CHAPTER 4

A NOVEL NON LOCAL LINEAR FILTERING FOR DENOISING AND ANFIS ALGORITHM FOR QUANTIZATION MATRIX ESTIMATION FOR JPEG ERROR ANALYSIS

4.1 Introduction

In the earlier chapter, an efficient JPEG error examination methods through the evaluation of quantization matrix results from Fuzzy Neural Network (FNN) is presented. A Discrete Cosine Transform (DCT) compression with Fuzzy Neural Network (FNN) is presented, and the focus was on the issue of the estimation of quantization steps that is based on the choice of histogram feature vectors in DCT frequency coefficients. The analysis of the entire quantization matrix is done by employing FNN.

In forensic analysis, Barni et al. (2010) assessed the entire image, knowing that the precise spot of the forgery in an image that is tampered is still an open problem, image resizing is not conducted, noises such as the Gaussian noise, salt and pepper noise speckle noise and sharpening, in the images samples are not removed in the double compression scheme. With the intent of overcoming these concerns and to reduce noise in the image sample, image denoising is carried out on the basis of the filtering techniques.

Image denoising (Kumar, 2013) is an extensively used practice in digital image processing, for the removal of noise, which possibly will lead to distortion of an image at a particular stage in its acquisition or transmission, and also simultaneously, keeping its quality intact. Even though denoising has been a focal point of research for a long time, there is always a constant space for improvement, specifically in image denoising. For images, noise suppression/elimination is a frail and a complicated process as there is a trade-off between noise reduction and the preservation of the original image features. When high-frequency noise is required to be removed from the distorted image,
the simple spatial filtering might be sufficient, even though, at the expense of computational complexity in performing the convolution.

With the goal of examining these filtering techniques and the corresponding complications, Non Local Means Filtering and its technique noise Thresholding through wavelets (NLFMT) have been developed for image denoising. In this work, JPEG double image compression is considered. In the first step, the image is converted into resized image with the help of Growcut based Seam Carving resizing scheme. Next, noise in the images are removed with the application of NLFMT filtering techniques, then it is quantized by means of DCT transformation matrix known as the primary quantization matrix. The quantization matrix used in the second compression is referred to as the secondary quantization matrix. These quantization matrices are evaluated by making use of Adaptive Neuro-Fuzzy Inference system (ANFIS). Multiple quality factors are utilized for the analysis of quantization results of single and double compression quantization matrix.

4.2 Proposed non local linear filtering and ANFIS algorithm methodology

In this work, a highly-organized double compression schema is developed for JPEG images with the help of enhanced DCT-SVD Methods. With the goal of diminishing the size of the images that follow JPEG compression, resizing of images are done by means of enhanced seam carving schemes. Even after the image resizing, a specific amount of noise resides in the JPEG image sample. With the intent of elimination of noise from the resized JPEG image sample, in this research work, a non local-means filter method is presented. Before that, few of the noises are added to the resized image. As a next step, a Non Local-Means Filter and its Method noise Thresholding is executed by means of wavelets (NLFMT) for the purpose of eliminating noise for resized JPEG image sample. Then the quantization step is executed from Chang and Lai (2009) for examining the error of compression techniques with the help of Adaptive Neuro-Fuzzy Inference System (ANFIS). An evaluation of error results from quantization matrix in both single and double compression techniques is exactly carried out.
The double compression scheme proposed has lower error rate results in comparison with the earlier double compression schemes, in lieu of the fact that it makes use of ANFIS for quantization matrix estimation in compressed images and performs image denoising. Before continuing with modified DCT decompression schemes, it is initially required to resize the compressed images through resizing methods. This helps in the reduction of the size of JPEG compressed image and then carry out image denoising. After that, it is provided as input to quantization process. The steps of the proposed work are explained in detail as follows.

4.2.1 Images Resizing

In Chapter 3, to decrease the size of the compressed image samples, seam carving based image resizing method is employed. Image resizing methods try to adapt the image content to the screen without distortion to the main objects in the scene. Seam carving (Avidan and Shamir, 2007) is an efficient technique for image resizing. It is referred to as content-aware resizing. The operator retargets the image to a new size taking the main content into consideration. While resizing the single image for an aspect ratio change, seam carving obtains much better results when compared to scaling and cropping. But, when the seam carving is employed, the only single way for determining seams is considering the change of intensities around the seam. If the intensities of the main content have lesser changes than those contained in the background, the carving or inserting seams will enter and result in distortion of the main content. The resizing methods in the literature prove effective for a single image. Nonetheless, these methods do not provide sufficient protection to the significant content. To get over these issues, image segmentation techniques have been incorporated into the Seam Carving methods.

