CHAPTER 3

A FUZZY FRAMEWORK FOR OFFLINE SIGNATURE VERIFICATION

3.1 INTRODUCTION

Data preprocessing is an important step in a PR process as discussed in section 1.3.1. If the data under consideration is an image, then the complexity of such preprocessing increases. Image enhancement techniques enable to increase the signal-to-noise-ratio and accentuate image features by modifying the colors or intensities of an image. Histogram equalization, adjusting the gamma value, linear, median and adaptive filtering are some of the methods performed in image preprocessing.

Signature verification system is a widely used biometric system in places like passport, payroll, driving license, credit cards for identity verification. Signatures are a behavioral biometric that change over a period of time and are influenced by physical and emotional conditions of the signatories (Jain et al 2004). Signature verification is a difficult discrimination problem since a handwritten signature is the result of a complex process depending on physical and psychological conditions of the signer, as well as on the conditions of the signing process (Impedevo & Pirlo 2007). Signatures of some people vary substantially: even successive impressions of their signature are significantly different. Further, professional forgers may be able to reproduce signatures that fool the system. Moreover, signatures possess highly complex geometrical patterns in which letters are not very clearly
legible. Hence, achieving high accuracy in signature verification of discriminating between original and forgery is a very challenging task.

Signature verification can be divided into on-line and off-line. On-line verification refers to a process of signing by a person using stylus that can utilize the pen location, speed and pressure. Off-line verification lacks any form of dynamic information and has to rely on the features that are extracted from the static signature image and hence much more difficult to verify.

Forgeries are of three different kinds: random, simple and skilled. A random forgery is one in which the forger does not know the signer’s name or signature shape. A simple forgery is produced knowing the name of the original signer but not the shape of the signature. A skilled forgery is a close imitation of the original signature produced by a forger who has seen and practiced writing the genuine signature. Skilled forgers are able to reproduce the signature without much variation due to practice. Sample genuine and forged signatures are shown in Figure 3.1.

![Figure 3.1 Sample Genuine and Forged Signature Images](image-url)
The uncertainties related to the complexity of patterns, variability in signing, mood of the signer and the lack of complete information about a signature motivated to develop a system for off-line signature verification for skilled forgeries. This chapter concentrates on the preprocessing phase of PR. Wiener median filter (Wiener 1964) has been applied for noise reduction and Fuzzy Set and Intuitionistic Fuzzy Set based contrast enhancement has been applied on the signature images in preprocessing stage for offline signature verification.

3.2 RELATED WORK

Signature verification system is an active area of research and many schemes have been proposed. The Centre of Excellence for Document Analysis & Recognition (CEDAR) signature data set available at CEDAR Database (2004) and published by Kalera et al (2004) is a commonly used data set for off-line signature verification. It consists of 55 signature sets, with each set consisting of 24 genuine and 24 forgery signatures adding to a total of 2640. Schemes that used the CEDAR data set are summarized in Table 3.1.

3.3 PROPOSED FUZZY FRAMEWORK

The grey levels at various pixels in a gray-scale image are imprecise as a gray level resembles a near-by pixel gray level to some extent, due to the inadequacy of contrast. While binarizing, the indefiniteness in deciding a pixel to be black or white is referred to as grayness ambiguity (Pal 1999). Therefore, fuzzy sets are more apt to represent the grayness ambiguity in images due to the vague definition of region boundaries. Hence, contrast enhancement is done using two methods of fuzzy sets (FS) and two methods of intuitionistic fuzzy sets (IFS) to enhance the changes of gray level of signature images along with intensification.
<table>
<thead>
<tr>
<th>Authors, Year</th>
<th>Approach Used</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kalera et al, 2004</td>
<td>Quasi-multi resolution technique using Gradient, Structural &amp; concavity (GSC) features are used for feature extraction and a correlation based similarity measure is used for verification</td>
<td>78.00 %</td>
</tr>
<tr>
<td>Srihari et al, 2004</td>
<td>Gradient, Structural &amp; concavity (GSC) features are used for feature extraction and Distance Statistics method is used for verification</td>
<td>78.10 %</td>
</tr>
<tr>
<td>Chen &amp; Srihari, 2005</td>
<td>Curves and shape descriptors based on Zernike moments are extracted as features. Harmonic distance is used for measuring similarity.</td>
<td>83.60 %</td>
</tr>
<tr>
<td>Chen &amp; Srihari, 2006</td>
<td>Method is based on graph-matching, thin-plate spline mapping and word-shape descriptors and matches extrema so that the location of corresponding cells is more precise</td>
<td>90.00 %</td>
</tr>
<tr>
<td>Larkins &amp; Mayo, 2008</td>
<td>Automatic Feature Thresholding combined with spatial pyramids &amp; equimass sampling grids using gradient direction for feature extraction and verification by a similarity score</td>
<td>90.00 %</td>
</tr>
<tr>
<td>Kumar et al, 2010</td>
<td>Set of morphological features from signature images and MLP based feature analysis and an ensemble of classifiers is applied for verification</td>
<td>88.41 %</td>
</tr>
<tr>
<td>Kumar et al, 2012</td>
<td>Novel set of features based on Surroundedness property of a signature image and verification is based on MLP and Support Vector Machine (SVM)</td>
<td>91.67 %</td>
</tr>
</tbody>
</table>

