CHAPTER 5

DETECTION OF DUPLICATE REGION AND HYBRID NON-LOCAL MEANS FILTERING FOR DENOISING WITH QUANTIZATION MATRIX ESTIMATION

5.1 Introduction

In the previous chapter, a novel JPEG error analysis method was proposed with estimation of quantization matrix results and also proposed an image denoising by Non local Linear Filter and its Method noise Thresholding by means of wavelets (NLFMT). Before carrying out the denoising methods primarily in the DCT-SVD technique, the image is resized by means of Growcut based Seam Carving approach. On the other hand, this JPEG error analysis scheme does not offer agreeable results, particularly when the duplicated area is small. Region duplication is an uncomplicated and efficient process to produce digital image forgeries, where a constant segment of pixels in an image, following feasible geometrical and illumination transformations, is copied and pasted into a different location in the same image.

In general, a common manipulation in tampering with digital images is recognized as region duplication, in which a continuous segment of the pixels is copied and pasted into a different location in that particular image. In order to make realistic forgeries, the duplicated sections are typically produced with geometrical or illumination modifications. These duplicated sections are well mingled into the surroundings at the target positions, and happen to be extremely complicated to notice visually. With the aim of solving duplicate detection problem, a novel Multi-directional Curvelet Transform with Fourier Transform matching Invariant Rotation (MCFTIR) region duplication detection scheme is proposed to identify duplicated regions for JPEG images. This scheme begins with estimating the overlapping blocks of a JPEG image and it is organized in accordance with the statistics of multiple curvelet sub-bands. During the second
phase, the amount of candidate block pairs of JPEG images has been significantly diminished by means of spatial distance between each pair of blocks for JPEG image. Shape-Preserving Image Resizing (SPIR) scheme is proposed for the purpose of image resizing. Noises are appended to image and eliminated with the help of Hybrid Non-Local Means Filtering (HNLMF) denoising framework. Image compression through Discrete Cosine Transform –Singular Value Decomposition (DCT-SVD) was carried out for single and double image compression. Images are quantized and estimated with Mamdani model based Adaptive Neural Fuzzy Inference System (MANFIS) and the quantization table of a JPEG image was detected.

5.2 Proposed Non Local Linear Filtering and MANFIS Algorithm Methodology

In this research work, a new method is proposed for reliable detection of duplicated and distorted regions in a JPEG digital image. This scheme depends on multi-resolution and multi-orientation curvelet transform. Statistical attributes are derived from curvelet sub-bands of overlapping blocks, and diminished features are generated for similarity measure. The formulated duplicate detection finds the duplicated detected regions which are matched in accordance with the Fourier-based matching. Following to the detection of duplicate regions, it is essential to eliminate noises from the duplicated region removed the image. For this purpose, hybrid novel non-local means filtering scheme is applied in this work. In order to reduce the size of the images subsequent to completion of JPEG compression, a scheme known as Shape-preserving image resizing is executed for compressed images. The quantization step is carried out from Chang and Lai (2009) to examine the error of compression schemes by means of Mamdani Adaptive Neural Fuzzy Inference System (MANFIS). It precisely finds the error results from quantization matrix in case of both single and double compression schemes. The formulated double compression scheme encompasses less error rate results when compared against previous double compression schemes, in
view of the fact that it makes use of a MANFIS for quantization matrix estimation in compressed images and duplicate regions are identified in preliminary stages of the work. Moreover, it diminishes the size of JPEG compressed image and subsequently it is transmitted as input to quantization process.

5.2.1 Multi-Directional Curvelet Transform

Through the continuous development in the reputation of digital media and the ubiquitous accessibility of media editing tools, inoffensive multimedia are tampered without any difficulty for malicious intentions. Copy-move forgery is one significant type of image forgery, where a section of an image is duplicated, and substituted for some other part of the same image at a different position. As a result, it is essential to have consistent and well-organized schemes to distinguish copy-move forgery for applications in law enforcement, forensics, etc. Here, in this research, with the assistance of multi-resolution and Multi-Orientation Curvelet Transform (Qiao et al., 2011), a blind forensics approach is proposed for the purpose of detection of copy-move forgery.

In curvelet transform, an input image is decomposed into a set of sub-bands, and each sub-band is then partitioned into several blocks for ridgelet analysis. The ridgelet transform is applied through the process of merging the Radon transform and the 1-D Wavelet Transform. In order to accomplish elevated levels of efficiency, curvelet transform is normally applied in the frequency domain. In view of the fact, that complex ridgelet transform has more computational complexity, fast discrete curvelet transform is done through the process of wrapping of the Fourier samples. The pyramid arrangement of curvelet transform produces multiple orientations at several scales, which significantly helps the recognition of duplicated sections in terms of both accuracy and robustness. Multi-directional decomposition offers a more accurate approximation of the association among nearby orientations, and additionally
supports the tolerance of rotation and shifting manipulations. As a result, the model of individual orientation is protected, and the changeovers of nearby orientations remain. This significant property provides the indication to enhance copy-move forgery detection. With the intention of minimizing the directions of the candidate blocks, the difference vectors are organized and use it as a rotation invariant descriptor of every candidate block. In case of each similar pair of blocks, Euclidean distance between their descriptors is computed as a similarity measure. In case of 3 levels decomposition, the descriptor of level 2 sub-bands is employed for the purpose of the similarity measure. In this representation, the local rotation invariant are not extracted, however in its place, initially construct a rotation variant and subsequently apply a global matching procedure. This global matching can be applied by means of a comprehensive search scheme for the purpose of finding the minimum distance in the entire candidate orientations and is however computationally extensive. Moreover, the extracted features can be employed for the purpose of estimating the principal orientations and consequently the matching distances can be computed along the principal orientations only.

