

Edge Detection Method for Latent Fingerprint Images Using Intuitionistic Type-2 Fuzzy Entropy

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Abstract: *A latent fingerprint is an interesting issue because of it has attained from crime places and moreover contained a low quality image, less number of features and unwanted noises. It is necessity to extract the original image with exact boundary from the surface for further processing such as authentication, identification and matching. In this work, a new distance measure has been proposed for latent fingerprint edge detection using Intuitionistic Type-2 Fuzzy Entropy (IT2FE) and a comprehensible definition is made for Intuitionistic Type-2 Fuzzy Sets (IT2FS). IT2FS takes into account of uncertainty in the form of membership function which is also termed as Intuitionistic Type-2 Fuzzy Divergence (IT2FD). The experiment is conducted with public domain fingerprint databases such as FVC-2004 and IIT-latent fingerprint. The edge detection is carried out with the proposed method and the results are discovered better regarding existing method.*

Keywords: *Intuitionistic type-2 fuzzy set, intuitionistic type-2 fuzzy divergence, fuzzy entropy, latent fingerprint image, edge detection*

1. Introduction

The notion of fuzzy set theory is introduced in 1965 by Z a d e h [1]. It has had a vital role in various files of image processing in past decades. In 1985, Intuitionistic fuzzy set theory was defined by A t a n a s s o v [2]. It takes into account the degree of membership function and non-membership function. Due to hesitation occurring in the intuitionistic fuzzy set, the 1-degree of membership is not constantly identical to degree of non-membership. Z a d e h [3] presented the definition of type- n fuzzy set and in order to Type-2 Fuzzy Set (T2FS) has been functioning based on the definition, introduced by K a r n i k and M e n d e l [4]. T2FS have been successfully used in many active areas, such as human resource management, forecasting of time-series, clustering, pattern recognition, fuzzy logic controller, industrial application, simulation, and neural network. The principle of the Hamming and Euclidean distance are derived from a few distance measures

between intuitionistic fuzzy set which is proposed by Szmidt and Kacprzyk [6, 7]. With the help of intuitionistic fuzzy sets, Grzegorzewski [8] has derived the Hamming and Euclidean distance in view of Hausdorff metric. The researchers have started using the intuitionistic fuzzy sets in pattern recognition which is based on similarity measures [9].

In this proposed work, a new distance measure has been used with respect to Intuitionistic Type-2 Fuzzy Entropy (IT2FE) for latent fingerprint edge detection (see Fig. 2). The significance of Intuitionistic Type-2 Fuzzy Divergence (IT2FD) is found in the degree of membership, non-membership and the hesitation degree. In practice wise, the proposed IT2FE is more suitable for edge detection.

The results are found better utilized the new distance measure as for the existing method.

The following order has been followed to compose the remaining paper: Section 2 gives brief description of background study of this work. Section 3 explains the notion of fuzzy set theory. Section 4 describes the proposed distance measure in order to IT2FE. An experimental result is presented in Section 5 and it deals with two different databases and finally in Section 6, the conclusion of the work is presented and it includes the future direction for research.

2. Background study of fingerprints

In this section, we explain the fundamentals of fingerprints and some related works of proposed method.

2.1. Fundamentals of fingerprints

The biometric security of human recognition is identified by two ways such as physical (fingerprint, palm veins, iris recognition, retina, face recognition, DNA, palm print, hand geometry and odor) and behaviour (typing rhythm, gait, and voice) which are very suitable for identification, authentication and matching due to their individuality, universality and invariability [10]. Among all the biometric characteristics, fingerprints have the largest amount of unwavering quality and widely utilized by criminological specialists as a part of criminal examinations. Fingerprints are full-fledged at around seven months of hatchling advancement and finger ridge design does not change for the duration of the life of a person with the exception of mishaps, for example, wounds and cuts on the fingers. Notwithstanding for twins, it will never show signs of change. [11]. Fingerprint patterns are formed in the epidermis on the fingertip. The ridge orientation map, frequency map, singular points, pores, incipient, dots and minutiae are the features of the fingerprint. Arch, Loop and Whorl are the three patterns of the fingerprint and have a nine-type of classification is explained by Hawthorne [12].

2.2. Related works

There are numerous normal edge detection strategies utilized in image processing such as Prewitt, Sobel, Roberts, Canny, as well as others (see [13]). Fuzzy if-then

rules are utilized for edge detection in T a o, T h o m p s o n and T a u r [14]. It maintains a strategic distance from the challenges of selecting parameter values in the greater part of the edge indicators strategy. Gamma distribution and fuzzy divergence are used for form a latest image threshold and defining the membership function of the pixel of the image [15]. H o and O h n i s h i [16] examined a fuzzy edge discovery strategy taking into account learning fuzzy edges by the system of fuzzy arrangement and grouping. For edge detection, the Sliding twofold window over an image is utilized the Jensen-Shannon uniqueness of gray level histogram [17]. Type-2 fuzzy set theory is used for medical image edge detection by C h a i r a and R a y [18]. It has worked based on max-min values of the intensity levels of the image in a 3×3-pixel neighbourhood to form two image matrices. The type-2 fuzzy set theory is used to tackle the uncertainty which is performed to select the threshold values automatically. Canny's edge detection algorithm is achieved to segment the gradient image [19]. An edge-detection system is carried out based on the morphological gradient method and comprehensive type-2 fuzzy logic [20]. The theory of alpha planes is utilized to implement generalized type-2 fuzzy logic for edge detection. A b o r i s a d e [21] has developed a fuzzy logic based edge detection technique in digital images. The area of intuitionistic type-2 fuzzy set in image processing is beginning to develop the concept.

