Chapter 3
Fingerprint Image Enhancement

Fingerprint biometrics has been used traditionally as a forensic criminological technique to identify criminals by the fingerprints they leave behind them at crime scenes. Forensic experts compare unique features of a latent sample left at a crime scene against a known sample available in their database or taken from a suspect to establish the identity of the perpetrator. Automated fingerprint recognition systems either accept or reject the user’s identity by matching against an existing fingerprint database. The primary goal while watermarking fingerprint images for security is to preserve their minutiae points as matching of fingerprints majorly depends on them.

However, a fingerprint image may not always be of good quality due to elements of noise that corrupt the clarity of the ridge structures. This corruption may occur due to variations in skin and impression conditions such as scars, humidity, dirt, and non-uniform contact with the fingerprint capture device. The results of most of the minutiae extraction algorithms depend on the quality of the input image. Thus, image enhancement techniques are often employed to reduce the noise and to enhance the definition of ridges against valleys so that no spurious features are identified and watermarking can be done effectively.

This chapter begins by introducing image enhancement and some of its techniques. Further, it presents a brief account of the related work in the area of fingerprint image enhancement. Sections 3.3 and 3.4 present the proposed work in this area with respect to impulse noise removal and contrast enhancement respectively.
3.1 Introduction to Image Enhancement

Image enhancement is the most appealing area of digital image processing. The enhancement techniques are applied to make an image look better in terms of clarity, sharpness and contrast. If an image gets degraded due to noise etc., enhancement techniques try to remove that noise to make the image clear. However, it is important to note that enhancement is a very subjective area of image processing. The enhancement techniques are basically heuristic procedures designed to manipulate an image in order to take advantage of the human vision system.

3.1.1 Image Enhancement Techniques

The principal objective of image enhancement is to process an image so that the result is more suitable as compared to the original image for a specific application. Image enhancement can be done in one of the two image domains: spatial domain, where the techniques are based on direct manipulation of pixels in an image and frequency domain, where the techniques are based on modifying the Fourier transform of an image. Since the proposed work for fingerprint image enhancement presented in the thesis, follows spatial domain approach, some of the main techniques of spatial image enhancement (Gonzalez et al, 2005) are briefly introduced here.

In spatial image enhancement methods, an operation $T$ (linear or non-linear) is performed on the pixels in the neighborhood of coordinate $(x, y)$ in the input image $f$, giving enhanced image $g$ as follows:

$$g(x, y) = T[f(x, y)]$$

The neighborhood can be of any shape, but generally it is rectangular ($3 \times 3$, $5 \times 5$, $9 \times 9$ etc).

Some of the common enhancement techniques are:

- Contrast Stretching
- Histogram Modification
- Noise Filtering
3. Fingerprint Image Enhancement

Contrast stretching: It produces a higher contrast in the resultant image than the original by darkening the levels below a particular threshold \( m \) in the original image and by brightening the levels above \( m \) in the original image. This results in stretching the narrow range of gray levels in the image to wider range, thereby enhancing the appearance of the image (Figure 3-1).

Histogram Modification: The histogram of an image reflects its characteristics such as intensity distribution. By modifying it, the image characteristics can be modified. One such modification is histogram equalization.

Histogram Equalization is a non-linear stretch that redistributes pixel values so that there
is approximately the same number of pixels with each pixel value within a range. Through this adjustment, the intensities can be better distributed on the histogram. This results in increasing the contrast as shown in Figure 3-2.

**Noise Filtering:** It is used to filter various types of noises from an image. A large number of filters like linear filters (e.g. mean), order statistics filters (e.g. median, max, min), and sharpening filters etc. are used for image enhancement. For example, median filtering can be used to remove impulse noise from an image. Median filtering replaces each pixel in an image with the median of all pixel intensities in its $3 \times 3$, $5 \times 5$ neighborhoods.

Impulse noise is sometimes called salt-and-pepper noise or spike noise. An image containing salt-and-pepper noise will have dark pixels in bright regions and bright pixels in dark regions. This type of noise can be caused by analog-to-digital converter errors, bit errors in transmission, etc. However, as evident from Figure 3-3, median filtering removes the impulse noise but slightly blurs the image.