5.2.2 Duplicate Region Detection for JPEG images using Multi-Directional Curvelet Transform

A novel approach is proposed to identify duplicated regions in accordance with the statistics of curvelet coefficients which is motivated by the observation of multi-directional curvelet transform. Here, a duplicate region of the JPEG image is identified with the assistance of the curvelet coefficients and their correlation coefficient values are matched in accordance with the Fourier Transform (FT) based rotation invariant matching schema. The proposed Multi-directional Curvelet Transform with Fourier Transform matching Invariant Rotation (MCFTIR) scheme includes two stages. During the first stage, the overlapping blocks of a JPEG image are arranged in accordance with their
statistics of multiple curvelet sub-bands. The complete procedure of the proposed MCFTIR scheme is described in Figure 5.1.

During the second stage, the amount of candidate block pairs of JPEG images has been significantly diminished, and the spatial distance between each pair of blocks for JPEG image is taken to decrease the false positive of similar blocks from same object or texture. Orientation associated block features are derived from Fourier transform pattern matching. Taking into account the relation among adjacent orientations, the rotation or shifting effects could be diminished.

![Diagram of MCFTIR approach](image)

**Figure 5.1 Working procedure of proposed MCFTIR approach**
5.2.3 Curvelet sub-band feature extraction

In order to extract the statistical characteristics, the grayscale image is partitioned into a sequence of overlapping blocks. Subsequently, fast curvelet transform is executed to individual blocks. Given a block $B[i,j]$ of dimension $N$ by $N$, the Curvelet Transform (CT) can be derived from the following equation:

$$CT(a, b, \theta) = B[i,j] \times \psi_{a,b,\theta}[i,j]$$

(5.1)

$$\psi_{a,b,\theta}[i,j] = a^{1/2} \left( \frac{i \cos \theta + y \sin \theta - b}{a} \right)$$

(5.2)

where $\theta$ indicates the orientation of the ridgelet. Ridgelets are steady alongside the lines $i \cos \theta + y \sin \theta = \text{const}$. In accordance with the setting of block size $N$ for every JPEG image, all blocks are decomposed into 3 or 4 levels of scales. Several scales involve different numbers of sub-bands. In case of 3 levels decomposition, the level 1, 2 and 3 consists of 1, 16, and 1 subbands correspondingly. The sub-band of curvelet transform are characterized as CT. Hence the 3 levels curvelet coefficients are given by equation (5.3)

$$CT = \{(ct_{1,1}), (ct_{2,1}, \ldots, ct_{2,16}), (ct_{3,1}, B[i,j]) * \psi_{a,b,\theta}[i,j]\}$$

(5.3)

With the intention of reducing the feature dimension of JPEG images and defending against rotation manipulation, the mean values of every sub-band are computed and arranged those in the same level of scale. In case of 3 levels decomposition, the levels 1 and 3 enclose only one sub-band. Subsequently, there is no additional processing. Level 2 includes 16 subbands, and the mean values of these are given by equation (5.4).

$$M_{CT(2)} = m_1, \ldots, m_{16}$$

(5.4)

The arranged features of 3 levels decomposition can be determined by using the following equation (5.5).

$$M_{CT} = \{M_{CT(1)}, M'_{CT(2)}, M_{CT(3)}\}$$

(5.5)

$M_{CT}$ is employed for the purpose of lexicographic sorting. Subsequently, adjacent pairs of blocks in the rank could be offered to the second phase as candidate blocks.
(i) *Adjacent Sub-band Transition*

At some point in the rotation manipulation, the entire sub-bands of the ordinations move at the identical degree. Consequently, the association among adjacent sub-bands fundamentally remains same. Even though the absolute values possibly will differ, the distributions of shifts are extremely close to the original ones despite of shifting. As a result, the dissimilarities among each adjacent pair of sub-bands in level 2 are given by equation (5.6).

\[ D(i) = \left| m_i - m_{\text{mod}(i+1)} \right|, \quad i = 1, \ldots, 16 \]  

(5.6)

(ii) *Rotation Invariant Fourier-based Pattern Matching*

To execute rotation-invariant object detection, a Fourier-based pattern matching scheme (Kingsbury, 2006) is indispensable which decides the correlation between a candidate locality in the search image and the complete possible rotations of a reference object in an efficient approach. With the intention of reducing the paths of the candidate blocks, the difference vector is organized and exploits the organized vector as a rotation invariant descriptor of the complete candidate block. Fourier Transform is a famous approach which assists in measuring correlation, mapping to the D(i) matrix. The fundamental concept is to generate matrices Dp(i) at each band i in the input image and to generate matrices Dq(i) at the entire candidate and possible rotations of a reference object in the search image. For a predetermined reference and candidate pair (p, q), it is necessary to compute the correlation among Dp(i) and Dq(i) for all feasible cyclic movements of their columns, including fractional sample moves at certain comparatively fine spacing. There are 12 samples in each column and when, typically, necessitate 1/4-sample intervals (corresponding to 30/4 = 75° rotational spacing) to obtain a precise estimation of correlation peaks, so 48 correlation samples are necessary on each of the 7-matrix columns for each pair (p, q). With the aim of evaluating N pairs, the order of N * 48 * 12 * 7 = 4032N complex multiply-and-add operations is essential.
The pair wise correlation process for every transformed matrix pair \( D_p(i) \) and \( D_q(i) \) then becomes:

- Multiply every Fourier Transform (FT) element of \( D_p(i) \) with the conjugate to the corresponding Fourier element of \( D_q(i) \) to obtain a matrix \( S_{pq}(12 \ast 7 = 84 \text{ complex multiplies}) \)
- Store the \( 12 \ast 7 = 84 \) elements of \( S_{pq} \) into 48-element spectrum vector \( S_{pq}(84 \text{ complex adds}) \)
- Take the real portion of the inverse FFT of \( S_{pq} \) in order to get hold of 48-point correlation result \( S_{pq} (\leq 48 \ast \log_2(48) = 270 \text{ complex multiple adds}) \)