The features of the signatures, the gray level intensities based on gradient direction histogram, are characterized by using interval-valued fuzzy sets (IVFS) to obtain a more reliable estimate of feature values and verified.
based on a similarity measure on IVFS. Hence the following methodology is proposed:

- FS / IFS based contrast enhancement is applied to modify the gray level intensity of the signature image, in preprocessing,
- gradient direction histogram combined with one, two and three levels of equimass, is used for feature extraction and
- similarity score based on IVFS, combined with adaptive threshold is used for verification.

The raw signature image undergoes preprocessing, feature extraction and verification phases.

### 3.3.1 Preprocessing of Signatures

Preprocessing is required to improve the representation of the extracted features by cleaning and repairing the signature’s structure. Each signature is binarized followed by Wiener noise reduction to eliminate single black pixels on white background. Figure 3.2 represents a sample original image and Figure 3.3 represents the binarized, Wiener filtered image.

**Image enhancement**

Image enhancement methods may be categorized into two broad classes:

- Transform domain methods : techniques based on modifying the frequency transform of an image
- Spatial Domain Methods : techniques that directly operate on the pixels of the image
Contrast enhancement is one of the important image enhancement techniques in spatial domain. A gray tone image possesses some ambiguity within the pixels due to the possible multi-valued levels of grayness. Grayness ambiguity meaning indefiniteness in deciding a pixel to be black or white during binarization, is modeled using FS and IFS. Fuzzy methods are often complimentary to existing techniques and contribute to better and more robust results. IFS addresses the problem of hesitancy in decision by way of taking the non-membership values also into consideration, an idea proposed by Atanassov (1986). Contrast enhancement which improves the overall visibility of the image gray levels, is achieved by transforming the dark pixels to appear darker and the light pixels to appear lighter. Hence, image contrast
enhancement using fuzzy sets and Intuitionistic fuzzy sets have been proposed. Moreover, the feature values are characterized by interval-valued fuzzy sets.

Definitions related to FS and IFS are presented.

**Definition 3.1: Fuzzy Set (Zadeh 1965)**

Let $X$ be a non-empty set. A FS $A$ in $X$ is defined as an object of the form $A = \{ (x, \mu_A(x)) : x \in X \}$ where $\mu_A(x)$ denotes the membership function of $A$ and $0 \leq \mu_A(x) \leq 1$, $\forall x \in X$. It is diagrammatically represented in Figure 3.4, where $\mu_A(4) = 1$.

![Figure 3.4 Membership Function in a Fuzzy Set](image)

**Definition 3.2: Intuitionistic Fuzzy Set (Atanassov 1986)**

Let $X$ be a non-empty set. An IFS $A$ in $X$ is defined as an object of the form $A = \{ (x, \mu_A(x), v_A(x)) : x \in X \}$ where $\mu_A(x)$ and $v_A(x)$ denote the membership and non-membership functions of $A$ respectively, and $0 \leq \mu_A(x) + v_A(x) \leq 1$, $\forall x \in X$. The visualization of membership and non-membership functions of IFS is shown in Figure 3.5 with
• **membership** = inside cell with 100% probability (i.e. thick portions)