4.2.2 GrowCut

Image segmentation is an important part of image processing applications. The availability of robust and efficient image segmentation techniques can help a broad range of computational vision algorithms. Between thousands of image
segmentation techniques explained in the literature, GrowCut is an interactive image cutout tool that is designed for extracting solid or opaque objects. With a small number of user labelled pixels, the rest of the image is automatically segmented with the help of a Cellular Automaton. The process is repetitive, while the automaton labels the image, the user is able to see the segmentation evolution and then provide guidance to the algorithm with human input at places where the segmentation is hard to compute (Vezhnevets and Konouchine, 2005). GrowCut is of the high degree of interactivity, which permits easy and intuitive correction, and hence controllable boundary smoothness can be achieved. Other valuable merits of GrowCut are its simplicity, multi-label assignment, rapidity and easy extension. Hence, GrowCut can satisfy the requirement of user control in image resizing just for the removal or protection of an object in the image. Thus, it is quite a motivation to make use of GrowCut in combination with seam carving.

4.2.3 Image resizing using Growcut based Seam Carving (GCSC)

In this work, first the JPEG images in the DCT compression image samples are resized with enhanced seam carving methods. This resizing technique chiefly chooses any one single pixel values in the JPEG image pairs and then does the fragmentation of the most important substance of the JPEG images. Let the actual JPEG images be $J_i = \{J_{i1}, J_{i2}, \ldots, J_{in}\}$ where $j \in n$ denotes the number of JPEG image samples in the training phase. Then enhanced seam carving approach is presented for the aid of image resizing. Image segmentation GrowCut (Vezhnevets and Konouchine, 2005) is used in integration with the actual seam carving approach in order to automatically select the region of significance by drawing one line on the inside of the object and one line along the exterior to the object. The concept that is behind the seam carving approach is the elimination of unrecognizable pixels which combine with their surroundings. An energy function is used for the calculation of the energy of each pixel. It is used for discovering and eliminating the seam of the lowest significance of the pixels for JPEG image compression. In the case of the actual seam carving
(Avidan and Shamir, 2007), the energy functions are defined by gradient magnitude as given in equation (4.1).

\[ e(JIP) = \left| \frac{\partial}{\partial x} (JIP) \right| + \left| \frac{\partial}{\partial y} (JIP) \right| \tag{4.1} \]

where \( JIP \) denotes the pixel value of JPEG image. A seam is found by tracing the pathway from one edge of the JPEG image to the other contradicting edge through the path with the smallest amount of energy given by equation (4.2).

\[ S^* = \min_s E(s) = \min_s \sum_{i=1}^{n} e(JIP(s_i)) \tag{4.2} \]

The second process is the transformation of JPEG image energy. It is actually making a selection of whether it is pixel elimination or pixel protection for JPEG images. In the case of it to be protected, the energy of the pixel by GrowCut is set high. Else, when the pixel selected by GrowCut is to be removed, its energy is set to be low. The third process is JPEG image resizing by making use of seam carving. After eliminating seams successively, the output JPEG image will achieve the desirable resized resolution (Figure 4.1)

![Figure 4.1 Growcut based image seam carving](image)
An image is frequently corrupted by noise during its acquisition and transmission. Image de-noising is utilized to eliminate the additive noise while retaining the significant signal features as much as possible. In the recent times, there has been a sufficient amount of research on wavelet thresholding and threshold selection for signal de-noising (Chang et al., (2000) & Donoho and Johnstone, (2005)).

Noise filtering techniques are one among the extensively employed techniques for removal of noise from image samples; it may either be linear or non-linear. The linear filtering technique uses the algorithm in a linear fashion to all the pixels in the image without categorizing the image as the corrupted or uncorrupted pixel. As the algorithm is applied to all the pixels in the image, this results in all the uncorrupted pixels to be filtered and therefore all these filtering techniques are not efficient in eliminating impulsive noises. On the other hand, non-linear filtering technique (Astola and Kuosmanen, (1997) & Pitas and Venetsanopoulos, (1990)) is a two-phase filtering process. In the primary phase, the pixels are recognized as corrupted or uncorrupted pixel and in the second phase, the corrupted pixel is filtered by making use of the specified algorithm when the uncorrupted pixel value is held back. Linear filter does the convolution of the image with a constant matrix in order to receive a linear combination of neighborhood values and has been largely used for noise reduction in the presence of additive noise. This results in a blurred and smoothed image with poor feature localization and incomplete noise suppression.