![Figure 3-3: Median filtering to remove impulse noise from an image](image)

### 3.1.2 Fuzzy Techniques in Image Enhancement

Uncertainties exist at every point in image enhancement. Fuzzy sets offer a means to manage this uncertainty because the reasoning in fuzzy logic is approximate instead of exact. An image $X$ of size $M \times N$ with $L$ gray levels can be considered as an array of fuzzy singletons, each having a value of membership denoting its degree of brightness relative to some brightness level $I$, $I = 0, 1, 2, \ldots L-1$. 
In the notation of fuzzy sets, we may therefore write \( X = \{ \mu_x(p) / p, p \in X \} \) where \( 0 \leq \mu_x(p) \leq 1 \) denotes the grade of possessing some property \( p \) (e.g., brightness, edginess, smoothness) or of belonging to some subset (e.g., object, skeleton or contour) by a pixel \( p \). In other words, a fuzzy subset of an image \( X \) is a mapping \( \mu \) from \( X \) into \([0, 1]\). For any point \( p \in X, \mu(p) \) is called the degree of membership of \( p \) in \( \mu \).

One may use either global or local information of an image in defining a membership function characterizing some property. For example, brightness or darkness property can be defined only in terms of gray value of a pixel, whereas edginess, darkness or textural properties need the neighborhood information of a pixel to define their membership functions. Similarly, positional or coordinate information is necessary, in addition to gray level and neighborhood information to characterize a dynamic property of an image. Again, the aforesaid information can be used in a number of ways (in their various functional forms), depending on individual opinions and/or the problem at hand, to define a requisite membership function for an image property or an image subset.

The fuzzy image enhancement approach is almost similar to the classic image enhancement scheme. The only difference is that before applying fuzzy logic, the image is transformed to the fuzzy domain. The scheme works in three main steps:

- **Fuzzification**: The mapping function \( F \) is defined on the basis of the image characteristics or concepts that are of interest that is brightness, contrast, edges, regions, connectivity, difference from its neighbours, etc. These characteristics or concepts are then represented by linguistic variables that describe them in a better way. Thus, the mapping function \( F \) converts the image from spatial to fuzzy domain. From this point, we should consider, \( I(x, y) \) as the original image in the spatial domain and \( I_F(x, y) \) as the original image in the fuzzy domain.

- **Modification of memberships**: In the fuzzy domain, memberships are modified based on the problem using some fuzzy operators. Let \( \Omega \) represents a set of fuzzy operators, then \( I_F'(x, y) \) is the new image in the fuzzy domain obtained by
application of $\Omega$.

- **Defuzzification**: Finally, defuzzification is done to convert back to the spatial domain to get the processed image. Assume $D$ to be the defuzzification function and $I'(x, y)$ to be the new image in the spatial domain.

These three steps are performed in sequence as follows:

$$I(x, y) \rightarrow F: I(x, y) \rightarrow I_F(x, y) \rightarrow \Omega[I_F(x, y)] = I_{F'}(x, y) \rightarrow D: I_{F'}(x, y) \rightarrow I'(x, y)$$

### 3.2 Related Work

Most of the classical linear filters like the averaging low pass filters tend to blur and destroy the lines, edges and other fine image details. The median filter is the most important non-linear order statistic filter for removing impulse noise from an image. Though simple and computationally efficient, the median filter causes an appreciable loss in image details (Astola and Kuosmanen, 1997), because it replaces all the pixels of the noisy image with the median of the pixels from the local neighborhood, irrespective of them being corrupted or not. To obtain improved performance many generalizations of median filters have been proposed in the literature including the Centre Weighted Median filter (Ko and Lee, 1991), the Rank Conditioned Median filter (Alparone, Baronti and Carla, 1995), the Tri-State Median filter (Chen, Ma and Chen, 1999), the Multi-State Median filter (Chen and Wu, 2001), Improved Median Filter (Zhang and Karim, 2002), Adaptive two pass rank order filter (Xu, Zhu, Peng and Wang, 2004) etc. To trade off detail preservation against noise reduction, the Centre Weighted Median (CWM) filter was proposed in which a weight adjustment was applied to the centre or origin pixel. In the Rank Conditioned Filter (RCM), a modified scheme is proposed in which pixels with extreme ranks are substituted by the sample median, while the others are left unaltered. In the Tri-State Median (TSM) filter, the impulse detection scheme successfully takes the output from the standard median and CWM filters and compares them with the original pixel value in order to make a tri state decision. In the Multi-State Median filter (MSM), the output of the filter is adaptively switched among a group of CWM filters with varying centre weights. It proposes an adaptive filtering scheme in which a CWM filter with a
space varying centre weight is activated for each pixel according to the local signal statistics. This can be realized by a simple thresholding operation where the switching logic is controlled by only one parameter. In Adaptive two pass filtering, two passes of filtering is done on the input image. The adaptive process selectively replaces some pixels changed by the first pass of filtering with their original observed pixel values. These pixels are then kept unchanged during the second filtering. In combination, the adaptive process and the second filter eliminate more impulse noise and restore some pixels that are mistakenly altered by the first filtering. As a final result, the reconstructed image maintains a higher degree of fidelity and has a smaller amount of noise. All these filters gave better performance than the classical median filter but the impulsiveness of a pixel was still modeled in crisp terms.