3. Elements of fuzzy set theory

Definition 3.1. Let A and X be the fuzzy and finite set respectively. A fuzzy set A can be mathematically representing the membership function by μ_A , which is termed as $\mu_A(x) : X \rightarrow [0, 1]$, such that for each $x \in X$ [1].

Definition 3.2. T2FS denoted by A , which is characteristic by type-2 fuzzy membership function $\mu_A(x, u)$, where $x \in X$ and $u \in J_x \subseteq [0, 1]$, i.e.,

$$A = \{(x, u), \mu_A(x, u) \mid \forall x \in X \quad \forall u \in J_x \subseteq [0, 1]\} \text{ in which } 0 \leq \mu_A(x, u) \leq 1.$$

Definition 3.3. Let X be a finite set. Then an intuitionistic fuzzy set A in X is a set ordered triplets $A = \{(x, \mu_A(x), \nu_A(x)) \mid x \in X\}$, where $\mu_A(x), \nu_A(x) : X \rightarrow [0, 1]$ are respectively. The membership and non membership function on an element x with the necessary condition $0 \leq \mu_A(x) + \nu_A(x) \leq 1, \forall x \in X$.

The hesitation degree x in A defined as follows $\pi_A(x) = 1 - \mu_A(x) - \nu_A(x)$. The measure of non-membership function is $1 - \mu_A(x)$.

Due to hesitation occur in the intuitionistic fuzzy set, the 1-degree of membership is not constantly identical to degree of non-membership. This is coherently valid however in certifiable, this may not be valid. In this way, logical invalidation is not equivalent to down to earth refutation which is because of absence of learning in characterizing the participation capacity.

It is obvious that $\mu_A(x) + \nu_A(x) + \pi_A(x) = 1$ and $0 \leq \pi_A(x) \leq 1$, for each $x \in X$.

Definition 3.4. A Intuitionistic Type-2 Fuzzy Sets (IT2FS) denoted by A , which is characteristic by Intuitionistic type-2 fuzzy membership function

$\mu_A(x, u), \nu_A(x, u)$ where $x \in X$ and $u \in J_x \subseteq [0, 1]$ [22], i.e., $A = \{((x, u), \mu_A(x, u), \nu_A(x, u)) \mid \forall x \in X, \forall u \in J_x \subseteq [0, 1]\}$ in which $0 \leq \mu_A(x, u), \nu_A(x, u) \leq 1$.

Definition 3.5. A function of $\delta: F \times F \rightarrow \mathbb{R}^+$ is defined distance measure, if δ fulfils the accompanying properties [23]:

1. $\delta(x_1, x_2) = \delta(x_2, x_1) \quad \forall x_2, x_1 \in F$
2. $\delta(x_1, x_1) = 0 \quad \forall x_1 \in F$
3. $\delta(\Delta, \Delta^c) = \max_{x_1, x_2 \in F} d(x_1, x_2) \quad \forall \Delta \in P(X)$

4. $\forall x_1, x_2, x_3 \in F$ if $x_1 \subset x_2 \subset x_3$, then $\delta(x_1, x_2) \leq \delta(x_1, x_3)$ and $\delta(x_2, x_3) \leq \delta(x_1, x_3)$, where $F(X)$ and $P(X)$ are represent fuzzy set and crisp set of X , respectively.

If we normalize e, δ, s we can confirm $0 \leq e(x_1) \leq 1, 0 \leq \delta(x_1, x_2) \leq 1, 0 \leq s(x_1, x_2) \leq 1$, for $x_1, x_2 \in F$. The relation between δ and s is $\delta = 1 - s$. $e(A) = s(A, A^c)$ as represents the fuzzy entropy, where, $e(x_1) = 1 - \delta(x_1, x_1^c)$ is termed the fuzzy entropy, where e represents the entropy, δ represents the distance and s represents the similarity.

4. Intuitionistic type-2 fuzzy distance measure

The two IT2FS are given below: $A = \{((x, u), \mu_A(x, u), \nu_A(x, u)) \mid \forall x \in X, \forall u \in J_x \subseteq [0, 1]\}$ and $B = \{((x, u), \mu_B(x, u), \nu_B(x, u)) \mid \forall x \in X, \forall u \in J_x \subseteq [0, 1]\}; \{\mu_A(x, u), (\mu_A(x, u) + \pi_A(x, u))\}$, and $\{\mu_B(x, u), (\mu_B(x, u) + \pi_B(x, u))\}$ are the representing the form of hesitation degree with membership degree of set A and B. Hesitation degree plays a major role to compute the distance measure between two IT2FS. Let p_0, p_1, \dots, p_{L-1} , is representing the probabilities of size $M \times M$ with L distinct gray levels of image, and $H = \sum_{i=0}^{L-1} p_i e^{1-p_i}$ is termed as exponential entropy.