In order to resolve these problems, Buades et al. (2005) & Xu et al. (2008) have given the extension of the Linear Filters to a wider class which is called as Non Local means (NL-means). This is based on the assumption that the image comprises of a great amount of self-similarity and is useful in finding the pixel weights in order to filter the noisy image. The most similar pixels in a given pixel need not be near to it. Consider the periodic patterns, or the elongated edges which make their appearance in most of the images. It is hence allowed for a vast portion of the image to be scanned to discover all the pixels that actually are
similar to the pixel to be denoised. The resemblance is assessed by making a comparison of an entire window around each pixel, not just the pixel value.

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

The aim of image denoising is the elimination of the noise while preserving the important resized JPEG image elements such as edges, aspects simultaneously as much as possible. Linear filter does the convolution of the resized JPEG image with a constant matrix to get hands on a linear combination of neighborhood values and has been widely used for noise removal in the presence of additive noise. This generates a blurred and smoothed resized JPEG image with decreased feature localization and not so perfect noise suppression. During this process, the following noises are appended to resized images and eliminated by making use of the NLFMT techniques.

(i) Salt and pepper noise

Salt and pepper noise results in on and off pixels. These noises are added to resized images and their intensity values are also calculated, and filtered by using NLFMT.

(ii) Speckle noise

Speckle Noise is a multiplicative noise; it adds multiplicative noise to resized image RSJI, with the consistent distribution of random noise with mean $\theta$ and variance $\nu$.

(iii) Gaussian noise

Gaussian noise is a white noise with stable mean and variance and has to be filtered by the use of NLFMT. Additive White Gaussian Noise (AWGN) is a basic noise model applied in information theory to resemble the result of various random processes that occur in nature. The modifiers represent exact features:

'Additive' since it is added to any noise that possibly is inherent to the information system. 'White' denotes that power is consistent across the frequency band for the information system. It is similar to the color white having consistent discharges at every frequency in the visible spectrum.
'Gaussian' due to its regular distribution in the time domain along with a mean time domain value of 0.

(iv) Sharpening

The sharpening of an image is also considered as a type of attack. It is a type of modification in order to expose the image aspects. The edges are highlighted, intending that the eye is able to make a notice of the image rapidly. The blurring of the image is reduced.

The image denoising framework through the blend of Non-local Linear Filter and its Method noise Thresholding by wavelets (NLFMT) is represented in Figure 4.2. A differentiation between the actual resized JPEG image and its denoised JPEG image shows that the noise is reduced by the algorithm, which is referred to as Method Noise (MN). By standard, the method noise has to appear resembling a noise. In lieu of the fact that even good quality JPEG images have some amount of noise, it just makes sense to evaluate any denoising technique in that way, without the traditional “add noise and then eliminate it” trick. Mathematically, it is given in equation (4.3).

\[ MN = RSJI - I_F \]  \hspace{1cm} (4.3)

where, \( RSJI \) denotes the original resized image and \( I_F \) represents the output of denoising operator for an input resized JPEG image \( RSJI \).

![Figure 4.2 Proposed Image Denoising Framework](image-url)
Non local means filter applied on the noisy resized JPEG image reduces the noise and gives clean edges without any loss to many of the fine structures and features. Even though the non local-means filter is highly efficient in the elimination of the noise at high Signal to Noise Ratio (SNR) (with a smaller amount noise) nonetheless with the increase in noise, its performance deteriorates. For capturing the kind of the noises that are removed from the noisy resized JPEG image by the means of the non local means filter, the characterization of the method noise is reinstated as the distinction between the noisy resized JPEG image and its denoised original JPEG image with a smaller size. As a result, equation (4.4) becomes

\[ MN = RJI - I_F \] (4.4)

where \( RJI = RSJI + Z \) denotes a noisy resized image obtained by the distortion of the original resized JPEG image \( RSJI \) by a noise \( Z \) and, \( I_F \) denotes the output of non local means filter for a resized input image. Denoising is then conducted by calculating the average gray value of these resembling pixels. As the resized JPEG image pixels that are in extreme correlation with noise are characteristically independent and have identical distribution, consequently averaging of these pixels lead to noise reduction and provides a pixel which is comparable with its actual value.

Given a discrete resized JPEG noisy image \( RSJNI = \{rsjni(i) | i \in I \} \) the estimated value \( NL(i) \) of a pixel \( i \), is computed as a weighted average of all the pixel intensities \( rsjni(j) \) in the resized JPEG image \( RSJI \)

\[ NL(i) = \sum_{j \in RSJI} w(i, j)rsjni(j) \] (4.5)

where \( w(i, j) \) denotes the weight assigned to value \( rsjni(j) \) for regenerating the pixel \( i \). Though the traditional definition of the NL-means filter regards that the intensity of each pixel can be related to pixel intensities of the entire resized JPEG image, the amount of pixels for resized JPEG images that are considered in the weighted average is restricted to a neighborhood search
window $S_i$ (More specifically, the weight $w(i,j)$ estimates the similarity between the intensities of the local neighborhoods patches $RSJNI(N_i)$ and $RSJNI(N_j)$).

