error values. In this study, take five different quantization error values to approximate quantization matrix results and it values depends on QF such as $QF_1 = 50, QF_2 = 75, QF_3 = 85, QF_4 = 95, QF_5 = 98$ $F = \{QF_1, QF_2, QF_3, QF_4, QF_5\}$. In the ANFIS outcome from the quantization estimation first quantization factor QF_1 error values are approximated depending on the error value $QF_1 = 0.2$ second quantization factor error values are fixed to $QF_2 = 0.1$ third quantization factor error values are fixed to $QF_3 = 0.13$ Fourth quantization factor QF_4 error values are fixed to $QF_4 = 0.03$ concluding quantization factor error values are fixed to $QF_5 = 0.005$. In order that every quantization factor at last belongs to JSd_2 (5) among the association between single and double compressed quantization results with feature vectors. The histogram dependent features is allocated to quantization estimation class c with less quantization error for each quantization matrix and precisely it is given as:

$$RJGCSd_2 = RJGCSd_1^{'} + DCT - SVD(RE) = RJGCSd_1^{'} + \varepsilon \tag{28}$$

Proposed DCT-SVD-ANFIS appropriately observe the quantization matrix results from DCT compression and their matching error values in the quantization step results also founded in ANFIS system, it is employed to categorize the quantized image samples into single and double compressed images independently.

EXPERIMENTAL RESULTS

In the experimentation to evaluate the proposed system for FNN based on DCT compression, make use of the MATLAB JPEG Toolbox (Sallee, year) for JPEG compression. Then 1000 images are randomly selected from each image dataset. At last, there are 5000 uncompressed color images. Those images are initially transformed into gray-scale images, which are then center-cropped into little blocks with sizes varying from 256×256 to 8×8. The experimental outcome for JPEG history estimation is specifically recognizing JPEG images, estimating quantization steps and discovering quantization table. To correctly assess the proposed feature histogram Jsh_{ij} initially use a minimum risk classification rule (Theodoridis and Koutroumbas, 2003) to discover a threshold. For a specified image size in the training stage, part of the uncompressed images and the matching JPEG compressed images with QF = 98, the maximum quality factor the proposed feature can discover consistently, are employed to achieve a proper threshold. These threshold values are then employed to recognize the rest of the JPEG images with QF = {95, 85, 75} and 50, correspondingly. The experimental results are given in Table 1. At this point, define the False Positive Rate (FPR) as the possibility of the uncompressed images being incorrectly determined as JPEG images and consequently it is permanent, once the threshold is specified for the same uncompressed image dataset. It can be observed that this method can accomplish adequate accuracy of around 95% even when the image size decreases to 8 × 8 and the quality factor is as high as 95, which demonstrates that the proposed feature is extremely robust to the quality factors employed previously as well as the image sizes.

The noises like Gaussian, salt and pepper, Speckle noise and sharpening noise are appended to resized image of the LENA. The outcome of the noisy LENA images is shown in Fig. 5.

Figure 6a and b shows the Alternate Current (AC) coefficients of AC (1, 1) and AC (2, 2). Choose the appropriate quality factors whose equivalent quantization steps are from 1 to 15. It shows the average accuracy as a function of the quantization steps. It is observed that the accuracy typically increases with increasing the quantization step and perform better than that of method without FFNN for DCT in most situations.

Table 1: Experimentation results

Quality factor	256 × 256 block	128 × 128 block	64 × 64 block	32 × 32 block	16 × 16 block	8 × 8 block
QF = 98	94.50	94.78	94.56	93.85	92.58	92.80
QF = 95	93.90	95.62	95.60	95.40	95.12	95.16
QF = 85	95.70	94.80	94.71	95.16	94.80	94.12
QF = 75	94.60	94.12	94.32	94.04	93.80	93.75
QF = 50	93.95	93.70	94.16	94.36	94.75	95.20