In fuzzy information circumstance, based on the Definition 3.5, the type-2 fuzzy entropy of an image A of size $M \times M$ is given as below [24, 23]:

$$(1) H(A) = \frac{1}{n(\sqrt{e}-1)} \sum_{i=0}^{M-1} \sum_{j=0}^{M-1} [(\mu_A(x_{ij}, u_{ij}) \exp\{1 - \mu_A(x_{ij}, u_{ij})\} + (1 - \mu_A(x_{ij}, u_{ij})) \exp\{1 - \mu_A(x_{ij}, u_{ij})\}) - 1],$$

where $n = M^2, i, j = 0, 1, 2, 3, \dots, M-1$ and $\mu_A(x_{ij}, u_{ij})$ is the membership degree of the (i, j) -th pixels (x_{ij}, u_{ij}) in the image A.

Let A and B be two image and the (i, j) -th pixels having the following amount of information among the two membership degree of the images:

- As a result of $m_1(A)$ and $m_1(B)$, i.e., $\mu_A(x_{ij}, u_{ij})$ and $\mu_B(y_{ij}, u_{ij})$ of the (i, j) -th pixels: $\exp\{\mu_A(x_{ij}, u_{ij}) - \mu_B(y_{ij}, u_{ij})\}$,

• As a result of $m_2(A)$ and $m_2(B)$, i.e., $\mu_A(x_{ij}, u_{ij}) + \pi_A(x_{ij}, u_{ij})$ and $\mu_B(y_{ij}, u_{ij}) + \pi_B(y_{ij}, u_{ij})$ of the (i, j) -th pixels:

$$\exp\{\mu_A(x_{ij}, u_{ij}) + \pi_A(x_{ij}, u_{ij})\} / \exp\{\mu_B(y_{ij}, u_{ij}) + \pi_B(y_{ij}, u_{ij})\}.$$

As a result of $m_1(A)$ and $m_1(B)$ may be represented as follows for the fuzzy divergence bounded by the images A and B which is coherent with type-2 fuzzy entropy,

$$(2) D_1(A, B) = \sum_i \sum_j (1 - (1 - \mu_A(x_{ij}, u_{ij})) \exp\{\mu_A(x_{ij}, u_{ij}) - \mu_B(y_{ij}, u_{ij})\} - \mu_A(x_{ij}, u_{ij}) \exp\{\mu_B(y_{ij}, u_{ij}) - \mu_A(x_{ij}, u_{ij})\}).$$

Similarly, the divergence of B against A is

$$(3) D_1(B, A) = \sum_i \sum_j (1 - (1 - \mu_B(y_{ij}, u_{ij})) \exp\{\mu_B(y_{ij}, u_{ij}) - \mu_A(x_{ij}, u_{ij})\} - \mu_B(y_{ij}, u_{ij}) \exp\{\mu_A(x_{ij}, u_{ij}) - \mu_B(y_{ij}, u_{ij})\}).$$

As a result of $m_2(A)$ and $m_2(B)$ may be represented as follows for the fuzzy divergence bounded by the images A and B which is coherent with type-2 fuzzy entropy,

$$(4) D_2(A, B) = \sum_i \sum_j (1 - (1 - \mu_A(x_{ij}, u_{ij}) + \pi_A(x_{ij}, u_{ij})) \exp\{(\mu_A(x_{ij}, u_{ij}) + \pi_A(x_{ij}, u_{ij})) - (\mu_B(y_{ij}, u_{ij}) + \pi_B(y_{ij}, u_{ij}))\} - (\mu_A(x_{ij}, u_{ij}) + \pi_A(x_{ij}, u_{ij})) \exp\{(\mu_B(y_{ij}, u_{ij}) + \pi_B(y_{ij}, u_{ij})) - (\mu_A(x_{ij}, u_{ij}) + \pi_A(x_{ij}, u_{ij}))\}).$$

Similarly, the divergence of B against A is

$$(5) D_2(B, A) = \sum_i \sum_j (1 - (1 - \mu_B(y_{ij}, u_{ij}) + \pi_B(y_{ij}, u_{ij})) \exp\{(\mu_B(y_{ij}, u_{ij}) + \pi_B(y_{ij}, u_{ij})) - (\mu_A(x_{ij}, u_{ij}) + \pi_A(x_{ij}, u_{ij}))\} - (\mu_B(y_{ij}, u_{ij}) + \pi_B(y_{ij}, u_{ij})) \exp\{(\mu_A(x_{ij}, u_{ij}) + \pi_A(x_{ij}, u_{ij})) - (\mu_B(y_{ij}, u_{ij}) + \pi_B(y_{ij}, u_{ij}))\}).$$

As a result of $m_1(A)$ and $m_1(B)$ may be represented as follows for the two images A and B having the total divergence between the pixels (x_{ij}, u_{ij}) and (y_{ij}, u_{ij}) :

$$(6) \text{Div} - m_1(A, B) = D_1(A, B) + D_1(B, A) = \sum_i \sum_j 2 - (1 - \mu_A(x_{ij}, u_{ij}) + \mu_B(y_{ij}, u_{ij})) \exp\{\mu_A(x_{ij}, u_{ij}) - \mu_B(y_{ij}, u_{ij})\} - (1 - \mu_B(y_{ij}, u_{ij}) + \mu_A(x_{ij}, u_{ij})) \exp\{\mu_B(y_{ij}, u_{ij}) - \mu_A(x_{ij}, u_{ij})\}.$$