Pixels $i$ and $j$ are centered such that $0 \leq w(i,j) \leq 1$ and $\sum_j w(i,j) = 1$, where $N_k$ represents a square neighborhood of preset size centered at a pixel $k$ and is present inside the search window $S_i$ that is centered at the pixel $i$. This similarity is resolved as a declining function of the weighted Euclidean distance,

$$\left| \left| RSJNI(N_i) - RSJNI(N_j) \right| \right|_{2,\sigma}^2$$

where $\sigma > 0$ represents the standard deviation of the Gaussian kernel. This distance is the traditional $L_2$-norm that is convolved with a Gaussian kernel of standard deviation $\sigma$. The weights $w(i,j)$ are computed as follows:

$$w(i,j) = \frac{1}{Z(i)} e^{-\left| \left| RSJNI(N_i) - RSJNI(N_j) \right| \right|_{2,\sigma}^2}$$

$$Z(i) = \sum_j e^{-\left| \left| RSJNI(N_i) - RSJNI(N_j) \right| \right|_{2,\sigma}^2}$$

At low SNR, the non local means filter along with reducing the noise, it also does the distortion of the JPEG resized image by the removal of much of the image information. Consequently, the method noise will be inclusive of the noise in addition to image information along with some edges. Hence, the method noise MN can be considered as a combination of image information $RSJID$ and a noise $N$ which is given as (Kumar, 2013),

$$MN = RSJID + N$$

Now the complexity is the approximation of the feature of the resized JPEG image $RSJID$, which has only the actual resized JPEG image features and edges/sharp boundaries which are removed by Non Local Means Filtered image, $I_F$ in order to retrieve the better denoised image with characteristics. In wavelet domain, Noisy wavelet coefficient is given by,

$$Y = W + N_w$$
where $Y$ denotes the noisy wavelet coefficient, $W$ represents the true wavelet coefficient and $N_w$ indicates a parameter independent of noises. In wavelet domain, the goal is the estimation of the true wavelet coefficient $W$ from $Y$ through thresholding $Y$ with a correct value of threshold that decreases Mean Square Error (MSE). This is for maintaining the original resized JPEG image features and edges/sharp boundaries extremely good in the last denoised image. The estimate of the true wavelet coefficient is given as $\hat{W}$, and its wavelet reconstruction yields an estimate of feature image $\text{RJ}^\text{ID}$. The summation of this feature resized JPEG image $\text{RJ}^\text{ID}$ with the NL-means filtered image $I_F$ will give the denoised image $B$, indeed with more JPEG resized image features and edges in comparison with NL-means filtered image $I_F$.

More power is appended to the present denoising framework BayesShrink system, that derives a wavelet threshold in a Bayesian framework by presuming a generalized Gaussian distribution of the wavelet coefficients (Kumar, 2013). BayesShrink is also an adaptive, data-driven thresholding approach making use of soft-thresholding deriving the threshold in a Bayesian framework, again assuming a generalized Gaussian distribution. This technique is suitable for every sub-band as it is based on data-driven estimates of the parameters. The threshold for a particular subband that is derived by the minimization of Bayesian risk is provided by equation (4.10).

$$T = \frac{\sigma^2_n}{\sigma_w}$$  \hspace{1cm} (4.10)

where $\sigma^2_n$ denotes the noise variance estimated from subband $HH_1$ by a robust median estimator written as follows,

$$\hat{\sigma}_n = \frac{\text{Median}(|Y_{i,j}|)}{0.6745}, Y_{i,j} \in \{HH_1\}$$  \hspace{1cm} (4.11)

and $\sigma^2_w$ denotes the variance of the wavelet coefficient in the subband whose estimate is computed with the help of equation (4.12) for noise removed image samples.
\[ \hat{\sigma}_w^2 = \max(\hat{\sigma}_v^2 - \hat{\sigma}_n^2, 0) \]  \hspace{1cm} (4.12)

Image compression is then carried out making use of DCT.

### 4.2.5 Image compression and decompression process with DCT SVD

Initially, LENA images are taken as input image I, later DCT-SVD transform function is executed on the input image. The transformed frequency coefficient \( I_{d_1} \) that results from DCT is resized with the aid of the GCSC. As a next step, Non Local linear Filter and its Method noise Thresholding is executed making use of wavelets (NLFMT) filtering technique for the elimination of noise from resized JPEG image samples. In the last step, quantization is performed. For the purpose of analyzing the results of DCT compression techniques, an error value is newly introduced in this phase by quantization. The quantization coefficient values of DCT compression results are evaluated with the aid of ANFIS.