Several methods have been proposed for enhancement of fingerprint images in particular which are based on image normalization and Gabor filtering (Hong, Wan and Jainl, 1998), Directional Fourier filtering (Sherlock, Montro and Millard, 1994), Enhancement using a neuro-fuzzy technique (Vijayaprasad and Abdalla, 2003), Binarization Method (Greenberg, Aladjem, Kogan and Dimitrov, 2000), Directional Filter Based Analysis (Oh, Lee, Park, Kim and Park, 2003) etc. Hong et al presented a fingerprint image enhancement algorithm using the computationally efficient Gabor filtering technique. This algorithm can adaptively enhance the ridge structures using both local ridge direction and local frequency information as inputs for filtering. In Directional Fourier Filtering, the enhancement consists of a filtering stage followed by a thresholding stage. The filtering stage produces a directionally smoothed version of the image which is free from noise but contains the desired ridge structures and the thresholding stage produces the binary enhanced image. The neuro-fuzzy technique uses type-1 fuzzy sets for the contrast intensification of the fingerprint image. Greenberg et al have proposed fingerprint enhancement with local histogram equalization, Wiener filtering and image binarization. In Directional Filter Based Analysis, the algorithm decomposes a fingerprint image into directional sub band images in the analysis stage, processes the sub band images in the processing stage, and reconstructs them as the enhanced image in the
synthesis stage. Hence, all these methods enhance the ridge structures in a fingerprint image.

Several fuzzy filters such as Fuzzy Mean Filter (Lee, Kuo and Yu, 1997; Lee and Kuo, 2000), FIRE filters (Russo, 1999), Fuzzy Switching Filter (Xu, Miller, Chen and Sarhadi, 2004), Fuzzy Thresholding Filter (Bansal, Sehgal and Bedi, 2007), etc. have also been proposed in the literature for image enhancement. Most of these methods either use IF-THEN rules or modification of some pixel property which is modeled as a type-1 fuzzy set. But, a drawback with type-1 fuzzy logic systems (FLS) is their limited ability to manage uncertainty. It is seen that type-1 fuzzy logic systems have difficulties in modeling and minimizing the effect of uncertainties (Mendel et al, 2002, 2006). The reason for this is that the membership function for a type-1 fuzzy set for a particular input is a crisp value. Type-2 Fuzzy Sets (Karnik et al, 1998) were introduced as an extension to ordinary or Type-1 Fuzzy sets. Type-2 fuzzy sets on the other hand, model the uncertainties more effectively, as these are characterized by membership functions that are themselves fuzzy. Thus, the use of type-2 FLS in image processing is now becoming increasingly important (Tizhoosh, 2005; Yildrim and Basturk, 2007).

We have proposed two algorithms for the enhancement of fingerprint images based on type-2 fuzzy sets. The first one is a type-2 fuzzy filter for enhancing fingerprint images corrupted by impulse noise (Bansal, Sehgal & Bedi, 2008). The details of the filter are presented in section 3.3. The second one presented in section 3.4, enhances the contrast of the fingerprint image by using the proposed contrast intensification operator based on type-2 fuzzy sets (Bansal, Gaur, Arora, Sehgal & Bedi, 2009).

3.3 Enhancing Fingerprint Images corrupted by Impulse Noise using type-2 Fuzzy Sets

A novel fuzzy filter which processes impulses as type-2 fuzzy sets is presented in this section. It firstly detects impulses by considering grayscale distribution amongst neighbouring pixels and models the set of impulsive pixels as a type-2 fuzzy set using an S – shaped fuzzy membership function that is itself fuzzy. Type-2 fuzzy switching is used
to modify the impulsive pixels depending on its neighbourhood information. The proposed filter is able to suppress impulse noise and preserve image details, yet being computationally efficient and algorithmically very simple to implement. The following subsections present how the impulses are detected, how they are modified by type-2 fuzzy switching and finally the experimental results.