As a result of $m_2(A)$ and $m_2(B)$ may be represented as follows for the two images A and B having the total divergence between the pixels (x_{ij}, u_{ij}) and (y_{ij}, u_{ij}) :

$$(7) \text{Div} - m_2(A, B) = D_2(A, B) + D_2(B, A) = \sum_i \sum_j 2 - [1 - \mu_A(x_{ij}, u_{ij}) - \mu_B(y_{ij}, u_{ij}) + (\pi_B(y_{ij}, u_{ij}) - \pi_A(x_{ij}, u_{ij}))] \times \exp\{\mu_A(x_{ij}, u_{ij}) - \mu_B(y_{ij}, u_{ij}) - ((\pi_B(y_{ij}, u_{ij}) - \pi_A(x_{ij}, u_{ij})))\} - [1 - (\pi_B(y_{ij}, u_{ij}) - \pi_A(x_{ij}, u_{ij})) + (\mu_A(x_{ij}, u_{ij}) - \mu_B(y_{ij}, u_{ij}))] \exp\{\pi_B(y_{ij}, u_{ij}) - \pi_A(x_{ij}, u_{ij}) - (\mu_A(x_{ij}, u_{ij}) - \mu_B(y_{ij}, u_{ij}))\}.$$

By adding (6) and (7), we computed the following equation of overall IT2FD between the image A and B:

$$(8) \text{IT2FD}(A, B) = \text{Div} - m_1(A, B) + \text{Div} - m_2(A, B) = \sum_i \sum_j 2 - (1 - \mu_A(x_{ij}, u_{ij}) + \mu_B(y_{ij}, u_{ij})) \times \exp\{\mu_A(x_{ij}, u_{ij}) - \mu_B(y_{ij}, u_{ij})\} - (1 - \mu_B(y_{ij}, u_{ij}) + \mu_A(x_{ij}, u_{ij})) \exp\{\mu_B(y_{ij}, u_{ij}) - \mu_A(x_{ij}, u_{ij})\} + (2 - [1 - (\mu_A(x_{ij}, u_{ij}) - \mu_B(y_{ij}, u_{ij})) + (\pi_B(y_{ij}, u_{ij}) - \pi_A(x_{ij}, u_{ij}))]) \exp\{\mu_A(x_{ij}, u_{ij}) - \mu_B(y_{ij}, u_{ij}) - ((\pi_B(y_{ij}, u_{ij}) - \pi_A(x_{ij}, u_{ij})))\} - [1 - (\pi_B(y_{ij}, u_{ij}) - \pi_A(x_{ij}, u_{ij})) + (\mu_A(x_{ij}, u_{ij}) - \mu_B(y_{ij}, u_{ij}))] \exp\{\pi_B(y_{ij}, u_{ij}) - \pi_A(x_{ij}, u_{ij}) - (\mu_A(x_{ij}, u_{ij}) - \mu_B(y_{ij}, u_{ij}))\}.$$

Fig. 1 shows a set of sixteen fuzzy edge detected templates which are used for edge detection. It has contained a size of 3×3 matrix. The edge profile of different kinds of templates has been used in the form of matrix (set of 16, 3×3 template). The type of templates and direction of edges are depending on strength of the optimal of templates. The matrix has contained the three different types of pixels of the edge templates such x , y and 0. It is selected by experiment and it should be less than that of an image. The centre of edge templates could be located over the normalized image for every (i, j) . The template was centered whenever the IT2FD measure at every pixel location (i, j) . Using the below max-min relationship, the IT2FD (i, j) is calculated between the image window and the template.

$$(9) \quad \text{IT2FD}(i, j) = \max_N [\min_r (\text{IT2FD}(A, B))],$$

where, N = number of templates, r = number of elements in the square template.

The IT2FD among all of the elements (x_{ij}, u_{ij}) and (y_{ij}, u_{ij}) of image window A and of template B is used the equation (5) to compute the IT2FD (A, B) and is represented as below

$$(10) \quad \text{IT2FD}((x_{ij}, u_{ij}), (y_{ij}, u_{ij})) = (2 - [(1 - \mu_A(x_{ij}, u_{ij}) + \mu_B(y_{ij}, u_{ij})) \exp\{\mu_A(x_{ij}, u_{ij}) - \mu_B(y_{ij}, u_{ij})\}] - (1 - \mu_B(y_{ij}, u_{ij}) + \mu_A(x_{ij}, u_{ij})) \exp\{\mu_B(y_{ij}, u_{ij}) - \mu_A(x_{ij}, u_{ij})\}] + (2 - [1 - (\mu_A(x_{ij}, u_{ij}) - \mu_B(y_{ij}, u_{ij})) + (\pi_B(y_{ij}, u_{ij}) - \pi_A(x_{ij}, u_{ij}))]) \exp\{\mu_A(x_{ij}, u_{ij}) - \mu_B(y_{ij}, u_{ij}) - ((\pi_B(y_{ij}, u_{ij}) - \pi_A(x_{ij}, u_{ij})))\}] - [1 - (\pi_B(y_{ij}, u_{ij}) - \pi_A(x_{ij}, u_{ij})) + (\mu_A(x_{ij}, u_{ij}) - \mu_B(y_{ij}, u_{ij}))]) \exp\{\pi_B(y_{ij}, u_{ij}) - \pi_A(x_{ij}, u_{ij}) - (\mu_A(x_{ij}, u_{ij}) - \mu_B(y_{ij}, u_{ij}))\}].$$

Among all element in the template (y_{ij}, u_{ij}) is the IT2FD $((x_{ij}, u_{ij}), (y_{ij}, u_{ij}))$ and those in image window (x_{ij}, u_{ij}) . From each pixel location of the image IT2FD (i, j) is computed. To conclude, the values of IT2FD (i, j) is should be same size of the IT2FD matrix at every point. Finally, it is threshold and thinned to get the output image (edge-detected image).