In the last stage, the resultant bit from ANFIS is incorporated into a header file for generating the particular JPEG file. In JPEG image decompression stage, the compressed JPEG file happens to be one of important entropy measures for decoding and recovering the quantization coefficient \( JSQ_{d_1} \) results exactly from FNN and it is multiplied by the quantization table \( JGSQ_{1} \) (JPEG GCSC QUANTIZATION) to get the dequantized coefficient \( JSD'_{1} \).

The DCT-FNN inverse transformation function is applied to dequantized outcome. Consequently, dequantized images, samples that are resulting from DCT-FNN are provided as input to second compression technique. This is carried out as a similar procedure as single DCT-FNN compression process, till all the images are compressed and decompressed again. Figures 4.3 (a) & (b) illustrates the representation of DCT-SVD-ANFIS based single and double compressed image samples.
With the target of making a reduction in the complexity of the DCT transformation technique, the singular value decomposition technique is employed for resized JPEG image compression phase. The SVD approach realized in DCT compression matrix $DCTC(k)$, is defined as provided in equation (4.13):

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

(4.13)

$$DCTC(k) = \sqrt{\frac{2}{N}} \sum_{n=0}^{N-1} f(RJGCS) \cos \left(\frac{2RJGCS + 1)k\pi}{2N}\right)$$

(4.14)

$$k = 1, \ldots, N - 1$$
The above DCTC(k) is then transformed into four quadrants through Zig-Zag mapping. The size of each quadrant is 8 × 8. The SVD is applied to every quadrant, and as a result a diagonal 8 × 8 matrix $S$ is obtained. The SVD of a $m \times n$ matrix $JGCS_d$ is characterized by the operation:

$$RJGCS_{DCTC(k)} = U \times S \times V^T$$  \hspace{1cm} (4.15)

where $U \in R^{m \times m}$, $V \in R^{n \times n}$ are unitary and $S = diag(\sigma_1, ..., \sigma_r)$ denotes a diagonal matrix. The diagonal matrix $S$ is referred to as a singular value of $JGCS_{DCTC(k)}$ and elements of $S$ are regarded to be organized in descending order $\sigma_i > \sigma_{i+1}$. The columns of the $U$ matrix are considered as the left singular vectors and simultaneously, the columns of the $V$ matrix are regarded as the right singular vectors of $A$. Each singular value $\sigma_i$ is an indication of the luminance of a data layer. At the same instant, the equivalent pair of singular vectors denotes the geometry of the data layer. As a result, inverse discrete cosine transform is given by equation (4.16).

$$f(RJGCS_{DCTC(k)}) = \frac{1}{\sqrt{N}} DCTC(0) + \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} DCTC(k) \cos\left(\frac{2\pi R_{JGCS_{DCTC(k)}}(k+1)}{2N}\right)$$

$RJGCS_{DCTC(k)} = 0, ..., N - 1$  \hspace{1cm} (4.16)

Prior to the estimation of the results of the quantization matrix from both single and double compressed images, it is initially necessary to calculate the association of frequency coefficient between the first image and the second image as,

$$RJGCSd_2 = DCT - SVD(I_1)$$

$$= DCT - SVD ([IDCT - SVD(RJGCSd_1)])$$

$$= DCT - SVD (IDCT (RJGCSd_1) + RE)$$

$$= DCT - SVD (IDCT - SVD (RJGCSd_1) + DCT - SVD (RE))$$

$$= RJGCSd_1^t + \varepsilon = \left[\frac{RJGCSd_1}{RJGCSQ_1}\right] \times RJGCSQ_1 + \varepsilon$$  \hspace{1cm} (4.17)

where $RE$ denotes the rounding error from the earlier DCT-SVD compression stages. It is considered that $\varepsilon(i, j)$ is approximated by a Gaussian distribution with zero mean and variance 1/12. In DCT-SVD compression
methods, the transformed frequency coefficient location values are observed as 
\((i,j) \in (0,7)\) correspondingly and their quantization matrices are provided 
as \(R_{jGCSQ} = R_{jGCSQ_{1i,j}}\). 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 work, an Adaptive Neuro-Fuzzy Inference 
System (ANFIS) algorithm is employed to estimate quantization of single and 
double compressed image samples.