3.3.1 Impulse detection

The impulse detection is usually based on the following two assumptions (Tizhoosh, 2005): (1) a noise-free image consists of locally smoothly varying areas separated by edges; (2) a noise pixel takes a grayscale value substantially larger or smaller than those of its neighbors. For each pixel $I(i,j)$ in the image, consider its $5 \times 5$ neighbouring window as shown in Figure 3.4 (a). The $5 \times 5$ filter window where the center pixel is $I(i,j)$, is first convolved with four one-dimension Laplacian operators that are shown in Figure 3.4 (b), respectively. Each of these operators is sensitive to edges in a different orientation. Then, the minimum absolute value $r(i,j)$ of these four convolutions is used for impulse detection, which can be obtained from Equation (3-1) as follows:

$$r(i,j) = \min\{|I(i,j) * K_p|; p = 1 - 4\} \quad (3-1)$$

where $K_p$ is the $p^{th}$ Laplacian operator (shown in Figure 3-4(b)). The physical significance of the value of $r(i,j)$ can be explained as follows:

1. $r(i,j)$ is large when the current pixel is an isolated impulse because the four convolutions are large and almost the same;
2. $r(i,j)$ is small when the current pixel is a noise-free flat-region pixel because the four convolutions are close to zero;
3. $r(i,j)$ is also small when the current pixel is an edge (including thin line) pixel because one of the convolutions is very small (close to zero) although the other three might be large.

From the above we can say that $r(i,j)$ is large when $I(i,j)$ is corrupted by noise, and $r(i,j)$ is small when $I(i,j)$ is noise-free.
3.3.2 Modifying impulsive pixels based on type-2 fuzzy switching

The impulsive pixels will be modified based on type-2 fuzzy switching. Let \( \mu[r(i,j)] \in [0, 1] \) be the type-1 membership function of \( r(i,j) \) which indicates the extent of the impulsiveness of the pixel \( I(i,j) \). The following fuzzy rules are applied:

[Rule 1] If \( r(i,j) \) is large, then \( \mu[r(i,j)] \) is large.

[Rule 2] If \( r(i,j) \) is small, then \( \mu[r(i,j)] \) is small.

With these rules, the \( S \)-function used to describe the type-1 membership function of the impulsiveness of the current pixel is given by:

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**Figure 3-4:** (a) 5 × 5 neighbouring window (b) Four 5 × 5 Laplacian operators
where, $\alpha$ and $\gamma$ are predefined thresholds such that if $r(i,j)$ is less than $\alpha$, the pixel is considered as noise free and if $r(i,j)$ is greater than $\gamma$, the pixel is considered as definitely impulsive and $\beta = (\alpha + \gamma)/2$.

As mentioned earlier, a type-2 fuzzy set may be obtained by blurring a type-1 membership function. For this purpose we use our type-1 fuzzy set and assign upper and lower membership degrees to each element to construct the Footprint of Uncertainty (FOU) as shown in Figure 3-5. The upper and lower membership degrees of the initial membership function $\mu$ can be defined using Equations (3-3) and (3-4) as:

$$
\mu_{upper}(r) = (\mu(r))^{0.5} \quad (3-3)
$$
$$
\mu_{lower}(r) = (\mu(r))^2 \quad (3-4)
$$

where $0 \leq \mu(r) \leq 1$ is the type-1 membership function for value $r$.

![Type-2 construction of a type-1 membership set](image)

**Figure 3-5: Type-2 construction of a type-1 membership set**

After calculating $\mu(r)$ using Equation (3-2), we calculate values of $\mu_{upper}(r)$ and $\mu_{lower}(r)$ from Equations (3-3) and (3-4) respectively. Now the FOU is bounded by
upper and lower membership functions. Here the uncertainties in the shape and position of the type-1 fuzzy set can be represented by means of the third dimension represented by the FOU. The proposed type-2 membership function is:

\[ \mu_{T2}[r(i,j)] = (\mu_{upper}(r) \times \partial) + (\mu_{lower}(r) \times (1 - \partial)) \]  

(3-5)

where, \(0 \leq \partial \leq 1\) and

\[ \partial = (|g_{mean} - (L/2)|)/(L/2) \]  