The process for \( N \) pairwise comparisons will involve \( \leq (84 + 270)N = 354N \) complex multiply-and-addition operations. Here, in case of Fourier domain, the correlation outcome is carried out from 12 up to 48 samples by means of padding the spectra with zeros prior to the inverse FFT is taken. However, this must be done rather carefully because different columns of \( S_{pq} \) are bandpass signals with differing center frequencies. Optimum interpolation is accomplished when the zero-padding is commenced over the element of the spectrum, which is expected to contain minimum energy, for each column of \( S_{pq} \), as follows. Let us consider generating a \( D(i) \) matrix from the adjacent sub-band transition of an uncomplicated object that is a single step edge which is revolved gradually through \( 360^0 \) from the horizontal and is centered on the 13-point pattern. The similarity between a pair of blocks \( p \) and \( q \) are derived from the equation (5.7):

\[
S_{pq} = \sum_{i=1}^{16} |D_p(i) - D_q(i)|^2, \quad i = 1, \ldots, 16 \quad (5.7)
\]

By taking small distortion established through the rotation, compression, or noise adding, a particular threshold is fixed to find out duplicated blocks. In case of different resolutions of the image and various levels of decomposition, the threshold must be regulated accordingly. The last phase of MCFTIR scheme is to process the region correlation maps to get hold of the duplicated regions.
Initially, a Hybrid Non-Local Means Filtering (HNLMF) of pixels is executed for the purpose of removing the following noises in the correlation maps of JPEG images. Based on equation (5.7), the similarity matched regions are taken as original regions and duplicated regions are eliminated. This image is named as dr1.

5.2.4 Non-Local Means Filtering (NLMF)

In this work, the noisy pixels are replaced by the weighted average of other image pixels with weights reflecting the similarity between local neighborhoods of the pixel being processed and the other pixels. The NL-means filter was proposed as an intuitive neighborhood filter based on theoretical connections to diffusion and non-parametric estimation approaches (Shamsi and Kim, 2013). The related Bayesian model facilitates to develop the relationships between these algorithms, to validate certain underlying statistical postulations and to give keys to set the control parameters of the NL-means filter. It is to be observed that this model could also be used to eliminate noise in applications where in the noise distribution is considered to be known and non-Gaussian. However, in NLMF method, the weight factor is based upon the Euclidean distance function which greatly minimizes the effectiveness of denoising. This problem is solved by using the similarity of the mean normal orientation of middle patch with remaining patches of duplicate region eliminated image in the search window. So, this method is named as the Hybrid Non-Local Means Filtering (HNLMF).

5.2.5 Noise Removal For Images Using Hybrid Non-Local Means Filtering (HNLMF)

The objective of image denoising is to eliminate the noises and at the same time preserving the important resized JPEG image characteristics like edges and details as much as possible. Linear Filter convolles the resized JPEG image with a steady matrix to get hold of a linear mixture of neighborhood
values and has been extensively employed for noise elimination in the existence of additive noise. This gives rise to blurred and smoothed resized JPEG image with poor feature localization and imperfect noise suppression. The image denoising framework by means of the Hybrid Non-local Means Filtering (HNLMF) (Shamsi and Kim, 2013) includes two phases has demonstrated in Figure 5.2.

![Figure 5.2 Schematic representation of the proposed hybrid non-local means filtering](image)

Initially, the accelerated version is executed in the wavelet transform domain to attain a pre-denoised JPEG image for the image without duplicate regions. Then, a modified version of traditional Non-Local Means Filtering is executed on the given duplicated regions eliminate the noisy image. In this phase, the weights are calculated by means of pre-denoised duplicated regions eliminated image obtained during the first step. The following noises such as Salt and pepper noise, Speckle noise, Gaussian noise and Sharpening noises are removed from image samples.

(i) Multiscale Accelerated Non-local Means

Inspired by numerous schemes (Dabov et al., 2007 & Kervrann et al., 2007), with the use of pre-denoised images to get hold of refined patches, tries to acquire the pre-denoised duplicate region removed the images. On the other hand, in contradiction of those schemes implement an extremely simple method. Initially, decompose the deduplicated region eliminated image drl by means of
two-dimensional Discrete Stationary Wavelet Transform (DSWT) up to the coarsest level $J$.

$$\text{DSWT}_{\text{drl}}(U) = \left( (w^x_{2j}), (w^y_{2j}), (w^{xy}_{2j}) \right)_{1 \leq j \leq J}, (S_{2j}) U \quad (5.8)$$

Subsequently, the accelerated version of NLMF (Kervrann et al., 2007) is done on detail bands, and for every scale level $j = 1, 2, ..., J$. At last, the reference pre-denoised image is acquired by means of the inverse stationary wavelet transform. Rotationally invariant and sparse representation of a noisy image in the DSWT domain, the duplicated region eliminated image can be resourcefully denoised by means of accelerated NLMF without much loss of texture, edges, and fine information.

(ii) Normal Vector Patches and Weight Factor

Initially, computed the gradient of the complete duplicated region eliminated image and subsequently generate the patches of horizontal and vertical elements of the gradient vector around each pixel $i$. These patches are indicated by $N_{ix}$ and $N_{iy}$, where the subscripts $x$ and $y$ indicate the partial derivatives in horizontal and vertical directions, respectively. The size, $m \times m$, of these patches is similar as the size of the photometric patch (Shamsi and Kim, 2013). The element-wise inner product of standard vectors of the central patch are calculated with the standard vectors of the remaining patches in the search window $\Delta i$, as given in what follows:

$$\Gamma = N_i \ast N_j = N_{ir} \ast + N_{iv} \ast N_{ij} \quad (5.9)$$

where $\ast$ indicates the point-wise multiplication of patches for duplicate region eliminated images and $\Gamma$ represents the patch or matrix containing the entire element-wise inner products. The weight factor is subsequently defined as $\Gamma_{kl}$.