A Fuzzy Neural Network (FNN) to estimate the error values or 
quantization results of the DCT compression is proposed. However, FNN has 
also had some major important drawbacks:

- There is no standard and systematic method for the transformation of the 
human knowledge or experience in the rule base of a fuzzy inference 
system, no general procedure for choosing the optimal number of rules, 
from a large number of factors that are involved in the decision, e.g. 
performance of the controller, efficiency of computation, human operator 
behaviour, the choice of linguistic variables etc.
- Even when human operators exist, their knowledge is often incomplete and 
episodic, rather than systematic.
- It is not possible to show the stability of the controlled system, since the 
model is not known.
- It is not guaranteed that rules are coherent. It is possible to have a mismatch 
between the rules.
- Computing time could be long, because of the complex operations such as 
fuzzification and particularly defuzzification.

In order to overcome these problems, in this work, Adaptive Neuro-Fuzzy 
Inference System (ANFIS) is proposed. ANFIS is a fuzzy rule based classifier in 
which the rules are learned from examples that use a standard back-propagation 
algorithm. This algorithm is also used in neural network training. ANFIS uses
Sugeno-type fuzzy system is observed. The subtractive clustering was used to divide the rule space. Five triangular membership functions are chosen for all inputs and output similar to the fuzzy system.

**4.2.6 Adaptive Neuro-Fuzzy Inference System (ANFIS) to estimate Quantization Matrix**

ANFIS classification method is employed in this research work 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) is an integration of the quantitative fuzzy logic approach and adaptive ANN. It builds the fuzzy inference progression by the use of a known quantization matrix from DCT-SVD and their corresponding fuzzy membership values of 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 $(RJGCSx_{DCT-SVD C(k)} x_1(i,j)$ is $A_1$) & $(RJGCSy_{DCT-SVD C(k)} y_1 S(i,j)$ is $B_1$) then $f_1 = p_1 RJGCSx_{DCT-SVD C(k)} x_1 + q_1 RJGCSy_{DCT-SVD C(k)} y_1 + r_1$

- **Rule 2:** If $(RJGCSx_{DCT-SVD C(k)} x_2$ is $A_2$) and $(RJGCSy_{DCT-SVD C(k)} y_2$ is $B_2$) then $(f_2 = p_2 RJGCSx_{DCT-SVD C(k)} x_2 + q_1 RJGCSy_{DCT-SVD C(k)} y_2 + r_2$

where inputs that are histogram dependent features from the DCT-SVD technique are characterized as variables $RJGCSx$ and $RJGCSy$. $A_1$ and $B_1$ are the fuzzy sets for estimation of the quantization matrix from the DCT-SVD with obtaining histogram features, $f_i$ represents the outputs of quantization estimation matrix results within the fuzzy region indicated by the fuzzy rule, $p_i, q_i$ and $r_i$ are
the design parameters that are established at some stage in the training process. The ANFIS construction for the development of fuzzy-if then rules is illustrated in Figure 4.4, in which fixed node of the structure is indicated by the circle, and the adaptive node of the structure is indicated by the square.

Figure 4.4 ANFIS architecture for quantization matrix estimation

In ANFIS framework, the input nodes are regarded as adaptive nodes wherein the input of these nodes takes histogram dependent features from the DCT-SVD matrix. The output result of layer 1 indicates the fuzzy membership ranking of the quantization matrix results, which are denoted by:

\[ O_1^i = \mu_{A_i}(RJGCS_{DCT-SVD} C(k)x) \quad i = 1,2 \]  
\[ O_1^i = \mu_{B_{i-2}}(RJGCS_{DCT-SVD} C(k)y) \quad i = 3,4 \]  

where the fuzzy membership function of the layer 1 is \( \mu_{A_i}(RJGCS_{DCT-SVD} C(k)x) \), \( \mu_{B_{i-2}}(RJGCS_{DCT-SVD} C(k)y) \). Required to compute membership functions to estimate the layer 1 results are \( \mu_{A_i}(x) \) given as:

\[ \mu_{A_i}(RJGCS_{DCT-SVD} C(k)x) = \frac{1}{1 + \left( \frac{(RJGCS_{DCT-SVD} C(k)x - c_i)}{a_i} \right)^{2b_i}} \]  

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

$$O_i^2 = w_i = \mu_A\left(\text{RJGCSh}_{DCT-SVD} c(k)x\right)$$  \hspace{1cm} (4.21)

$$\mu_{B_i}\left(\text{RJGCSh}_{DCT-SVD} c(k)y\right) \hspace{0.5cm} i = 1, 2$$

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 the third layer can be indicated as:

$$O_i^3 = \overline{w_i} = \frac{w_i}{w_1 + w_2}$$  \hspace{1cm} (4.22)

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

$$O_i^4 = \overline{w_i}f_i$$  \hspace{1cm} (4.23)

$$= \overline{w_i}\left(p_i\text{RJGCSh}_{DCT-SVD} c(k)x_1 + q_i\text{RJGCSh}_{DCT-SVD} c(k)y_1 + r_i\right)$$

where $i = 1, 2$.

