ISSN: 0974-5823 Vol. 7 No. 2 February, 2022

International Journal of Mechanical Engineering

Fingerprint Using Intuitionistic Fuzzy Relation

S. Kavitha[a], K. Selvakumari[b,*]

[a]Research Scholar, Department of Mathematics, VELS Institute of Science, Technology and Advanced Studies, Chennai.

[b,*]Professor, Department of Mathematics, VELS Institute of Science, Technology and Advanced Studies, Chennai.

Abstract

Fingerprint impression is a key to find an individual person. It's unique, difficult to create, permanent pattern from birth to death and developed from deeper level of skin. In this paper, we analyse three generation fingerprints from a family with the help of Intuitionistic fuzzy relation.

Keywords: *Fingerprint, membership function, Intuitionistic fuzzy relation.*

1. Introduction

Lotfi A. Zadeh is a father of "Fuzzy set theory" published in the year 1965. Fuzzy atmosphere has a possible to solve a type of uncertainty and uses the membership function [0, 1] to get a result like human thinking with mathematical tools. [1, 5, 6] Intuitionistic fuzzy set is an extension of fuzzy set introduced by Atanassov (1986). [4, 7, 12] Fingerprint is a very difficult process to compare and analyze the patterns. So, we choose fuzzy set to receive an exact result.

In fingerprint, they have three common patterns: loops (ulnar and radial) it has one core and one delta, arches (plain and tented) it has no or one core and delta and whorls (plain, peacock or central pocket, accidental, double loop) they have more than one delta and core. These patterns have twelve types of minutiae which make unique prints. It may use in many fields to save our details and electronic things like Aadhar, laptop, mobile, attendance, etc. [2]

Fingerprint recognition is more used in biometric technology. They save the fingerprint with person details. [3] A high-quality of fingerprint image have around 20-70 minutiae points. The genuine number based on the dimension of the sensor surface and how the user set his / her finger on the scanner. Recognition has two types verification and identification. In fingerprint verification method, a person places a fingerprint on scanner then the it scans and sends to feature extraction. Extraction provides the feature set and it match with already saved data. If it is match then, shows the person details otherwise not. [8, 9]

Fingerprint identification is used to identify the right person. Scanner captures the fingerprint and sends to feature extraction. It split the ridges give to template. Then template match with saved data. [9] Suppose the result will be more than one then the pre-selection used automatically used to match again to reduce and get the result. Because identification will have large and expensive database. The problem will be observing fingerprint while finger cut, burn or scraps but few days later it could be came back to normal pattern. [11]

2. Preliminaries

2.1 Intuitionistic fuzzy relation [10, 12]

An Intuitionistic fuzzy relation (IFR) R: X x Y → [0, 1] is given by

$$\mu_R(x, y) = \{(x, y), \mu_I(x, y), \gamma_I(x, y) / x \in X\}$$

where $\mu_I(x, y)$: X x Y → [0, 1] is a degree of membership function and $\gamma_I(x, y)$: X x Y → [0, 1] denotes the degree of non-membership function such as $0 \le \mu_I(x, y) + \gamma_I(x, y) \le 1$. [10, 12]

2.2 Membership Function [4, 11]

The membership function of IFR gives a degree of equivalence of a member to fuzzy relations. That is,

$$\mu_I(x) = \begin{cases} 0, & 0 < x \\ \frac{x}{(b-a) \times 5}, & a < x < b \\ 0.5, & x \le 0.5 \end{cases}$$

and

$$\gamma_I(x) = \begin{cases} 0.5, & 0.5 \le x \\ \frac{x}{(d-c) \times 5}, & a < x < b \\ 1, & \text{Otherwise} \end{cases}$$

where a = 6, b = 8, c = 1, d = 3 and I denote a fuzzy set.