$$\eta(i, j)_{xj} = \exp \left( -\frac{1}{(m^2 - 1)} \max_{1 \leq k, l \leq m} \{ \Gamma_{kl} \} \sum_{1 \leq k, l \leq m} \Gamma_{kl} \right) \quad (5.10)$$

Subsequent to reaching pre-denoised image, execute the modified version of standard NLMF on providing noisy duplicate region eliminated image, in
accordance with the similarity of reference patches from the pre-denoised duplicate region eliminated image. The modified similarity measure is given as,

$$w(i,j)_{i\neq j} = \exp\left(-\frac{D(p)\eta(i,j)}{h^2}\right)$$ \hspace{1cm} (5.11)

where $D(p)$ is Mahalanobis distances of an observation of the patches $p = (p_1, \ldots, p_N)$ from a collection of patches with mean $\mu = (\mu_1, \ldots, \mu_n)$ and covariance matrix $S$ is given as:

$$D(p) = \sqrt{(p - \mu)^T S^{-1} (p - \mu)}$$ \hspace{1cm} (5.12)

On the other hand, the proposed weight factor depends upon the similarity of the mean normal orientation of middle patch with remaining patches of duplicate region eliminated image in the search window. The standard non-local means allocate the maximum of the entire computed weights with remaining patches in the search window. Mathematically, this is given by equation (5.13).

$$w(i,j) = \max_{j \in \Delta i, j \neq i} \{w(i,j)\}$$ \hspace{1cm} (5.13)

Furthermore, the weight is determined based on a heuristic scheme. For low or medium noise levels in the duplicate region eliminated image, a slightly higher self-similarity weight is allocated than employed in traditional NLMF; self-similarity weight is given as,

$$w(i,j) = \frac{4}{3} \max_{j \in \Delta i, j \neq i} \{w(i,j)\}$$ \hspace{1cm} (5.14)

The intuitive justification for allocating higher self-similarity weight depends on the hypothesis that occurrence of low or medium level of noise affects the self-similarity to a certain extent. After the removal of noises from image samples, Shape-Preserving Image Resizing is applied for image resizing. Seam Carving and GrowCut approaches are proposed to protect the region of interest by formulating the image energy function to construct the new map of energy to direct the seam to be an optimal seam and improve the visual effects after image resizing. But, the major limitation is a warping of the background to
highlight the ROIs through which the context of the original image is lost (Farag et al., 2011). It becomes impossible to tell how big the ROI is in comparison to the rest of the image. To solve these issues in here proposed a shape preserving method for image resizing.

5.2.6 Shape-Preserving Image Resizing

A novel technique is proposed which ensures that the new shapes of important objects are geometrically analogous to their original shapes both locally and globally. Wang et al., (2008) used a grid mesh and optimally diffuse distortion into less important regions in all directions. But, different to Wang et al., (2008) approach, this proposed technique facilitates quads to endure a similarity transformation and preserves important edge features. Consequently, distortion is better diffused, and large, prominent objects are better preserved by edge similarity constraints (Zhang et al., 2009).

Shape-Preserving Image Resizing for Denoised Image

In order to diminish the size of the compressed image with denoised image sample, in this research work formulated a Shape-Preserving Image Resizing (SPIR) scheme and the compressed image samples are indicated as a grid mesh $M = (V_1, F)$ with vertices $V_1$ and quad face $F$, where $V_1 = \{v_i\}$ indicates initial vertex locations. In order to better capture important objects for compressed JPEG image, moreover, additional edge points are inserted on compressed image edges, indicated by $V_2 = \{v_i\}$. It must be noted down that $V_+ = V_1 \cup V_2$, for the set containing the entire points. The image resizing approach tries to discover deformed mesh geometry $V'_+ \ (V'_1)$ under similarity transformation constraints on the unique control points for JPEG compressed images. The outcome of the resized JPEG image is acquired from the last locations of the mesh vertices for every JPEG image $V'_1$ by means of cubic interpolation. The similar JPEG image control points are grouped into specific sets given as handles, indicated by $H = \{H_i\}$. Every handle values of the JPEG compressed
image is allocated to a quadratic energy term. This is called as distortion energy $\mathcal{E}(H'_i, H_i)$ which determines the dissimilarity among the deformed handles $H'_i$ and its original shape $H_i$. The overall distortion energy for JPEG compressed image is

$$E = \sum_{H_i \in \mathcal{H}} \omega_i \mathcal{E}(H'_i, H_i) \quad (5.15)$$

The recent locations of the vertices $V'_+ \text{ for the compressed JPEG images}$ in reducing the quadratic energy $E$ with suitable boundary conditions are obtained. Three categories of handles are defined to carry out the image resizing for JPEG images:

**Q-Handle:** Q-Handle includes four corners of a quad face which does not enclose a supplementary control point. A Q-Handle is appended to $H$ for each such quad face.

**B-Handle:** B-Handle is a subset of $V_+$, every element belonging to the similar image edge. For every image edge containing a minimum of 3 points in $V_+$, a B-Handle to $H$ is appended containing the entire points in $V_+$.

**K-Handle:** K-Handle is a set containing the four corners and the inner control point of a quad face which encloses a supplementary control point. K-Handle to $P$ is appended for each such quad face. Generally, these K-Handles are deployed to link the similarity constraints for Q-Handles and B-Handles.