• **non-membership** = outside cell with 100% probability (i.e. dotted portions)

• **hesitancy** = ignorance whether inside or outside the cell (i.e. solid thin portions)

![Figure 3.5 IFS Membership and Non-membership Function visualization](image)

**Contrast Enhancement Methods**

The image is subjected to four different types of contrast intensification of gray levels. The methodology is to first fuzzify the gray level, contrast intensify the fuzzy gray level and defuzzify the fuzzy value back to gray level values. The minimum and maximum gray levels of the input image are computed as mn and mx. The following methods are used:

**Fuzzy Contrast Intensification Method 1**

The gray level of the image pixel x, gr(x) is fuzzified as:
The fuzzy gray level is contrast intensified by applying the INT operator (Pal & King 1981) as follows:

\[
\mu_g(x) = \begin{cases} 
0, & 0 \leq gr(x) < mn \\
\frac{(gr(x) - mn)}{(mx - mn)}, & mn \leq gr(x) \leq mx \\
1, & mx < gr(x) \leq 255
\end{cases}
\] (3.1)

This transformation function is applied thrice successively as suggested (Pal & King 1981), to reduce the fuzziness of the image by decreasing the fuzzy values below 0.5 and increasing the fuzzy values above 0.5.

Further, the contrast intensified fuzzy gray level of each pixel \( x \) is defuzzified back to enhanced gray level by the inverse transformation:

\[
\mu_E(x) = \begin{cases} 
gr(x), & 0 \leq gr(x) < mn \\
(mx - mn) \ast \mu_I(x), & mn \leq gr(x) \leq mx \\
gr(x), & mx < gr(x) \leq 255
\end{cases}
\] (3.3)

The fuzzy contrast enhanced image is shown in Figure 3.6.

**Fuzzy Contrast Intensification Method 2**

The image is fuzzified as

\[
\mu_g(x) = \left[ 1 + \frac{(mx - gr(x))}{fd} \right]^{-fe}
\] (3.4)
where \( gr(x) \) is the gray level of the pixel \( x \) in the image, \( fe = 2 \) and \( fd = \frac{(mx - mn)}{\frac{1}{(0.5)^{fe}} - 1} \) are the exponential and denominational fuzzifiers (Pal & King 1981).

Figure 3.6 Fuzzy Contrast Enhanced Image : Method 1

The fuzzy gray level is contrast intensified as \( \mu_I(x) \) by applying the INT operator as in (3.6). Again, the contrast intensified fuzzy gray level of each pixel \( x \) is defuzzified back to enhanced gray level by inverse transformation:

\[
\mu_E(x) = mx - fd \ast \{[\mu_I(x)]^{-1} \} + fd
\]  

(3.5)

The fuzzy contrast enhanced image is shown in Figure 3.7.

Type I IFS Contrast Intensification Method (Parvathy et al 2008)

As already noted, fuzzy membership and non-membership functions have to be defined for IFS. The fuzzy membership function of the gray level of the image pixel \( x \) is computed as in (3.8). The non-membership is defined as :
such that $0 \leq \mu_g(x) + v_g(x) \leq 1$

The membership and non-membership functions for contrast intensified gray level of a pixel $x$ is computed as:

$$
\mu_I(x) = 1 - \left( 1 - \mu_g^2(x) \right)^2, \quad 0 \leq \mu_g(x) \leq 1
$$

$$
v_I(x) = \left( 1 - \left( 1 - v_g(x) \right)^2 \right)^2, \quad 0 \leq v_g(x) \leq 1
$$

The defuzzified gray level is given by

$$
\mu_E(x) = \frac{1}{x} \cdot \left( \sqrt{\mu_I(x) \cdot \left( c_1 - v_I(x) \right)^{-\frac{1}{c_2}}} \right) + f d
$$

where $c_1$, $c_2$ are arbitrary constants. No values for $c_1$ and $c_2$ have been specified. Hence $c_1$ and $c_2$ are duly computed as 0.85 and 0.3 by experiments.
on the signature images. The method used for computation is described below. The Type I IFS contrast intensified image is shown in Figure 3.8.