(3-6)

where, \(g_{mean}\) is the mean value of each sub-image and \(L\) is the number of gray levels used. Finally, using \(\mu_{T2}\), the proposed type-2 filter calculates the output value using Equation (3-7) as follows:

\[ Y(i,j) = (\mu_{T2} \times Med) + (I(i,j) \times (1 - \mu_{T2})) \]  

(3-7)

The idea behind the \(\mu_{T2}\) equation is that pixels with extreme values (pixel values in a darker or a lighter neighbourhood) will have greater proportion of \(\mu_{upper}\) than \(\mu_{lower}\). As a result, each impulsive pixel is treated depending on the level of contamination present in it calculated using type-2 fuzzy logic.

3.3.3 Experimental Results and Analysis

The performance of the proposed filter has been evaluated and compared with those of several existing median type filters based on fuzzy and non-fuzzy techniques for image restoration. In our implementations, a group of standard 512 × 512 grayscale fingerprint images (FVC 2004 DB1) were corrupted by impulsive noise with various occurrence probabilities. All implementations have been done using Matlab 7.0. The objective quantitative measure used for comparison is the peak signal-to-noise ratio (PSNR) in dB between the original and restored images defined by Equation (3-8):

\[ PSNR = 10 \times \log_{10} \left( \frac{\sum_{i=0}^{M-1} \sum_{j=0}^{N-1} 255^2}{\sum_{i=0}^{M-1} \sum_{j=0}^{N-1} [Y(i,j) - Y(i,j)]^2} \right) \]  

(3-8)

where, \(I(i,j)\) and \(Y(i,j)\) are the original and restored images, respectively. PSNR is the ratio between the maximum power of a signal to the power of corrupting noise. Higher the value of PSNR, closer is the restored image to the original image.
Tables 3-1, 3-2 and 3-3 give comparative restoration results in PSNR of filtering five standard test fingerprint images (Figure 3-6) corrupted by different levels of impulse noise. The results have been tabulated for the proposed method and existing Median filtering approaches in the literature and its variations like Centre Weighted Median filter (CWM), Switching Median filter (SM) and the Tri-State Median filter (TSM), and some fuzzy filters like Fuzzy Media Filter (FMF), Fuzzy Thresholding Filter (FTF) and the Fuzzy Switching Filter (FSF).

Table 3-1: PSNR values of different filtering methods for standard images corrupted with 5% impulse noise

<table>
<thead>
<tr>
<th>Filters</th>
<th>I1</th>
<th>I2</th>
<th>I3</th>
<th>I4</th>
<th>I5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Median</td>
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<td>23.65</td>
<td>23.15</td>
<td>23.54</td>
<td>34.25</td>
</tr>
<tr>
<td>CWM</td>
<td>29.25</td>
<td>28.93</td>
<td>29.98</td>
<td>31.61</td>
<td>38.03</td>
</tr>
<tr>
<td>SM</td>
<td>29.46</td>
<td>29.25</td>
<td>30.27</td>
<td>31.84</td>
<td>39.77</td>
</tr>
<tr>
<td>TSM</td>
<td>28.74</td>
<td>28.98</td>
<td>29.78</td>
<td>32.26</td>
<td>38.11</td>
</tr>
<tr>
<td>FMF</td>
<td>29.79</td>
<td>29.78</td>
<td>30.23</td>
<td>32.25</td>
<td>38.91</td>
</tr>
<tr>
<td>FTF</td>
<td>30.3</td>
<td>30.31</td>
<td>32.75</td>
<td>33.86</td>
<td>39.29</td>
</tr>
<tr>
<td>FSF</td>
<td>30.4</td>
<td>30.8</td>
<td>32.86</td>
<td>34.92</td>
<td>39.86</td>
</tr>
<tr>
<td>Proposed</td>
<td>33.34</td>
<td>33.09</td>
<td>33.92</td>
<td>36.88</td>
<td>42.25</td>
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</table>
Table 3-2: PSNR values of different filtering methods for standard images corrupted with 10% impulse noise