Then, it also calls the distortion energy terms for Q Handles and K-Handles the local similarity parameters and call energy terms for B-Handles the edge similarity parameters for JPEG compressed image. The handle for JPEG compressed image $H = \{h_i\}$ with $m$ distinct control points are provided, its deformed locations of the current JPEG image as $H' = \{h'_i\}$, $m \geq 3$. Its distortion energy is given as,

$$\mathcal{E}(H'_i, H_i) = \min_{s \in \mathcal{S}} \sum_{i=1}^{m} |s(h_i) - h'_i|^2 \quad (5.16)$$

where $s$ indicates the collection of similarity transformation $s$ in $\mathbb{R}^2$ having the general form,
where \( c, d, x, y \) are the four constraints determining a distinctive similarity transformation. Intuitively, the energy determines the shape distortion of the handle of the JPEG compressed image \( H' \) in relation to \( H \), at the same time ignoring translation and rotation. It is the smallest possible square distance between \( H' \) and \( H \), when \( H \) might be substituted by any similarity transformation of itself.

\[
\mathcal{E}(H', H) = |C_H b_{H'}|^2
\]  

(5.18)

where, \( C_H = A_H (A_H^T A_H)^{-1} A_H^T - I \)  

(5.19)

\[
\begin{bmatrix}
x_1 & -y_1 & 1 & 0 \\
y_1 & x_1 & 0 & 1 \\
\vdots & \vdots & \vdots & \vdots \\
x_m & -y_m & 1 & 0 \\
y_m & x_m & 0 & 1
\end{bmatrix}
, b_{H'} =
\begin{bmatrix}
x'_1 \\
y'_1 \\
\vdots \\
x'_m \\
y'_m
\end{bmatrix}
\]

(5.20)

For every handle \( h \) of the JPEG compressed image, the equivalent \( C_H \) is computed, and subsequently discovers the minimal solution of \( E \) directly. The \( C_H \) matrix is the same for the entire Q-Handles. The locations of the vertices for compressed JPEG images are found by reducing a quadratic total energy function. In case of a triangle \( T \) and its image \( T' \), the quadratic conformal energy for JPEG compressed image is indicated as \( C(T', T) \). Total conformal energy is given as,

\[
C(T) = \sum_{T' \in \mathcal{E}} C(T', T)
\]  

(5.21)

where \( T \) indicates the set of the entire triangles for the complete control points of the JPEG compressed image. In the image resizing scheme to discover the significance value of compressed image pixel, weight is calculated. The weight \( w_c \) for a Q-Handle or a K-Handle is subsequently given as the average of the significance values of those compressed image JPEG pixels in the equivalent quad. The weight of a B-Handle \( h_B \) is given as \( \omega_{c_{hb}} \), where \( \omega_{c_{hb}} \) indicates the
average weights of JPEG compressed image pixels in the entire quads which include at least one point in \( h_t \); \( \alpha \) indicates a steady number determining the significance of the edge similarity parameters for JPEG image edges and is regularly fixed to 1. It is essential to enforce boundary stipulations when computing the optimal resize solution. In order to resize the JPEG compressed image from \( w \times h \) to \( w' \times h' \), the boundary conditions are,

\[
\begin{align*}
    v_{ix} &= 0 \quad \text{if } v_{ix} = 0 \\
    v_{ix} &= h' \quad \text{if } v_{ix} = h \\
    v_{iy} &= 0 \quad \text{if } v_{iy} = 0 \\
    v_{iy} &= w \quad \text{if } v_{iy} = w
\end{align*}
\]  
(5.22)

5.2.7 Compression and Decompression Process with DCT -SVD

Figures 5.3 (a) & (b) demonstrate the representation of DCT-SVD-MANFIS dependent single and double compressed image samples.

At first, LENA images are taken as input image I, subsequently apply DCT-SVD transform function to the input image. The transformed frequency coefficients \( I_{DCT-SVD} \) resulting from DCT are resized by means of the SPIR. In order to assess the results of DCT compression schemes, an error value is introduced in this step which is known as quantization and the quantization coefficient values of DCT compression results is analyzed by means of using ANFIS. During the
final stage, the resultant bit from MANFIS is integrated into a header file to generate the specific JPEG file. On JPEG image decompression stage, the compressed JPEG file is considered as one of the important entropy measures to decode and recover the quantization coefficient JSQd₁ and it is multiplied with quantization table JPSPQ₁ (JPEG SPIR QUANTIZATION) to obtain the dequantized coefficient RJPSPId₁'. The DCT-MANFIS inverse transformation function is applied to dequantized results. Subsequently, dequantized images samples results from DCT-MANFIS are transmitted as input to the second compression scheme, which carries out a similar procedure as single DCT-MANFIS compression process, until the entire images are compressed and decompressed again.

Figure 5.3(b) Double image compression for resized images RJPSPI

With the aim of diminishing the complexity in the DCT transformation scheme, SVD approach is employed for resized JPEG image compression step. The SVD is applied to DCT compression matrix DTC(k), as given in equation (5.23):

\[
DTC(0) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} f(RJPSPI) \quad (5.23)
\]

\[
DTC(k) = \sqrt{\frac{2}{N}} \sum_{n=0}^{N-1} f(RJPSPI) \cos \left( \frac{(2RJPSPI + 1)k\pi}{2N} \right), \quad k = 1, \ldots, N - 1 \quad (5.24)
\]
The above DCTC(k) is partitioned into four quadrants with the help of a Zig-Zag mapping. The size of every quadrant is 8×8. The SVD is applied to all quadrants, and subsequently a diagonal 8×8 matrix $S$ is obtained. The SVD of a $m \times n$ matrix $RJPSP_A$ is given as:

$$RJPSP_{DCTC(k)} = U \cdot S \cdot V^T$$

(5.25)

where $U \in \mathbb{R}^{m \times m}$, $V \in \mathbb{R}^{n \times n}$ are unitary and $S = \text{diag}(\sigma_1, ..., \sigma_r)$ indicates a diagonal matrix. The diagonal matrix $S$ is known as a singular value of $RJPSP_{DCTC(k)}$ and are presumed to be organized in descending order $\sigma_1 > \sigma_{i+1}$. The columns of the $U$ matrix are known as the left singular vectors and at the same time, the columns of the $V$ matrix are known as the right singular vectors of $A$. Every singular value $\sigma_i$ indicates the luminance of a data layer at the same time the corresponding pair of singular vectors indicates the geometry of the data layer. Subsequently, inverse discrete cosine transform defined in equation (5.26).