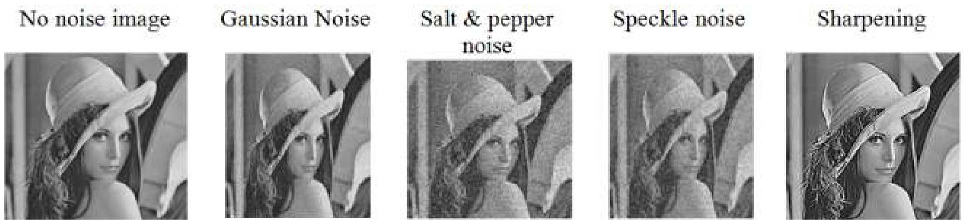

Fig. 5: Image noise comparison results for LENA image

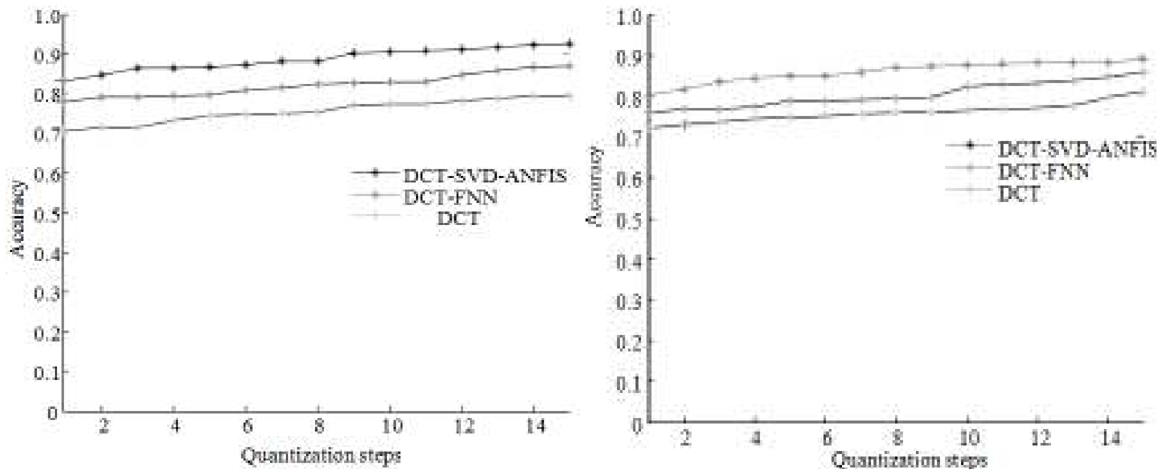

Fig. 6: (a): Quantization results for AC (1, 1); (b): Quantization results for AC (2, 2)

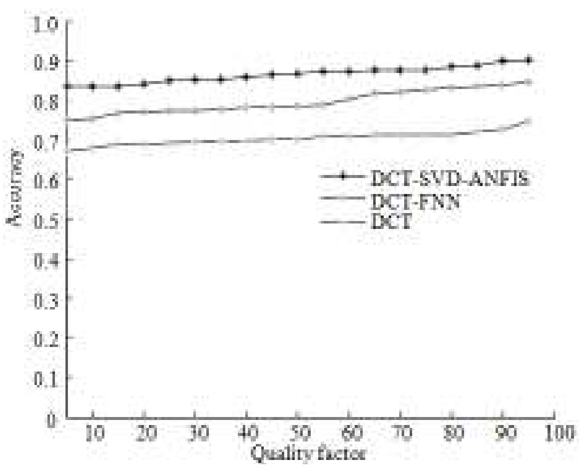

Fig. 7: Detection accuracy as a function of the quality factors

Figure 7 shows the average accuracy evaluated on the test images in different cases. The detection accuracy of proposed DCT-SVD-ANFIS system also significant how well algorithm properly detects single and double quantization matrix efficiently detects for DCT-SVD compression images, in view of the fact that the proposed system eliminates noise from image samples. It is also high in DCT-SVD-ANFIS compression for different quality factors than existing, DCT-FFNN (Vishnu Priyan and Srivatsa, 2014), DCT double compression methods.

The filtering results of the proposed NLFMT systems with different noise after removal are measured using the parameters such as Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE).

Peak Signal to Noise Ratio (PSNR): The ratio among the maximum possible powers to the power of distorting noise is recognized as Peak Signal to Noise Ratio. It influences the fidelity of its representation. It can be also said that it is the logarithmic function of peak value of image and mean square error:

$$PSNR = 10\log_{10}(MAX_i^2 / MSE) \tag{29}$$

Mean Square Error (MSE) and MAX_I is the maximum possible pixel value of the image. When the