4.1. Algorithm for edge detection using IT2FD

In this subsection, we developed a template based algorithm for latent fingerprint edge detection using IT2FD.

Step 1. Design the set of 16, 3×3 edge-detected templates with values of x and y .

Step 2. The centre of edge templates could be positioned over the normalized image for every (i, j) .

Step 3. Compute the IT2FD for all element from 16 edge-detected template and the image window and select the smallest IT2FD value.

Step 4. Select minimum IT2FD from the maximum of the complete 16 edge-detected template.

Step 5. The template was centered over the image whenever the point takes the position at maximum value.

Step 6. The max-min value is chosen and situated for complete the pixel locations.

Step 7. A current IT2FD matrix is designed.

Step 8. The IT2FD matrix is threshold and thinned.

Step 9. Obtained the final form of the edge detected image.

$$\begin{array}{cccccc}
 \begin{bmatrix} 0 & y & x \\ 0 & y & x \\ 0 & y & x \end{bmatrix} & \begin{bmatrix} x & x & x \\ 0 & 0 & 0 \\ y & y & y \end{bmatrix} & \begin{bmatrix} x & x & y \\ x & y & 0 \\ y & 0 & 0 \end{bmatrix} & \begin{bmatrix} y & y & y \\ 0 & 0 & 0 \\ x & x & x \end{bmatrix} & \begin{bmatrix} y & x & x \\ 0 & y & x \\ 0 & 0 & y \end{bmatrix} & \begin{bmatrix} y & x & 0 \\ y & x & 0 \\ y & x & 0 \end{bmatrix} & \begin{bmatrix} x & 0 & y \\ x & 0 & y \\ x & 0 & y \end{bmatrix} & \begin{bmatrix} 0 & 0 & 0 \\ y & y & y \\ x & x & x \end{bmatrix} \\
 \begin{bmatrix} x & x & x \\ y & y & y \\ 0 & 0 & 0 \end{bmatrix} & \begin{bmatrix} x & y & 0 \\ x & y & 0 \\ x & y & 0 \end{bmatrix} & \begin{bmatrix} 0 & 0 & 0 \\ x & x & x \\ y & y & y \end{bmatrix} & \begin{bmatrix} 0 & x & y \\ 0 & x & y \\ 0 & x & y \end{bmatrix} & \begin{bmatrix} y & y & y \\ x & x & x \\ 0 & 0 & 0 \end{bmatrix} & \begin{bmatrix} y & 0 & x \\ y & 0 & x \\ y & 0 & x \end{bmatrix} & \begin{bmatrix} y & 0 & 0 \\ x & b & 0 \\ x & x & y \end{bmatrix} & \begin{bmatrix} 0 & 0 & y \\ 0 & y & x \\ y & x & x \end{bmatrix}
 \end{array}$$

Fig. 1. Set of 16, 3×3 template

4.2. Pseudo code for latent fingerprint image edge detection

In this subsection, we discussed about the pseudo code for latent fingerprint image edge detection.

Pseudo code:

Input: Latent fingerprint image

Output: Fingerprint image binary edge detection

1. Specify the **input image with dimension**
2. The **template pixel values** of **x** and **y**
3. Set of **16 Type-2 fuzzy edge template**, likewise m_1, m_2, \dots, m_{16}

4. **Calculate**

$$\begin{aligned}
 \text{IT2FD}(A, B) = & \sum_i \sum_j 2 - (1 - \mu_A(x_{ij}, u_{ij}) + \mu_B(y_{ij}, u_{ij}) \exp\{\mu_A(x_{ij}, u_{ij}) - \mu_B(y_{ij}, u_{ij})\} - \\
 & -(1 - \mu_B(y_{ij}, u_{ij}) + \mu_A(x_{ij}, u_{ij}) \exp\{\mu_B(y_{ij}, u_{ij}) - \mu_A(x_{ij}, u_{ij})\}.
 \end{aligned}$$

5. For each pixel location compute the **max-min divergence:**

$$\text{IT2FD}(i, j) = \max_r [\min_r (\text{IT2FD}(A, B))] .$$

6. To get an edge – detection image threshold the divergence matrix

for $i1 = 1 : \text{dim}$

for $j1 = 1 : \text{dim}$

if $\text{maxim}(i1, j1) > \text{Threshold value}$

$$w2(i1, j1) = 1$$

else $w2(i1, j1) = 0$

end

end

end

7. **Thinned** the image

8. Final **binary edge detected image** will be display on the screen.

5. Results and discussions

The experiment is dealing with two different fingerprint databases such as Fingerprint Verification Competition-2004 (FVC-2004) and latent fingerprint database (Indraprastha Institute of Information Technology – IIIT) for better results. These are both public available fingerprint databases. FVC-2004 [25] consists of four databases and each database image has different size and resolution. IIIT latent fingerprint database [26] contains 15 subjects. Each subject has all 10 fingerprints. Each image is of 4752×3168 pixel in size and has been scanned at 500 pixels per inch as a gray-scale image. We obtain the unacceptable computation error in latent fingerprint images due to large pixel size. So, it has changed the size of 508×661 for edge detection.