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

(5.26)

Prior to estimating the results of the quantization matrix from both single and double compressed images, primarily it is essential to measure the association of frequency coefficient between the first image and second images are considered as,

$$RJPSPId_2 = \text{DCT} - \text{SVD}(I_1)$$

$$= \text{DCT} - \text{SVD} ( [\text{IDCT} - \text{SVD}(RJGCSd_1)] )$$

$$= \text{DCT} - \text{SVD} ( \text{IDCT}(RJGCSd_1) + \text{RE} )$$

$$= \text{DCT} - \text{SVD} ( \text{IDCT} (RJGCSd_1') + \text{DCT} - \text{SVD} (\text{RE})$$

$$= RJPSPId_1' + \varepsilon = \frac{RJPSPId_1}{RJPSPIQ_1} \times RJPSPIQ_1 + \varepsilon$$

(5.27)

where $\varepsilon(i,j)$ indicates rounding error from previous DCT-SVD compression phases. Considering that $\varepsilon(i,j)$ is estimated to have Gaussian distribution with zero mean and variance $1/12$. In case of DCT-SVD compression schemes, the transformed frequency coefficient location values are taken as $(i,j) \in (0,7)$
respectively and their quantization matrices are given as $RJPSPQ = RJPSPQ_{1}(i,j)$. The results of quantization matrix are assessed in accordance with the rounding error function. The rounding error function is not simple to realize results for various sizes of images. In order to overcome this complication, in this research work, an Mamdani model based Adaptive Neural Fuzzy Inference System (MANFIS) is used and weight updating formula in consideration with qualitative representation of inference consequent parts in fuzzy neural networks to estimate quantization of single and double compressed image samples.

5.2.8 Mamdani Model based Adaptive Neural Fuzzy Inference System (MANFIS) to estimate Quantization Matrix

In the recent past, quantization matrix estimation is done by using the ANFIS model, but in the ANFIS model weight updation is done in a random manner which is solved by using MANFIS. Mamdani framework is based on Adaptive Neural Fuzzy Inference System (M-ANFIS) and weight updating formula in consideration with qualitative representation of inference consequent parts in fuzzy neural networks. M-ANFIS model adopts Mamdani fuzzy inference system which has advantages in consequent part.

MANFIS classification system (Chai et al., 2009) is formulated here to estimate the quantization results of JPSPIQ_{1}(i,j) & JPSPIQ_{2}(i,j) through the association between two compression images. The proposed approach initially extracts histogram dependent features from resized images to evaluate the quantization results into two dissimilar classes such as single and double quantization. MANFIS is a grouping of the quantitative fuzzy logic approach and adaptive ANN. It builds the fuzzy inference process through known quantization matrix from DCT-SVD and their corresponding fuzzy membership values for histogram characteristics of the JPEG resized image are regulated automatically through back propagation approach. Weight updating formulas is extremely vital for regulating M-ANFIS model based on basic back propagation in NN, which enhances the quantization matrix estimation results. The MANFIS scheme is
employed for estimation of quantization matrix results of the experiment by permitting for only two major classes \( r_{d_1} \) & \( r_{d_2} \). MANFIS framework is taken in the form of fuzzy –if then rules. The generalized structure of fuzzy-if then rules are described as follows:

**Rule1:** If \( (RJPSP\text{h}_{DCT-SVD C(k)} x_1(i, j) \text{ is } A_1) \& (RJPSP\text{h}_{DCT-SVD C(k)} y_1 S(i, j) \text{ is } B_1) \)

then \( (f_1 = p_1 RJPSP\text{h}_{DCT-SVD C(k)} x_1 + q_1 RJPSP\text{h}_{DCT-SVD C(k)} y_1 + r_1) \)

**Rule2:** If \( (RJPSP\text{h}_{DCT-SVD C(k)} x_2 \text{ is } A_2) \& (RJPSP\text{h}_{DCT-SVD C(k)} y_2 \text{ is } B_2) \)

then \( (f_2 = p_2 RJPSP\text{h}_{DCT-SVD C(k)} x_2 + q_1 RJGCS\text{h}_{DCT-SVD C(k)} y_2 + r_2) \)

where inputs that are histogram based features from the DCT-SVD scheme are given as variables \( RJGCS\text{h}x \) and \( RJGCS\text{h}y \). \( A_1 \) and \( B_1 \) indicate the fuzzy sets for estimation of the quantization matrix from the DCT-SVD with obtained histogram features, \( f_i \) are the outputs of quantization estimation matrix outcome inside the fuzzy region indicated by the fuzzy rule, and \( p_i, q_i \) and \( r_i \) are the design constraints that are decided at some point in the training phase. In MANFIS framework, the input nodes is taken as adaptive nodes where input of these nodes takes histogram based features from the DCT-SVD matrix. The output result of layer 1 is the fuzzy membership ranking of the quantization matrix results, which are given as:

\[
O^1_i = \mu_{A_i}(RJPSP\text{h}_{DCT-SVD C(k)} x^i), \quad i = 1, 2 \quad (5.28)
\]

\[
O^1_i = \mu_{B_{i-2}}(RJPSP\text{h}_{DCT-SVD C(k)} y^i), \quad i = 3, 4 \quad (5.29)
\]

where fuzzy membership function of the layer 1 is \( \mu_{A_i}(RJPSP\text{h}_{DCT-SVD C(k)} x), \mu_{B_{i-2}}(RJPSP\text{h}_{DCT-SVD C(k)} y) \). It is necessary to compute membership function in order to find the layer 1 results of \( \mu_{A_i}(x) \), and it is given as:

\[
\mu_{A_i}(RJPSP\text{h}_{DCT-SVD C(k)} x) = \frac{1}{1 + \left( \frac{RJPSP\text{h}_{DCT-SVD C(k)} x - c_i}{a_i} \right)^2} b_i \quad (5.30)
\]
where \( a_i, b_i \) and \( c_i \) indicate the constraints of fuzzy membership function for quantization matrix results from DCT-SVD. In case of the first layer, the nodes are fixed nodes. They are labelled as \( M \), representative that they complete as a simple multiplier. The outputs of the second layer can be given as:

\[
O_i^2 = w_1 = \mu_{A_i}(R|PSPLh_{DCT-SVD C(k)}x_i) \\
\mu_{B_i}(R|PSPLh_{DCT-SVD C(k)}y_i) \quad i = 1,2
\] (5.31)