\[ \mu_f(x) = 1 - \left( 1 - \mu_g(x) \right)^2, \quad 0 \leq \mu_g(x) \leq 1 \]  
(3.10)

\[ v_f(x) = \left( 1 - \left( 1 - v_g(x) \right)^2 \right)^4, \quad 0 \leq v_g(x) \leq 1 \]  
(3.11)

The defuzzified gray level is given by (3.9) but with \( c_3 \) and \( c_4 \) instead of \( c_1 \) and \( c_2 \). Similarly, \( c_3 \) and \( c_4 \) are duly computed as 0.5 and 1.0 by experiments on the signature images. The Type II IFS contrast intensified image is shown in Figure 3.9.
Figure 3.9 IFS Type II Contrast Enhanced Image

Computation of constants c1, c2 and c3, c4

The arbitrary constants ranging between 0 and 1, are computed based on the quality measure of an image called the linear index of fuzziness (Kaufmann 1975). The index reflects the grayness ambiguity in an image by measuring the distance between the gray tone image and its nearest two-tone version. Increase in the index of fuzziness ensures proper contrast enhancement of the image. The index of fuzziness is defined as

$$\gamma = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} \min(\mu_{ij}(x), 1 - \mu_{ij}(x))$$  \hspace{1cm} (3.12)

where $M \times N$ is the size of the image and $\mu_{ij}(x)$ is the fuzzy membership value of the pixel $x$.

Computation of constants is presented in Algorithm 1 specified in Figure 3.10. A random set of 25 images (original / forgery) are used to arrive at the appropriate c1 and c2 values. Similarly c3 and c4 was computed by the same algorithm with IFS Type II operator. Random values of constants gave accuracy around 90% only. Identifying appropriate values by using the linear index of fuzziness has appreciably increased the accuracy. Subtle changes in
the gray level intensity enhance the contrast of the signature and thereby improve verification accuracy.

**Algorithm 1 : Computation of constants c1, c2**

1: Take a signature image
2: for x1 from 0 to 1 in steps of 0.05 do
3:     for x2 from 0.1 to 1 in steps of 0.05 do
4:         Fuzzify the image using IFS Type I
5:         Contrast Intensify and defuzzify the fuzzy image
6:         Compute the fuzziness of the defuzzified image using (3.12)
7:         Store the fuzziness index in a matrix
8:     end for
9: end for
10: Find the maximum of the fuzziness values in the matrix
11: The corresponding x1 and x2 are the c1 and c2 values.

**Figure 3.10 Algorithm 1 : Computation of constants c1, c2**

### 3.3.2 Feature Extraction

Feature extraction is a process by which the signature image is broken down into components of essential information that are more useful for describing its structure, differentiating it from other signatures when compared. A feature vector is created for each signature based solely on the gradient direction of each pixel from across a signature. This direction θ of a pixel at co-ordinates (x, y) is found by $\theta = \tan^{-1}(\frac{G_y}{G_x})$, where $G_x$ is the gradient computed using the Sobel kernel for horizontal change and $G_y$ for
vertical change. The resulting direction is a value that ranges between 0 to 2\pi radians. This range is split into 18 non-overlapping segments allowing a gradient direction histogram to be created from the count of each direction. Equimass is an adaptive grid based on the number of black pixels or Mass M of a signature, where the grid lines are found at the equimass divisions of the horizontal and vertical mass histogram. An effective approach as specified in (Larkins & Mayo 2008) by combining the spatial pyramids (Lazebnik et al 2006) and the equimass sampling grids (Favata & Srikantan 1996) are used. The features extracted as above are then normalized and used.

As each box contains 18 segments, the signature image provides a 1st level of 36 features (2*18) as shown in Figure 3.11, 2nd level of 144 features (8 * 18) as shown in Figure 3.12, and 3rd level of 576 (32 *18) features as shown in Figure 3.13 by equimass, giving rise to 756 (36+144+576) in total. 3 spatial pyramids are used for the finest level of region sampling. The features are extracted for all the 55 signature sets.