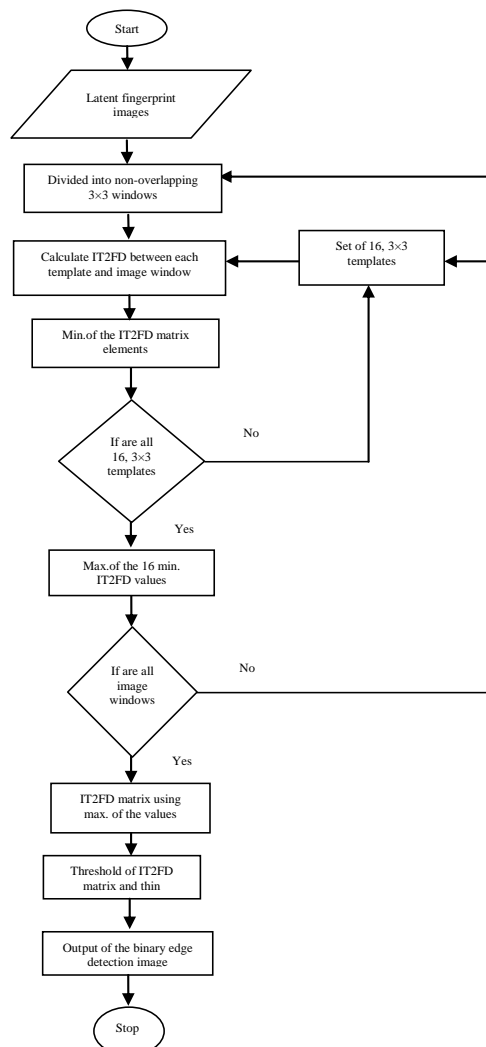


Fig. 2. Flow chart of proposed method

The pixels of the edge template values of x and y are picked by experimentation technique. The edge detection results are not clear by using the edge template values of $x = 0.20$, $y = 0.6$. Results with $x = 0.3$, $y = 0.8$ are found better edge template values for edge detection by trial and error. It is additionally examined that, the numerous edges are observed to miss while diminishing the quantity of templates, where as on extending the amount of templates, there is no exceptional change in the edge discovery comes. The set of 16, 3×3 templates are found for better edge detection to overcome the template values difficulties. The value of r , the amount of elements in the square template in Equation (8) is $3^2 = 9$.

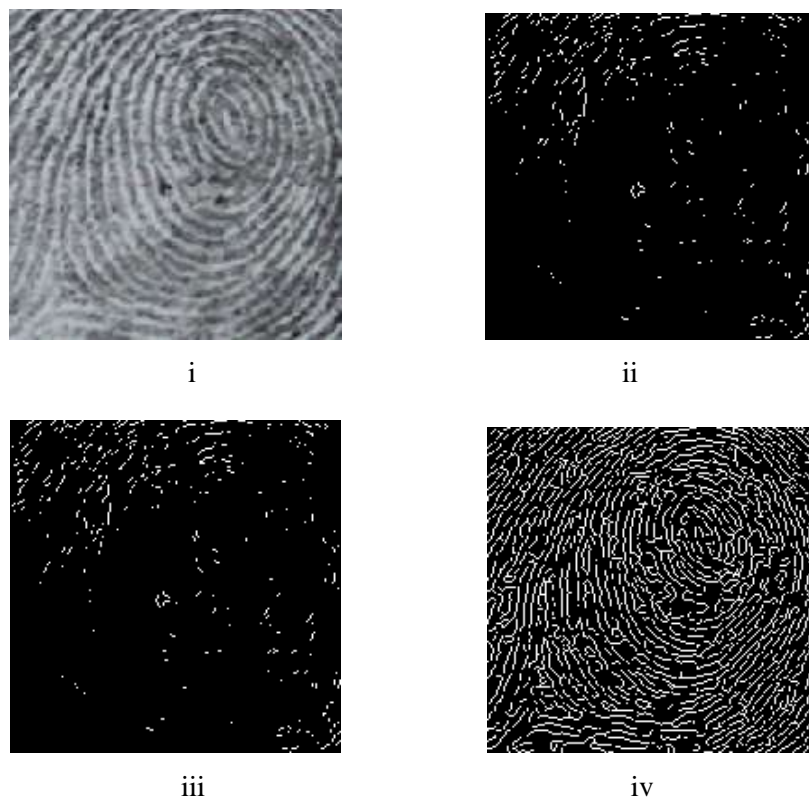


Fig. 3. Latent fingerprint original image (i); edge detected image by: Prewitt technique (ii); Sobel technique (iii); proposed technique (iv)

Fig. 3i shows an image of a Latent fingerprint (IIT) size of 508×661 with threshold values of 0.08 and $x = 0.3$, $y = 0.8$. Fig. 3ii and iii displays the result of Prewitt and Sobel method with outer edges are not clear. Fig. 3iv shows the results of proposed method with much better edge detection than other methods.