This is also the noticeable strengths of the fuzzy-if then rules. In case of the third layer, the nodes are also fixed nodes. These nodes are labelled with a parameter \( N \), which indicates the normalization to the noticeable strengths of the fuzzy-if then rules from the second layer. The outputs of the third layer can be given as:

\[
O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2}
\] (5.32)

which are the expected normalized noticeable strengths. In case of the fourth layer, the nodes are adaptive. The output of each node in fourth layer is predominantly the product of the normalized noticeable strength and a first order polynomial. As a result, the outputs of the fourth layer are given by:

\[
O_i^4 = \bar{w}_i f_i = \bar{w}_i \left( p_i R|PSPLh_{DCT-SVD C(k)}x_1 q_i R|PSPLh_{DCT-SVD C(k)}y_1 + r_i \right)
\] (5.33)

In case of the fifth or final layer, there is only one solitary fixed node labelled with \( S \). This node carries out the summing up of the entire received signals. Thus, the whole output is given as:

\[
O_i^5 = \sum_{i=1}^{2} \bar{w}_i f_i = \frac{\sum_{i=1}^{2} w_i f_i}{w_1 + w_2}
\] (5.34)

In MANFIS architecture, there are two adaptive layers present in the structure they are first and fifth layer. In the first layer, there are three fuzzy membership functions associated adjustable constraints \( a_i, b_i \) and \( c_i \) for each one of the quantization matrices with histogram feature extracted. There are known as basis parameters. The first order polynomial function in the fourth layer is
obtained with the assistance of three adjustable parameters $p_1$, $q_1$ and $r_1$. When the adjustable parameters $a_i$, $b_i$ and $c_i$ for fuzzy membership functions are fixed, the product of the ANFIS is given as:

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2$$  \hspace{5cm} (5.35)

Subsequently, now the equation is transformed as

$$f = \bar{w}_1 f_1 + \bar{w}_2 f_2$$  \hspace{5cm} (5.36)

Substitution of fuzzy if-then rules in the above equation leads to

$$f = \bar{w}_1 (p_1 RJPSPIlh_{DCT-SVD C(k)}x_1 + q_1 RJPSPIlh_{DCT-SVD C(k)}y_1 + r_1) + \bar{w}_2 (p_2 RJPSPIlh_{DCT-SVD C(k)}x_2 + q_2 RJPSPIlh_{DCT-SVD C(k)}y_2 + r_2)$$  \hspace{5cm} (5.37)

which is a linear integration of the adaptable resultant parameters from $f$. The least squares scheme is capable of categorizing the optimal quantization matrix outcome of the single and double compression image values of these resultant constraints. At last, after the completion of the above-mentioned phases, the quantization matrix result is found. A pattern is allocated to single quantization and double quantization class ($rd_1$ & $rd_2$) with the maximum class membership value with less error value. In this research work, five different quantization error values are taken into account to estimate quantization matrix results and its values depend on QF such as $QF_1 = 50$, $QF_2 = 75$, $QF_3 = 85$, $QF_4 = 95$ and $QF_5 = 98$. The job is to diminish an overall error measure for the quantization matrix estimation which is given as:

$$QE = \sum_{k=1}^{N} (d_k - x_{i,k})^2$$  \hspace{5cm} (5.38)

where $d_k$ indicates the $k^{th}$ element of the $p^{th}$ desired quantization matrix results from the DCT-SVD output vector and $x_{i,k}$ indicates the $k^{th}$ element of the anticipated output vector form MANFIS scheme by presenting input vector $JPSPIQ_1(i,j)$ & $JPSPIQ_2(i,j)$ to the network. The general weight-updating
formula of the layer 3 is substituted with the following equation for every node in the network for quantization matrix estimation is,

$$\Delta \omega_{ij} = -\eta(d_i - x_i)x_i X.$$ \hspace{1cm} (5.39)

where $\eta$ indicates the learning step, $d_i$ represents the preferred output for a node in the neural network for quantization matrix estimation results from MANFIS model and $x_i$ represents the real quantization matrix estimation results from the compression algorithm. $X$ indicates polynomial, usually $(x_i * (1 - x_i))$.

With the MANFIS results based on the quantization estimation, first quantization factor $QF_1$ error values are estimated in accordance with 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 $QF_4 = 0.03$, last quantization factor error values are fixed to $QF_5 = 0.005$. These quantization factors at last belong to $JSD_2(5)$ among the association between single and double compressed quantization outcome with feature vectors. The histogram based features is allocated to quantization estimation class $c$ with less quantization error for all quantization matrices and mathematically it is given as,

$$RJPSPId_2(h_{ij}) = F_c(RJPSPId_2) \geq F_j(JPSPIh_{ij})$$ \hspace{1cm} (5.40)

where $F_j(RJPSPId_2)$ indicates the activation function value of the $j^{th}$ neuron in MANFIS and it is taken as the output of MANFIS system. Based on these steps, the fuzzification result of histogram quantization class $F_c(RJPSPIh_{ij})$ result is compared to multiple quantization phases to assess quantization results. Based on the analyzed results, eliminating rounding error (RE) and how to carry out dequantization $JPSPId'_1$ become significant issues. This can be solved with the assistance of the following equation,

$$RJPSPId_2 = RJPSPId'_1 + DCT - SVD(RE) = RJPSPId'_1 + \epsilon$$ \hspace{1cm} (5.41)
Our proposed DCT-SVD-MANFIS correctly examines the quantization matrix results from DCT compression and their corresponding error values in the quantization step results are also founded in MANFIS system. They are used to categorize the quantized image samples into single and double compressed images separately.