![Signature Image](image)

**Figure 3.11 One Level of Equimass in a Signature Image**
The features of the signature image are characterized as IVFS based on the gray levels. The upper and lower membership degrees of each feature, are defined as $\mu_U(x) = \left[\mu(x)\right]^\alpha$ and $\mu_L(x) = \left[\mu(x)\right]^\alpha$ where $\mu(x)$ is the membership value of a pixel and $\alpha = 2$ as $\alpha > 2$ is not meaningful for image data (Tizhoosh 2005). Algorithm 2 (Figure 3.14) states the procedure for feature extraction and its time complexity would be $O(n \times w \times h)$ where $n$ would be the number of signatures per signer and $w \times h$ would be the size of the image.
Algorithm 2 : Feature Extraction

1: for each image in a set
2:    Apply Wiener filter to reduce noise
3:    Apply fuzzification operator to the image
4:    Apply Contrast Intensification to the fuzzified image
5:    Apply defuzzification operator to intensified image
6:    Divide the image into one level of equimass (2 boxes)
7:    Get Gradient direction histogram for the 18 segments in each box
8:    Normalize the data
9:    Store the feature values of each image
10:   end for
11:   Save the feature values for all sets

Figure 3.14 Algorithm 2 : Feature Extraction

3.3.3 Verification

The features extracted after contrast intensification are characterized as IVFS, a sufficiently complete generalization of the concept of a fuzzy set (Gorzalczany 1987) and first introduced by Zadeh (1975). In economics, intervals are used to represent values in case of uncertainty. Gehrke et al (1996) state people believe that assigning an exact number (fuzzy membership) to an expert’s opinion is too restrictive and that the assignment of an interval is more realistic. Hence, in order to obtain a more reliable estimate of feature values, IVFS has been used to characterize the signature image.
A similarity measure based on IVFS combined with an adaptive threshold is used to determine if a signature is genuine or forged. The proposed method utilizes the similarity measure of IVFS introduced by Zeng \& Li (2006). False Acceptance Rate (FAR), a type II error that expresses the percentage of forgeries accepted as genuine and False Rejection Rate (FRR), a type I error that expresses the percentage of genuine rejected as forgery are used to compute the accuracy. Definitions related to IVFS and its similarity measure is presented.

**Definition 3.3 : Interval-valued Fuzzy Set (Gorzalczany 1987)**

An interval-valued fuzzy set \( X \) on an universe \( U \) is a mapping such that \( X : U \to \text{Int}([0,1]) \); where \( \text{Int}([0,1]) \) stands for the set of all closed subintervals of \( [0,1] \), and the set of all interval-valued fuzzy sets on \( U \) is denoted by \( P(U) \). Figure 3.15 represents IVFS membership function.

Suppose \( X \in P(U), \forall y \in U, \mu_X(y) = [\mu_X^-(y), \mu_X^+(y)] \), is called the degree of membership of \( y \) to \( X \). \( \mu_X^- \) and \( \mu_X^+ \) are referred to as the lower and upper degrees of membership of \( y \) to \( X \) where \( 0 \leq \mu_X^- \leq \mu_X^+ \leq 1 \).

![Figure 3.15 IVFS Membership Function](image-url)
Definition 3.4: Similarity measure of IVFS (Zeng & Li 2006)

If $X = [x_1, x_2, \ldots, x_n]$, $A, B \in IVFS$ over $X$, then

$$N(A, B) = 1 - \frac{1}{2n} \sum_{i=1}^{n} |A^-(x_i) - B^-(x_i)| + |A^+(x_i) - B^+(x_i)|$$

(3.13)

is the similarity measure of IVFS between $A$ and $B$.

**Threshold computation**

A subset of randomly chosen genuine signatures is used as the reference set $R$ with IVFS feature vectors. The similarity scores of each signature against the rest of the signatures in $R$ is computed.

Let $D$ be the set of similarity scores and $\mu$ be its mean. Then $S_L$ is computed as the lower sample standard deviation (only the values below $\mu$) are used:

$$S_L = \frac{1}{(D_L - 1)} \sum_{i=1}^{n} (D_i - \mu)^2 \quad \forall D_i < \mu$$

(3.14)

where $D_L$ is the number of values in $D$ which are less than $\mu$ and $D_i$ is the similarity score in the set $D$ and $n$ is the total number of $D_i$. The threshold is fixed as:

$$\text{threshold} (t) = (\mu - S_L)$$

(3.15)

As the values are not normally distributed and to adjust for the skew, the lower threshold of $(\mu - S_L)$ is used for verification so as to maximize the classification accuracy of both genuine and forgery signatures (Larkins & Mayo 2008). The class of unknown signature is then determined by
Verification procedure

Algorithm 3, specified in Figure 3.16, is applied for all 55 sets and accuracy is computed. The time complexity would be $O(n^*(n+1)/2))$ since similarity matrix would be a triangular matrix and $n$ represents the number of signatures in the training set with which each signature is compared.