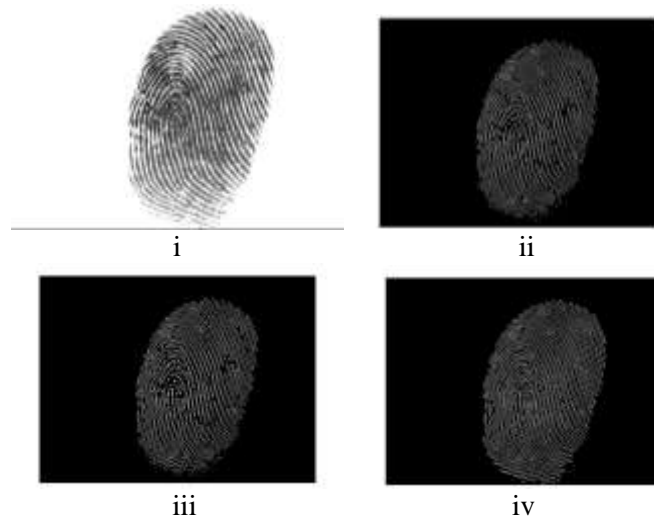


Fig. 4. Fingerprint original image (i); edge detected image by: Canny technique (ii); Sobel technique (iii); proposed technique (iv)

Fig. 4i shows an image of a fingerprint (FVC-2004 Database 1) size of 640×480 with threshold values of 0.13 and $x = 0.3$, $y = 0.8$. Fig. 4ii displays the results of Sobel method with edges are not properly detected. Fig. 4iii displays the results of Canny method with outer edges are detected but not clear ridge and valley structure. Fig. 4iv displays the results of proposed system considerable better edge detection than the previous techniques.

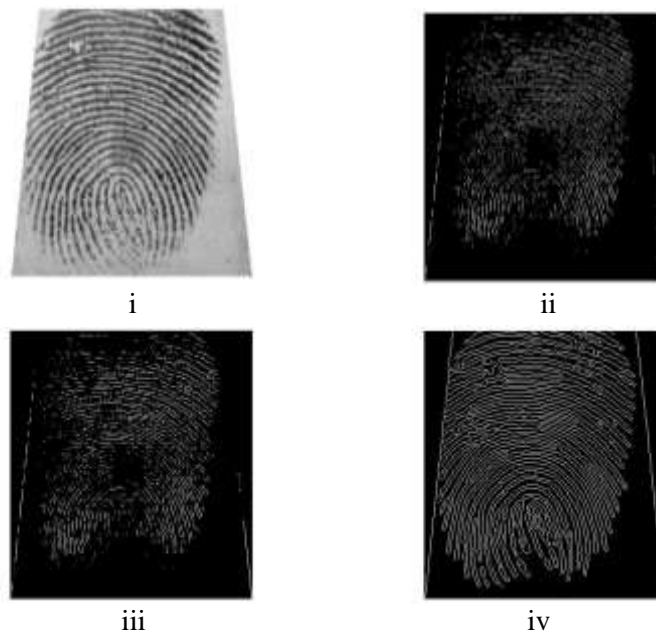


Fig. 5. Fingerprint original image (i); edge detected image by: Sobel technique (ii); Prewitt technique (iii); proposed method (iv)

Fig. 5i shows an image of a fingerprint (FVC- 2004 Database 2) size of 328×364 with threshold values of 0.19 and $x = 0.3$, $y = 0.8$. Fig. 5ii and iii shows the results of Sobel and Prewitt method with unclear edge structure. Fig. 5iv shows the results of proposed method is found better.

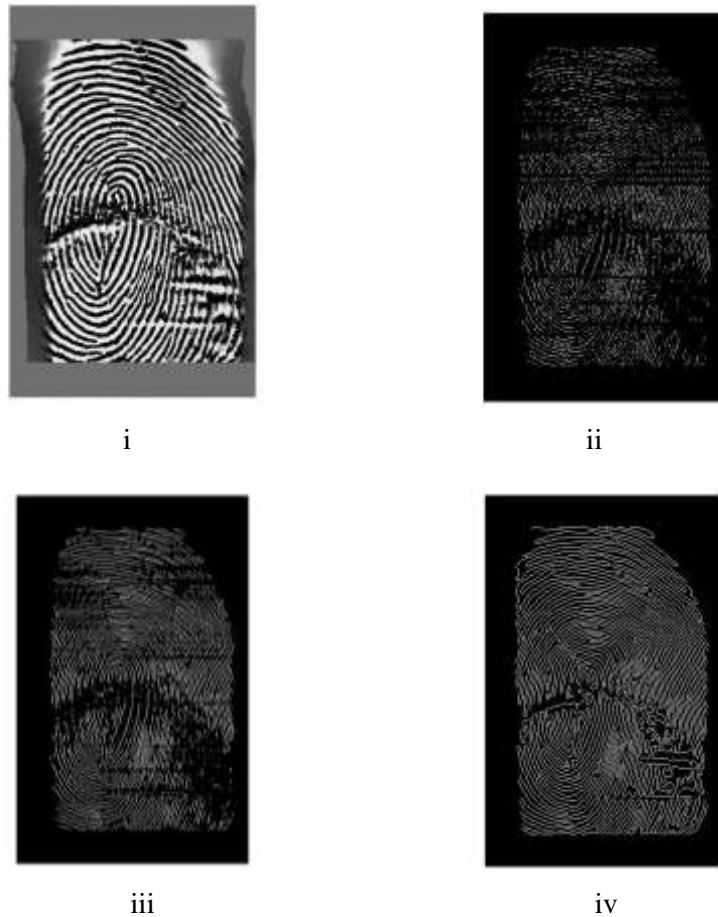


Fig. 6. Fingerprint original image (i); edge detected image by: Robert technique (ii); Canny technique (iii); proposed method (i)