5.3 Results and Discussion

In order to assess the proposed system, MATLAB JPEG Toolbox is used. Randomly selected 1000 images from image dataset are used for experimentation. Altogether, there are 5000 uncompressed color images available. These images are initially transformed into gray-scale images, which are subsequently center-cropped into small blocks with sizes ranging from $256 \times 256$ to $8 \times 8$. In order to appropriately assess the proposed feature histogram $J_{S}h_{ij}$, here initially used a minimum risk classification rule to determine the threshold. The experimental results are shown in Table 5.1. False Positive Rate (FPR) is defined as the probability of the uncompressed images being incorrectly identified as JPEG images, and consequently it is fixed once the threshold is specified for the same uncompressed image dataset (Luo et al., 2010). It can be observed that this scheme can achieve an 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 scheme is very robust to the quality factors employed previously as well as the image sizes.

**Table 5.1: Experimental results**

| Quality factor | $256 \times 256$ block | $128 \times 128$ block | $64 \times 64$ block | $32 \times 32$ block | $16 \times 16$ block | $8 \times 8$ 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               |
Following the noises are appended to resized image of the LENA, then the outcome of the noise appended to LENA images is shown in Figure 5.4

| No noise image | Gaussian Noise | Salt & pepper noise | Speckle noise | Sharpening |
|----------------|----------------|---------------------|---------------|------------|

Figure 5.4. Image noise comparison results for LENA image

Following the Figures 5.5 (a) & (b) shows the Alternate Current (AC) coefficients of AC(1,1) and AC(2,2). Then, select the proper quality factors whose corresponding quantization steps are from 1 to 15. It demonstrates the average accuracy as a function of the quantization steps. It is found that the accuracy of the proposed DCT-SVD-MANFIS typically increases with increasing the quantization step, in view of the fact that in the proposed scheme duplicate regions are initially eliminated with the assistance of the Multi-directional Curvelet transform with Fourier Transform matching Invariant Rotation (MCFTIR) and outperforms the other approaches are taken for comparison.

Figure 5.5 (a) Quantization results for AC (1,1)
Figure 5.5 (b) Quantization results for AC(2,2)

Figure 5.6 Detection accuracy as a function of the quality factors

Figure 5.6 shows the average accuracy evaluated on the test images in different cases. The detection accuracy of proposed DCT-SVD-MANFIS system is also important. This algorithm properly detects single and double quantization matrix efficiently and identifies for DCT-SVD compression images, in view of the fact that the proposed system duplicate region are eliminated in the initial stage of the work by MCFTIR approach and noise in the image samples is eliminated with the help of HNLMF noise from image samples. Average
accuracy is also high in DCT–SVD-MANFIS compression for different quality factors than in the existing schemes like DCT-SVD-ANFIS, DCT-FFNN, DCT double compression schemes. The filtering results of the proposed HNLMF 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) for each one of the methods after the removal of the salt and pepper noise, speckle noise, Gaussian and Gaussian noise is shown in Figure 5.7. It demonstrates that the PSNR results of the proposed DCT-SVD-MANFIS is high when compared to existing schemes for all the types of noises, since in the proposed work, duplicate region are eliminated during the initial stage of the work by MCFTIR approach and noise in the image samples is eliminated with the help of HNLMF noise from image samples. This demonstrates that the proposed scheme works well when noises occur in the system.

![Figure 5.7 PSNR comparison for image](image.png)

Mean Square Error (MSE) is found for all the methods subsequent to the elimination of noises and is shown in Figure.5.8. It shows that the MSE results of the proposed DCT-SVD-MANFIS is less when compared against existing
schemes with different noises, since in the proposed work, duplicate region are eliminated in the initial stage of the work by MCFTIR approach and noise in the image samples is eliminated with the help of HNLMF noise from image samples. This shows that proposed methods work effectively for all kinds of noises in the system. In earlier work, some of the works are also done based on the family of the classification methods such as Fuzzy Neural Network (FNN) (Rajkumar et al., 2015), Adaptive Neuro-Fuzzy Inference System (ANFIS) Rezvani et al., 2015), Hybrid Higher Order Neural Classifier (HHON) (Panigrahi et al., 2014) for prediction, missing value imputation and various applications. So, the neural network methods are applicable and easy for any application. For this purpose, in this work, MANFIS is used for error prediction.

Figure 5.8. MSE vs. methods

5.4 Summary

In this chapter, a new Multi-directional Curvelet Transform is proposed with Fourier Transform matching Invariant Rotation (MCFTIR) region duplication detection scheme which is formulated to detect duplicated and distorted regions. The duplicate regions in the JPEG images are identified with the help of the extracted statistical features from curvelet sub-bands of
overlapping blocks, and diminished features are produced for similarity measure. The similarity measure values are matched in accordance with the Fourier-based matching. This work includes five major phases: at first they have developed three image forensic analyses, initially in DCT-SVD methods the image is resized by means of Shape-preserving Image Resizing (SPIR) scheme which is represented as a grid mesh. After resizing the images, noises are eliminated with the help of HNLMF. Compression and decompression process with DCT–SVD estimate the quantization steps by MANFIS. It is an integration of the quantitative MANFIS approach which is proposed for quantization matrix estimation from DCT-SVD. The performance comparison results of all the methods and their significance results is also discussed and summarized in the next chapter 6.