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:

$$O_i^5 = \sum_{i=1}^{2} \overline{w_i}f_i = \frac{\sum_{i=1}^{2} w_i f_i}{w_1 + w_2}$$  \hspace{1cm} (4.24)

In ANFIS architecture, there are two adaptive layers in the structure; there is a first and fifth layer. In the first layer, there are three fuzzy membership functions associated adjustable parameters $a_i$, $b_i$ and $c_i$ for each one of the quantization matrices with histogram feature obtained which are regarded as
basis parameters. The intention is to influence the first order polynomial function in the fourth layer with the help of three adjustable parameters $p_i$, $q_i$ and $r_i$. If the adjustable parameters $a_i$, $b_i$ and $c_i$ for fuzzy membership functions are fixed, the result of the ANFIS representation can be given as:

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2$$  \hspace{1cm} (4.25)

Subsequently, the equation is transformed into,

$$f = \bar{w}_1 f_1 + \bar{w}_2 f_2$$  \hspace{1cm} (4.26)

Replacing the fuzzy if-then rules, above equation is transformed as,

$$f = \bar{w}_1 (p_i R)\text{GCSH}_{DCT-SVD \text{C}(k)} x_1 + q_i R\text{GCSH}_{DCT-SVD \text{C}(k)} y_1 + r_1 + \bar{w}_2 (p_i R)\text{GCSH}_{DCT-SVD \text{C}(k)} x_2 + q_i R\text{GCSH}_{DCT-SVD \text{C}(k)} y_2 + r_2$$  \hspace{1cm} (4.27)

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. At last, after completion of the previously mentioned steps, quantization matrix result is found. A model is allocated to single quantization and double quantization class ($r_{d_1}$ & $r_{d_2}$) with the maximum class membership value with less error value.

In this research, we take five different quantization error values to approximate quantization matrix results and their values depends on $QF$ such as $QF_1 = 50, QF_2 = 75, QF_3 = 85, QF_4 = 95, QF_5 = 98$; 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 $J$.$d_2$ 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,

$$ R_{JGCS}d_2(h_{ij}) = F_c(R_{JGCS}d_2) \geq F_j(R_{JGCS}h_{ij}) $$  \hspace{1cm} (4.28) \\
\forall \ j \in 1,2, ..., C \ \text{and} \ j \neq c $$

where $F_j(R_{JGCS}d_2)$ indicates the activation function value of the $j^{th}$ neuron in ANFIS and it is taken as the output of ANFIS system. From these phases, the fuzzification outcome of histogram quantization class $F_c(R_{JGCS}h_{ij})$ result is compared with multiple quantization steps to approximate quantization outcome. Based on the analyzed outcome, how to eliminate rounding error $(RE)$ and how to carry out dequantization $JCSD_1$ become most important concerns. It can be solved by using the following equation,

$$ R_{JGCS}d_2 = R_{JGCS}d_1 + DCT - SVD(RE) = R_{JGCS}d_1 + \epsilon $$  \hspace{1cm} (4.29) 

In the proposed DCT-SVD-ANFIS appropriately, we observe the quantization matrix results from DCT compression and their matching error values in the quantization step. It is employed to categorize the quantized image samples into single and double compressed images independently.

### 4.3 Results and Discussion

In the experiment to evaluate the proposed system for FNN based on DCT compression, we make use of the MATLAB JPEG Toolbox for JPEG compression. Then 1000 images are randomly selected from each image data set. At last, there are 5000 uncompressed color images. Those images are initially transformed into gray-scale images, which are then centered-cropped into little blocks with sizes varying from $256 \times 256$ to $8 \times 8$. The experimental outcome for JPEG history estimation is specifically recognizing JPEG images, estimating quantization steps, and discovering quantization table. For a specified image size in the training stage, part of the uncompressed image 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, respectively. The experimental results are given in Table 4.1. At this point, we 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 in 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 $8 \times 8$ 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.