<table>
<thead>
<tr>
<th>Filters</th>
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<th>I3</th>
<th>I4</th>
<th>I5</th>
</tr>
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<tbody>
<tr>
<td>Median</td>
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<td>22.46</td>
<td>22.52</td>
<td>22.82</td>
<td>32.12</td>
</tr>
<tr>
<td>CWM</td>
<td>26.75</td>
<td>25.29</td>
<td>26.12</td>
<td>29.89</td>
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</tr>
<tr>
<td>SM</td>
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<td>27.84</td>
<td>28.28</td>
<td>30.12</td>
<td>35.96</td>
</tr>
<tr>
<td>TSM</td>
<td>26.87</td>
<td>26.92</td>
<td>28.32</td>
<td>30.83</td>
<td>35.09</td>
</tr>
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<td>FMF</td>
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<td>28.44</td>
<td>30.24</td>
<td>35.67</td>
</tr>
<tr>
<td>FTF</td>
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<td>31.23</td>
<td>37.36</td>
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<td>30.84</td>
<td>32.36</td>
<td>37.97</td>
</tr>
<tr>
<td>Proposed</td>
<td>31.03</td>
<td>31.74</td>
<td>31.87</td>
<td>34.23</td>
<td>39.25</td>
</tr>
</tbody>
</table>

Table 3-3: PSNR values of different filtering methods for standard images corrupted with 20% impulse noise

<table>
<thead>
<tr>
<th>Filters</th>
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<th>I3</th>
<th>I4</th>
<th>I5</th>
</tr>
</thead>
<tbody>
<tr>
<td>CWM</td>
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<td>24.17</td>
<td>25.82</td>
<td>28.87</td>
<td>33.52</td>
</tr>
<tr>
<td>SM</td>
<td>26.12</td>
<td>25.45</td>
<td>26.68</td>
<td>28.86</td>
<td>34.18</td>
</tr>
<tr>
<td>TSM</td>
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<td>25.55</td>
<td>26.28</td>
<td>28.23</td>
<td>34.05</td>
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<tr>
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<td>26.12</td>
<td>26.58</td>
<td>27.21</td>
<td>29.93</td>
<td>34.87</td>
</tr>
<tr>
<td>FTF</td>
<td>27.8</td>
<td>27.11</td>
<td>29.32</td>
<td>30.6</td>
<td>36.76</td>
</tr>
<tr>
<td>FSF</td>
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<td>27.4</td>
<td>29.18</td>
<td>30.78</td>
<td>36.88</td>
</tr>
<tr>
<td>Proposed</td>
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<td>30.98</td>
<td>30.78</td>
<td>33.34</td>
<td>38.12</td>
</tr>
</tbody>
</table>
Figure 3-7: PSNR values of different filtering methods for the Standard Image I1 corrupted with different percentages of impulse noise

Figure 3-8: PSNR values of different filtering methods for the Standard Image I2 corrupted with different percentages of impulse noise
It is observed that the blurring is more in median filtering and lesser in fuzzy filters based on type-1 fuzzy logic, for impulse noise removal. The blurring is minimum in the proposed method based on type-2 fuzzy logic as is evident from the better values of PSNR obtained here. The graphs in Figures 3-7 and 3-8 present the comparative performance of the proposed and the existing filters in PSNR for different levels of impulse noise for images I1 and I2 respectively. It can be seen that as the level of impulse noise increases, the value of PSNR decreases.

### 3.4 Contrast Enhancement in Fingerprint Images using type-2 Fuzzy Sets

The proposed method enhances a fingerprint image by contrast enhancement using type-2 fuzzy set. For this purpose, initially the contrast intensification operator NINT (Hanmandlu, Tandon and Mir, 1997; Hanmandlu, Jha and Sharma, 2003) based on type-1 fuzzy sets is used and then the concept is extended using type-2 fuzzy logic to further enhance the image. The quality of the original and the enhanced images are calculated and the results are compared.

#### 3.4.1 Proposed type-2 Contrast Intensification

In the proposed approach the brightness property of a pixel is modeled into a fuzzy set using a membership function. Applying an intensification operator globally modifies the membership function. The entropy of a fuzzy set which measures its degree of fuzziness is used to derive a measure of image quality in the fuzzy domain (Pal and King, 1981). Then, the proposed algorithm transforms the intensification operator based on type-1 membership function to an operator based on type-2 membership function by using interval based sets. Finally, the image is converted back from the fuzzy domain to the spatial domain to give us the desired enhanced image. The steps of the algorithm in detail are as follows:
**Fuzzification based on fuzzy histogram**