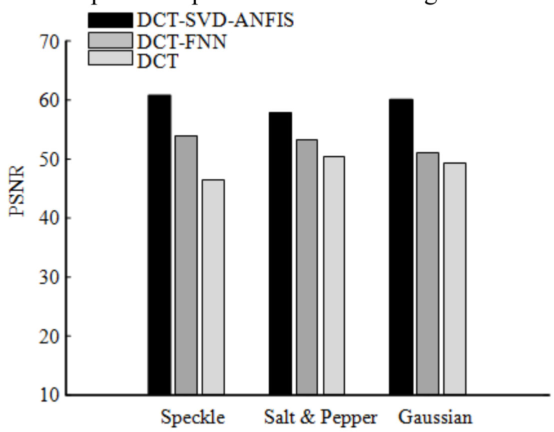

Fig. 8: Noises results comparison for image

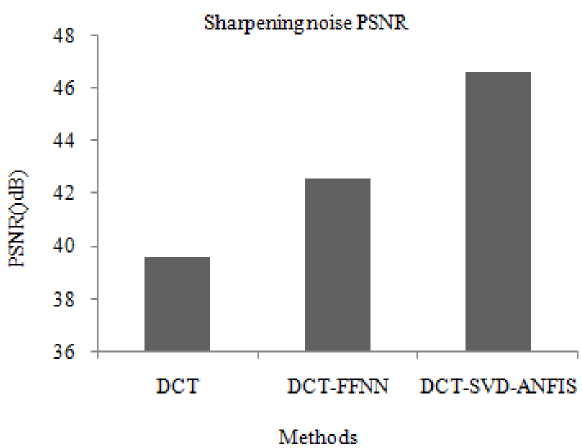

Fig. 9: Sharpening noise results comparison for image

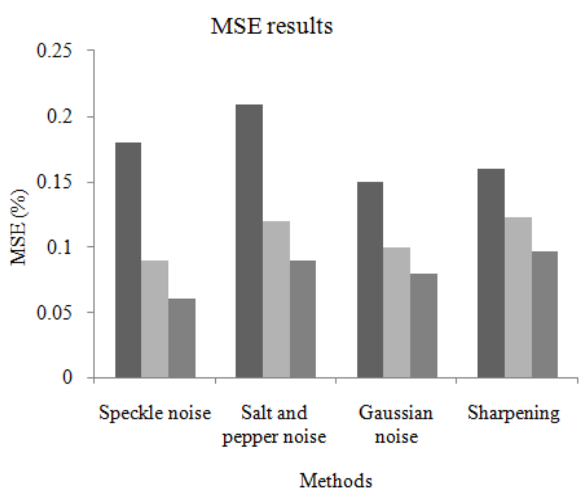

Fig. 10: MSE vs. methods

pixels are represented by means of 8 bits/sample, this is 255.

Mean Square Error (MSE): Mean Square Error (MSE) of an estimator is to enumerate the difference among an estimator and the true value of the quantity being estimated:

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2 \tag{30}$$

I (i, j) represents a vector of n predictions for image and K (i, j) represents the vector of the true values prediction with noise removal results.

PSNR for each one technique following the elimination of the salt and pepper noise, speckle noise and Gaussian noise is shown in Fig. 8. It demonstrates that the PSNR results of the proposed DCT-SVD-ANFIS is have high when comparing against existing techniques for all noises, because the proposed system eliminate noises from JPEG image samples by means of the NLFMT methods, it shows that proposed methods perform well when the salt and pepper noise takes place in the system.

PSNR for each one technique following the removal of the sharpening noise is shown in Fig. 9. It shows that the PSNR results of the proposed DCT-SVD-ANFIS is have high when compare to existing methods with sharpening, since the proposed system remove noises from JPEG image samples using the NLFMT methods, it shows that proposed methods work well if the sharpening occurs in the system.

MSE for each one technique following the removal of noises is shown in Fig. 10. It shows that the MSE results of the proposed DCT-SVD-ANFIS is less when compare to existing methods with different noises, since the proposed system remove noises from JPEG image samples using the NLFMT methods, it shows that proposed methods work well for all noises in the system.

CONCLUSION AND RECOMMENDATIONS

This study proposes a novel JPEG error analysis method with estimation of quantization matrix results and image denoising techniques by Non local Linear Filter (NL) and its Method Noise Thresholding by means of wavelets (NLFMT). Prior to carrying out the denoising methods primarily in DCT-SVD techniques the image are resized by means of Growcut based seam covering approach. Growcut based seam carving approach for image resizing that maintains content-aware image resizing for both size reduction and development. Following the images are resized, subsequently some of the noises such as the Gaussian noise, salt and pepper noise, speckle noise are appended to image and subsequently noises are eliminated by means of NLFMT. ANFIS concentrated on the complication of estimating quantization steps for chosen histogram based feature vector for DCT-SVD coefficients. Experimental results demonstrated the efficiency and the adaptability of the proposed DCT-SVD-ANFIS approach. This DCT-SVD-ANFIS framework may be regarded as a foremost approach to examine quantization factors and productively elimination of the noise from resized image samples for error values in JPEG images. This technique has enhanced the results with slight increase in performance based on method noise, PSNR and MSE. Further, it is feasible to enhance the denoised images results by means of shift invariant wavelet transform and improved sub-band denoising approaches for method noise decomposition and thresholding. These concerns and the detailed examination of parameter selection for the proposed framework, in addition to the application of other non-linear filters rather than NL-means filter are left as future work and will motivate further research towards understanding and removing noise in real images.

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