### Table 4.1 Experimental results

<table>
<thead>
<tr>
<th>Quality factor</th>
<th>$256 \times 256$ block</th>
<th>$128 \times 128$ block</th>
<th>$64 \times 64$ block</th>
<th>$32 \times 32$ block</th>
<th>$16 \times 16$ block</th>
<th>$8 \times 8$ block</th>
</tr>
</thead>
<tbody>
<tr>
<td>$QF = 98$</td>
<td>94.50</td>
<td>94.78</td>
<td>94.56</td>
<td>93.85</td>
<td>92.58</td>
<td>92.80</td>
</tr>
<tr>
<td>$QF = 95$</td>
<td>93.90</td>
<td>95.62</td>
<td>95.60</td>
<td>95.40</td>
<td>95.12</td>
<td>95.16</td>
</tr>
<tr>
<td>$QF = 85$</td>
<td>95.70</td>
<td>94.80</td>
<td>94.71</td>
<td>95.16</td>
<td>94.80</td>
<td>94.12</td>
</tr>
<tr>
<td>$QF = 75$</td>
<td>94.60</td>
<td>94.12</td>
<td>94.32</td>
<td>94.04</td>
<td>93.80</td>
<td>93.75</td>
</tr>
<tr>
<td>$QF = 50$</td>
<td>93.95</td>
<td>93.70</td>
<td>94.16</td>
<td>94.36</td>
<td>94.75</td>
<td>95.20</td>
</tr>
</tbody>
</table>

Following noises are appended to resized image of the LENA, then the outcome of the noise appended to LENA images is shown in Figure 4.5.

![Figure 4.5 Image noise comparison results for LENA image](image-url)
Figures 4.6 (a) & (b) show the Alternate Current (AC) coefficients of AC(1,1) and AC(2,2). We are choosing 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 performs better than that of the method without FFNN for DCT in most situations.

**Figure 4.6 (a) Quantization results for AC(1,1)**

**Figure 4.6 (b) Quantization results for AC(2,2)**
Figure 4.7 shows the average accuracy evaluated on the test images in different cases. The detection accuracy of proposed DCT-SVD-ANFIS system is also significant on how well algorithm properly detects single and double quantization matrix efficiently 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, 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).

![Figure 4.7 Detection accuracy as a function of the quality factors](image)

**Figure 4.7 Detection accuracy as a function of the quality factors**

(i) **Peak Signal to Noise Ratio (PSNR)**

The ratio between 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 also be said that it is the logarithmic function of the peak value of the image and mean square error.

\[
PSNR = 10 \log_{10}(MAX^2_i/MSE)
\]  

(4.30)
where MSE is Mean Square Error and $MAX_i$ is the maximum possible pixel value of the image. When the pixels are represented by means of 8 bits per sample, this is 255.

(ii) **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.

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2 \quad (4.31)$$

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

PSNR for each one technique following the elimination of the speckle noise, salt and pepper noise and Gaussian noise are shown in Figure 4.8. It demonstrates that the PSNR results of the proposed DCT-SVD-ANFIS is having high value when compared to the existing techniques for all noises, because the proposed system eliminates noises from JPEG image samples by means of the NLFMT methods.

![Figure 4.8 Comparison results of the image with different types of noises](image)
When compared to the speckle noise, salt and pepper noise produces only less significance difference between proposed and existing methods. Since Salt-and-pepper noise is a form of noise sometimes seen on images. It presents itself as sparsely occurring black and white pixels. So the reduction of the salt and pepper noise will not always reduce even if the many filtering methods are applied.

MSE for each one technique following the removal of noises is shown in Figure 4.9. It shows that the MSE results of the proposed DCT-SVD-ANFIS is lesser than the existing methods DCT-FNN and DCT methods with different noises respectively, 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.

![Figure 4.9 MSE vs. methods](image)

Application of DCT to the image, mapping DCT coefficients in a zig-zag order into four quadrants and then the SVD is applied to each quadrant. These four quadrants represent frequency bands from the lowest to the highest. The singular values in each quadrant are then modified by the singular values of the DCT. The square-error of the reconstructed image is much smaller when reducing all singular values proportionally instead of neglecting the smaller ones.
ANFIS are employed to make a distinction among singly and doubly compressed images from the elevated frequency coefficients in quantization matrix, but in previous methods, modification of singular values in the DCT coefficients are not done, so the square-error of the reconstructed image is higher.

### 4.4 Summary

In this chapter, a novel JPEG error analysis method with estimation of quantization matrix results and image denoising techniques by Non Local linear Filter and its Method noise Thresholding by means of wavelets (NLFMT) is proposed. Prior to carrying out the denoising methods primarily in DCT-SVD techniques, the image is resized by means of Growcut based seam carving approach. Growcut based seam carving approach for image resizing 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 the image and subsequently noises are eliminated by means of NLFMT. ANFIS concentrated on the complication of estimating quantization steps for choosing histogram based feature vector for DCT-SVD coefficients. However, the major issue of the proposed schema is that it does not find duplicate regions. The existing DCT-SVD coefficient detection methods are based on the direct matching blocks of image pixels or transform coefficients, and are not effective when the duplicated regions have geometrical or illumination distortions which are focused in the next Chapter 5.