Fig. 6i shows an image of a fingerprint (FVC-2004 Database 3) size of 300×480 with threshold values of 0.25 and $x = 0.3$, $y = 0.8$. Fig. 6ii displays the results of Robert method with discontinuous ridge structure. Fig. 6iii displays the results of Canny method with better than Robert method. Fig. 6iv displays the results of proposed method is continuous ridge structure with better edge detection.

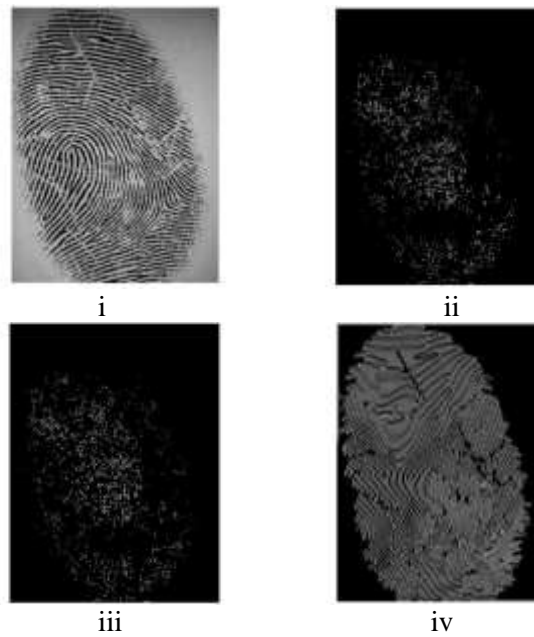


Fig. 7 Fingerprint original image (i); edge detected image by: Prewitt technique (ii); Sobel technique (iii); proposed technique (iv)

Fig. 7i shows an image of a fingerprint (FVC-2004 Database 4) size of 288×384 with threshold values of 0.13 and $x = 0.3$, $y = 0.8$. Fig. 7ii and iii shows the results of Prewitt and Sobel method with edges are not properly detected. Fig. 7iv shows the results of proposed way much better edge detection than the current methods.

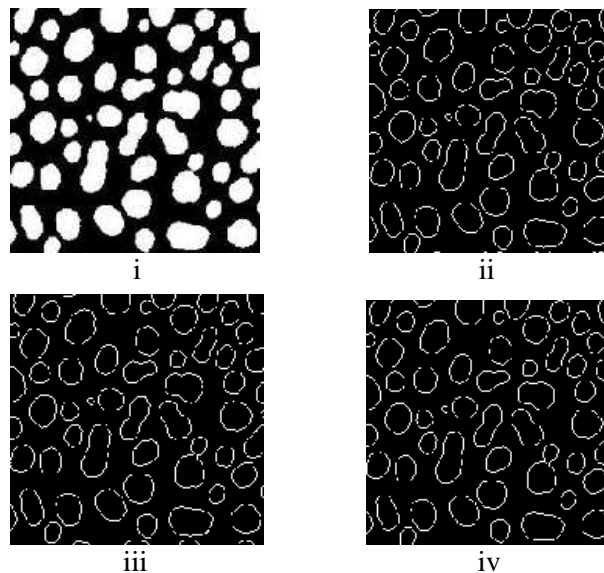


Fig. 8. Blood cell original image (i); edge detected image by: Prewitt technique (ii); Canny technique (iii); proposed technique (iv)

Fig. 8i shows an image of a blood cell with the size of 204×203 with threshold values of 0.08 and $x = 0.3$, $y = 0.8$. Fig. 8ii shows the results of the Sobel method with entirely the edges are not acceptably recognized. Fig. 8iii shows the results of Canny method with outer edges are detected but not slightly unclear structure. Better edge detection results are obtained in Fig. 8iv.

For comparison, IT2FD have applied appropriately for better edge detection. The threshold values are manually adjusted sometimes for getting the final edge-detected results in Fig. 4 ($T=0.13$), Fig. 5 ($T=0.19$) and Fig. 6 ($T=0.25$) but remain and pixel of the edge template is fixed to all the images. In our belief, the outcome is discovered better because of the utilization of IT2FD in order to IT2FE.

6. Conclusions

The state-of-the-art of this work is latent fingerprint image edge detection using IT2FE. It contains a new distance measure and divergence based on fuzzy entropy. The edge detection results are carried out by using a fuzzy measure on images. The experimental result shows, the pixel value, threshold and IT2FD are decided the level of edge detection. The proposed technique distinguishes the overwhelming edges visibly, while evacuating the undesirable edges. The membership degree is considered to be uncertain due to IT2FS, the outcome is discovered better. Moreover, this method is applicable for all type of other applications. The interesting finger impression conspicuous verification is one of the methods used in legitimate science to help criminal examinations in consistently life, giving access control in budgetary security; visa related organizations and so on. In the near future, we are aiming to use partial latent fingerprint images for authentication using fuzzy set theory concept.

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