An image $I$ of size $M \times N$ with intensity levels in the range $(0 \text{ to } L - 1)$ can be considered as a collection of fuzzy singletons in the fuzzy set notation

$$X = \bigcup \{\mu(k), p(k)\} = \{\mu_{mn} / k_{mn}\}, \quad m = 1, \ldots, M, n = 1, \ldots, N$$

where $\mu(k)$ represents the membership or grade of some property of $k_{mn}$, $k_{mn}$ being the intensity value at $(m, n)$ pixel and $p(k)$ is the number of occurrences of the intensity value $k$, in image $I$. A fuzzy histogram is used to obtain the frequency of occurrence of membership functions of gray levels in the fuzzy image. The distribution of $p(k)$ is normalized such that:

$$\sum_{k=0}^{L-1} p(k) = 1 \quad (3-9)$$

Using spatial properties like the intensity values, the image is converted to fuzzy domain by using a modified Gaussian membership function as suggested by Hanmandlu et al., 1997, that contains only one fuzzifier $f_h$, and is given as:

$$\mu(k) = e^{-\frac{(k_{max} - k)^2}{2f_h^2}} \quad (3-10)$$

where, $k_{max} \leq L - 1$ and is the maximum intensity value present in the image, $L$ being the number of levels of intensity. The fuzzifier is calculated as:

$$f_h^2 = \frac{\sum_{k=0}^{L-1} (k_{max} - k)^2 p(k)}{\sum_{k=0}^{L-1} (k_{max} - k)^2} \quad (3-11)$$

**Contrast Intensification**

After the image has been mapped to the fuzzy domain, then the next step is to apply an enhancement technique i.e. a fuzzy contrast intensification operator on it. The operator employed here is a variation of the original contrast intensification operator INT (Zadeh, 1973) called NINT, which works with a Gaussian-based membership function.

Mathematically the new intensification (NINT) operator is written as:

$$\mu'(k) = \frac{1}{1 + e^{-t(\mu(k) - k_c)}} \quad (3-12)$$
Here $\mu'(k)$ is the modified membership function, the intensification parameter $t$ is determined experimentally, $\mu(k)$ is the original membership function and $k_c$ is the crossover point whose initial value is taken as 0.5.

**Entropy Optimization**

Entropy $E$ that makes use of Shanon’s function is regarded as a measure of quality of information in an image. It gives the value of indefiniteness of an image in the fuzzy domain and is defined by the following equation:

$$ E = \frac{1}{\ln 2} \sum_{k=0}^{L-1} \left[ \mu'(k) \ln \mu'(k) + (1 - \mu'(k)) \ln(1 - \mu'(k)) \right] p(k) $$

(3-13)

Since $E$ provides the basis on which the information can be quantified, we optimize $k_c$ by taking some preset initial value for it. The derivative of $E$ with respect to $k_c$ is obtained as:

$$ \frac{\partial E}{\partial k_c} = \frac{1}{\ln 2} \sum_{k=0}^{L-1} t^2 (\mu(k) - k_c) g(\mu') p(k) $$

(3-14)

where, $g(\mu')$ is calculated as:

$$ g(\mu') = \mu'(k) (1 - \mu'(k)) $$

(3-15)

This derivative is used in the learning of the parameter $k_c$ by the gradient descent technique.

$$ k_{c,\text{new}} = k_{c,\text{old}} - \varepsilon \frac{\partial E}{\partial k_c} $$

(3-16)

Here, $\varepsilon$ is learning factor for parameter $k_c$. If $k_c$ converges or diverges too quickly the value of $\varepsilon$ has to be altered respectively in order that the convergence of $k_c$ is ensured.

**Type-2 Fuzzification**

A type-2 fuzzy set is obtained by blurring a type-1 membership function. For this purpose, interval-based sets are used to construct a type-2 fuzzy set by defining upper and lower membership values using the following equations:

$$ \mu_{upper}(k) = (\mu'(k))^{0.5} $$

(3-17)

$$ \mu_{lower}(k) = (\mu'(k))^2 $$

(3-18)
where, $0 \leq \mu'(k) \leq 1$ is the membership for value $k$. The Footprint of Uncertainty is bounded by upper and lower membership functions. Here the uncertainties in the shape and position of the type-1 fuzzy set can be represented by means of the third dimension represented by the FOU. The proposed type-2 membership function is:

$$
\mu_{T2}(k) = (\mu_{\text{lower}} \times \delta) + (\mu_{\text{upper}} \times (1 - \delta))
$$

(3-19)

where, $0 \leq \delta \leq 1$ and $\delta = \frac{M}{L}$

(3-20)

$M$ symbolizes the corresponding mean value of each sub image and $L$ is the number of gray levels. Using $\mu_{T2}$ values result in new gray levels which gives an enhanced image. The mean of sub images is calculated by creating a mask and moving it over each and every pixel, so that the mean value can be calculated in all neighborhoods.