3.4 EXPERIMENTAL RESULTS AND DISCUSSION

The CEDAR signature dataset (Kalera et al 2004), a popular benchmark dataset used for off-line signature verification, consists of 55 signature sets, with each set being composed by one writer. The forgeries for this dataset were obtained by asking arbitrary people to skillfully forge the signatures. In this fashion, 24 forgery samples were collected per writer from about 20 skillful forgers. Each set consists of 24 genuine and 24 skilled forgery signatures in a space measuring 2 x 2 inches, scanned at 300 dpi in 8-bit gray scale. In total, the dataset contains 1,320 genuine signatures and 1,320 forgeries.

**Algorithm 3 : Verification**

1: Get a reference Set R of 16 randomly chosen genuine signatures

2: Compute threshold $t$ using (3.15)

3: for other images(genuine+forgery) in the set do

4: Get the IVFS feature vector (fv)

5: Compute a similarity score set $S$ using (3.13) for fv against all elements in R

6: Compute mean of $S$ to be $S_{\mu}$
7: if ($S_\mu \geq t$) then
8:    if genuine signature then
9:        add 1 to true positive (TP)
10:    else
11:        add 1 to false positive (FP)
12: end if
13: else // forgery
14:    if forgery signature then
15:        add 1 to true negative (TN)
16:    else
17:        add 1 to false negative (FN)
18: end if
19: end if
20: end for
21: Compute accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} for a set

Figure 3.16 Algorithm 3: Verification

3.4.1 Performance Analysis

The experiment process was carried out on each signature set, where 16 randomly chosen signatures are used as reference and rest (8 genuine and 24 forgeries) are used for testing. The use of 16 signatures for training was to make the results comparable with (Kalera et al 2004), (Chen & Srihari 2005), (Chen & Srihari 2006) and (Larkins & Mayo 2008). The reference set keeps changing for each trial and 10 such trials are conducted to obtain a reliable estimate of the accuracy. The experiments described above
have been written in MATLAB running on Intel Core 2 Quad CPU @ 2.66 GHz PC with 2GB of RAM.

Table 3.2 Verification Results using IFS Type II Contrast Intensification

<table>
<thead>
<tr>
<th>Trial No.</th>
<th>Acc %</th>
<th>FRR</th>
<th>FAR</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>94.91</td>
<td>2.24</td>
<td>7.93</td>
</tr>
<tr>
<td>2</td>
<td>95.39</td>
<td>2.48</td>
<td>6.73</td>
</tr>
<tr>
<td>3</td>
<td>94.59</td>
<td>2.40</td>
<td>8.41</td>
</tr>
<tr>
<td>4</td>
<td>95.15</td>
<td>1.76</td>
<td>7.93</td>
</tr>
<tr>
<td>5</td>
<td>93.03</td>
<td>1.92</td>
<td>12.02</td>
</tr>
<tr>
<td>6</td>
<td>94.83</td>
<td>1.92</td>
<td>8.41</td>
</tr>
<tr>
<td>7</td>
<td>93.47</td>
<td>1.76</td>
<td>11.30</td>
</tr>
<tr>
<td>8</td>
<td>94.59</td>
<td>1.68</td>
<td>9.13</td>
</tr>
<tr>
<td>9</td>
<td>94.71</td>
<td>1.92</td>
<td>8.65</td>
</tr>
<tr>
<td>10</td>
<td>93.67</td>
<td>1.60</td>
<td>11.06</td>
</tr>
</tbody>
</table>

The evaluation was carried out on all the 55 sets. Table 3.2 shows the 10 trials of verification for IFS type II contrast enhancement. Table 3.3 compares the error rates and the accuracy against the existing methods and Figure 3.17 gives a graphical representation. FRR keeps decreasing from fuzzy to type 2 IFS contrast intensification in the proposed methods implying that forgeries are being identified more accurately by contrast enhancement. Table 3.4 depicts the results by varying the number of training instances and Figure 3.18, its corresponding graphical representation and this shows that the proposed method remains fairly stable.
Table 3.3 Verification Results when Training Set Size is 16