2.3 Union of Fuzzy Relations [4, 10]

Any two fuzzy relations I_1 and I_2. Then

$$I_1 \cup I_2 = \{(x, y), \max\{\mu_{I_1}(x, y), \mu_{I_2}(x, y)\}, \min\{\gamma_{I_1}(x, y), \gamma_{I_2}(x, y)\} / x \in X, y \in Y\}$$

is called as union of IFR.

2.4 Intersection of Fuzzy Relations [4, 10]

Let I_1 and I_2 be any two fuzzy relations. Then the intersection of IFR is denoted by

$$I_1 \cap I_2 = \{(x, y), \min\{\mu_{I_1}(x, y), \mu_{I_2}(x, y)\}, \max\{\gamma_{I_1}(x, y), \gamma_{I_2}(x, y)\} / x \in X, y \in Y\}$$

2.5 Properties of IFR [1, 4, 10]

Any three fuzzy relation I_1, I_2 and I_3. Then the properties of IFR will be present the combination of union and intersection. That is,

(i) $(I_1 \cup I_2) \cup I_3 = I_1 \cup (I_2 \cup I_3)$

(ii) $(I_1 \cap I_2) \cap I_3 = I_1 \cap (I_2 \cap I_3)$

(iii) $(I_1 \cap I_2) \cup I_3 = (I_1 \cup I_3) \cap (I_2 \cup I_3)$

(iv) $(I_1 \cup I_2) \cap I_3 = (I_1 \cap I_3) \cup (I_2 \cap I_3)$

is called properties of union and intersection where $x \in X$ and $y \in Y$.

3. Numerical Examples

We collect 25 family fingerprint images and compare the three generation prints from a family with help of IFS. First, we tag the variables G_1, G_2 and G_3 for ancestor, mom/dad and child/teenager.

Ancestor = G_1

Mom / Dad = G_2

Child / Teenager = G_3

Then insert a gridline and select in the way of 3x3 matrix (3 rows and columns) to analyse the difference between them. Now pair the fingerprint like (G_1, G_2), (G_2, G_3) and (G_3, G_1). The first cell compared with pair fingerprint and did for complete matrix and similarly we done for other two pairs.

For this comparison we fix some values by using definition 2.2. If both cells have perfect similarity, then the value is (1.0, 0.0); more similarity the value is (0.9, 0.1); less similarity then the value is (0.8, 0.2) and non-similarity then the value is (0.7, 0.3). Then form a matrix table for each pair.

	Membership	Non-Membership
Non-similarity	0.7	0.3
Less similarity	0.8	0.2
More similarity	0.9	0.1
Perfect similarity	1.0	0.0

After using definition 2.5 to get an equal result on both right and left hand side. Then use definition 2.3 to identify a max value for each row and column and definition 2.4 to find min value from max value row and column it must be equal result.

For example,

Nagoor (81) - Ancestor

Bala Murugan (46) - Mom/Dad

Swathi (13) - Child / Teenager

Table 1. Liken G_1 and G_2

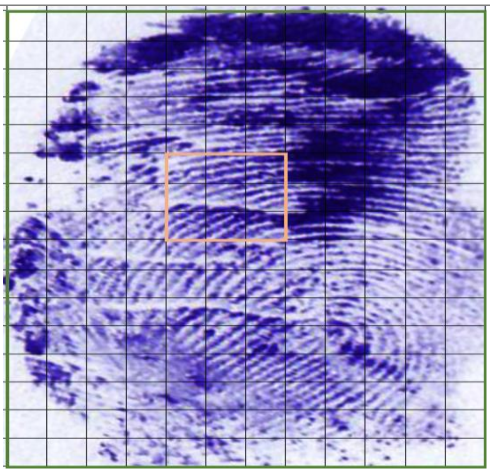
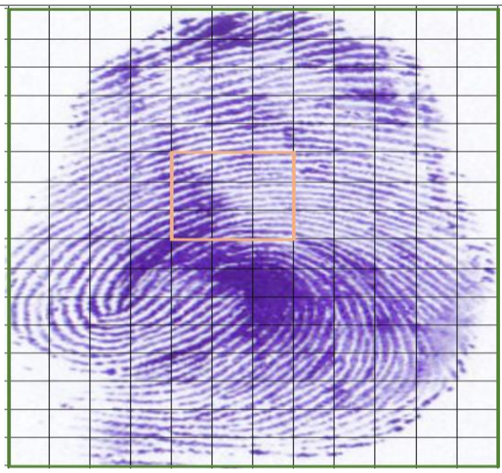
G_1	G_2
	