The intuitive concept behind Equation (3-19) is that pixels in a lighter neighborhood will get a larger proportion of $\mu_{\text{lower}}$ and will become proportionately darker and the pixels in a darker neighbourhood will get a larger proportion of $\mu_{\text{upper}}$ and will become proportionately lighter and hence the contrast will be enhanced.

**Defuzzification**

The fuzzy membership values of an image are transformed back to the spatial domain after the desired operator is applied in the fuzzy domain. The inverse operator to shift from the fuzzy domain to the spatial domain is given as:

$$
k' = k_{\max} - \left(-2\ln[\mu_{T2}(k)]{f_h}^2\right)^{\frac{1}{2}}
$$

(3-21)

where, $\mu_{T2}(k)$ and $k'$ are the modified membership function and intensity values respectively.

### 3.4.2 Experimental Results and Analysis

The quality factor for the original image is defined as the ratio of absolute average fuzzy contrast to the fuzzy contrast (Hanmandlu and Jha, 2006). Fuzzy contrast depends on how far the membership functions are stretched by an operator with respect to the crossover point. This turns out to be the cumulative variance of the difference between
the membership function and the crossover point over all pixels. Thus, the fuzzy contrast is written as:

$$C_f = \frac{1}{L} \sum_{k=0}^{L-1} [\mu(k) - k_c]^2 p(k)$$  \hspace{1cm} (3-22)

The fuzzy average contrast is defined as:

$$C_{af} = \frac{1}{L} \sum_{k=0}^{L-1} [\mu(k) - k_c] p(k)$$  \hspace{1cm} (3-23)

The fuzzy average contrast gives the overall intensity of the image whereas the fuzzy contrast gives the spread of the gradient with respect to the reference (the crossover point). A ratio of these quantities gives us the quality of the original image:

$$Q_{fo} = \frac{|C_{af}|}{C_f} = \frac{\sum_{k=0}^{L-1} [\mu(k) - k_c] p(k)}{\sum_{k=0}^{L-1} [\mu(k) - k_c]^2 p(k)}$$  \hspace{1cm} (3-24)

The quality for the enhanced image is calculated using the same quality formula as discussed above. For this we convert back to the spatial domain and recompute the membership value with the new values of intensity values $k$ (thus, $p(k)$) and $k_c$.

Each of the input images is first input to an implementation of the Hong’s algorithm (Hong et al, 1998), to enhance them. The output is then applied to the fuzzy algorithm for contrast intensification. The algorithm is implemented taking the intensification parameter and fuzzifier as constant while updating the crossover point. Experiments are conducted using real fingerprint images in order to provide a well balanced evaluation on the performance of the implemented algorithm. The value of intensification parameter has been taken as 7 after experimentation with fingerprint images. The mask size can be of any size between 10 and 20. In our current implementation we have updated the value of $k_c$ only.

For comparison of results, quality is observed for the following:

1. The image which is not enhanced.
2. When the image is passed through Hong’s algorithm and then type-1 fuzzification is applied.
3. When type-2 fuzzification is applied on the image after it has been passed through the Hong’s algorithm. Figures 3-9, 3-10 and 3-11 show the qualitative comparison of three images by enhancing them using type-1 fuzzification and type-2 fuzzification.

![Figure 3-9: Results for Img 1](image1.png)
(i) Original  (ii) After type-1 fuzzification  (iii) After type-2 fuzzification

![Figure 3-10: Results for Img 2](image2.png)
(i) Original  (ii) After type-1 fuzzification  (iii) After type-2 fuzzification

![Figure 3-11: Results for Img 3](image3.png)
(i) Original  (ii) After type-1 fuzzification  (iii) After type-2 fuzzification
Table 3-4 tabulates the quantitative comparison of three images. The higher values of quality show that application of our algorithm gives better image quality with respect to contrast intensification as compared to the type-1 fuzzification based algorithm.

Thus through a series of experimentations, we have demonstrated the effectiveness of applying type-2 fuzzy sets in enhancement of fingerprint images.