<table>
<thead>
<tr>
<th>Method</th>
<th>Acc %</th>
<th>FRR</th>
<th>FAR</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>EXISTING</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gradient, Structural &amp; Concavity (Kalera et al 2004)</td>
<td>78.50</td>
<td>22.45</td>
<td>19.50</td>
</tr>
<tr>
<td>Zernike Moments (Chen &amp; Srihari 2005)</td>
<td>83.60</td>
<td>16.60</td>
<td>16.30</td>
</tr>
<tr>
<td>Graph Matching (Chen &amp; Srihari 2006)</td>
<td>92.10</td>
<td>7.70</td>
<td>8.20</td>
</tr>
<tr>
<td>Automatic Feature Thresholding (Larkins &amp; Mayo 2008)</td>
<td>90.44</td>
<td>1.86</td>
<td>10.96</td>
</tr>
<tr>
<td>Signature Morphology (Kumar et al 2010)</td>
<td>88.41</td>
<td>11.59</td>
<td>11.59</td>
</tr>
<tr>
<td>Surroundedness (Kumar et al 2012)</td>
<td>91.67</td>
<td>8.33</td>
<td>8.33</td>
</tr>
<tr>
<td><strong>PROPOSED</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wiener filter + IVFS</td>
<td>88.30</td>
<td>13.48</td>
<td>9.93</td>
</tr>
<tr>
<td>Fuzzy Method 1 + IVFS</td>
<td>89.73</td>
<td>10.92</td>
<td>9.62</td>
</tr>
<tr>
<td>Fuzzy Method 2 + IVFS</td>
<td>92.47</td>
<td>5.88</td>
<td>9.18</td>
</tr>
<tr>
<td>Type 1 IFS + IVFS</td>
<td>92.92</td>
<td>5.05</td>
<td>9.11</td>
</tr>
<tr>
<td>Type 2 IFS + IVFS</td>
<td>94.44</td>
<td>1.97</td>
<td>9.16</td>
</tr>
</tbody>
</table>
Figure 3.17 Comparative Results using Bar Chart

Table 3.4 Results when Training Set Size is Varied

<table>
<thead>
<tr>
<th>Method</th>
<th>Training Set Size</th>
<th>Accuracy %</th>
<th>FRR</th>
<th>FAR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Only IVFS</td>
<td>12</td>
<td>87.44</td>
<td>12.93</td>
<td>12.18</td>
</tr>
<tr>
<td></td>
<td>14</td>
<td>87.99</td>
<td>13.25</td>
<td>10.75</td>
</tr>
<tr>
<td></td>
<td>16</td>
<td>88.30</td>
<td>13.48</td>
<td>9.93</td>
</tr>
<tr>
<td></td>
<td>18</td>
<td>88.47</td>
<td>14.30</td>
<td>8.75</td>
</tr>
</tbody>
</table>
Differentiating skilled forgeries from genuine with high accuracy is a very difficult task in signature verification. Due to its high applicability in various fields, new methods and schemes are being devised in signature verification. In this chapter, a scheme based on fuzzy techniques for signature verification has been proposed. The algorithm was tested on the CEDAR data set and their performances are evaluated based on their FAR and FRR.

The method used a similarity measure based on IVFS and obtained 88.30% accuracy. Contrast Intensification and enhancement is applied to the image and IVFS method is again verified. The accuracy for the same data set is increased to 89.75%, 92.47%, 92.92% and 94.44% respectively for the

Figure 3.18 Results for IVFS when training set size is varied
four fuzzy contrast intensification methods. With all the uncertainties involved with signature verification and the test set being skilled forgeries, it can be concluded that the fuzzy techniques in contrast enhancement, feature extraction and verification are more promising compared to other techniques in terms of accuracy and time complexity \[ \max(O(n^*w^*h), O(n^*n)) \] and IFS based contrast intensification methods are more useful in such circumstances. The use of adaptive threshold helped to boost the classification accuracy.