Table 2. Build matrix table I_1, by applying definition 2.1 and table 3.1

	y_1	y_2	y_3
x_1	(0.8, 0.2)	(0.8, 0.2)	(0.8, 0.2)
x_2	(0.9, 0.1)	(0.7, 0.3)	(0.8, 0.2)
x_3	(0.8, 0.2)	(0.8, 0.2)	(0.7, 0.3)

Table 3. Liken G_2 and G_3

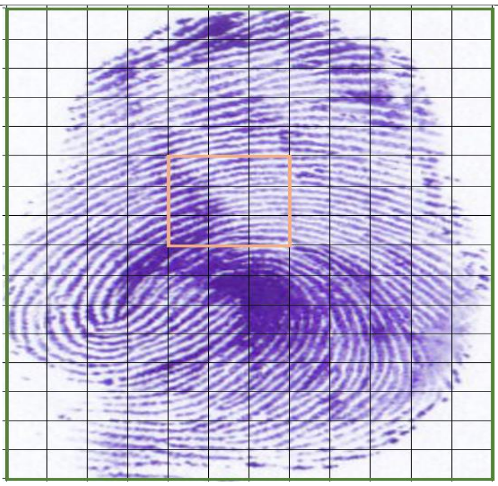
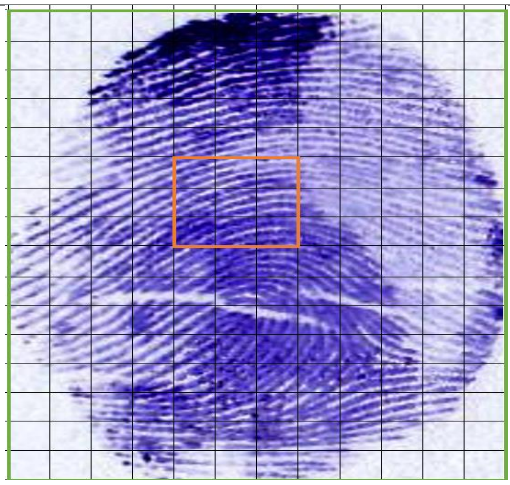
G_2	G_3
	

Table 4. Build matrix table I_2, by applying definition 2.1 and table 3.3

	y_1	y_2	y_3
x_1	(0.9, 0.1)	(0.9, 0.1)	(0.8, 0.2)
x_2	(0.9, 0.1)	(0.8, 0.2)	(0.9, 0.1)
x_3	(0.9, 0.1)	(0.8, 0.2)	(0.8, 0.2)

Table 5. Liken G_3 and G_1

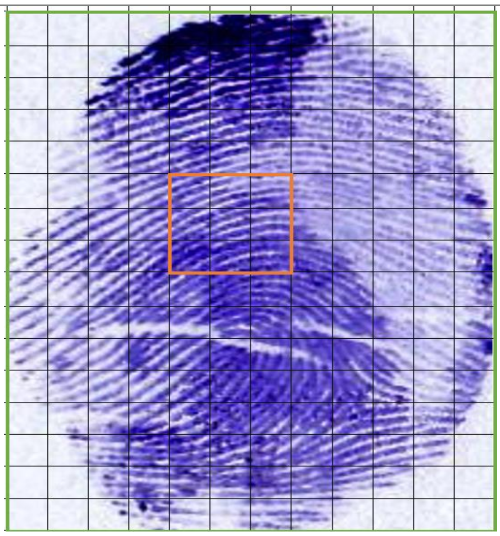
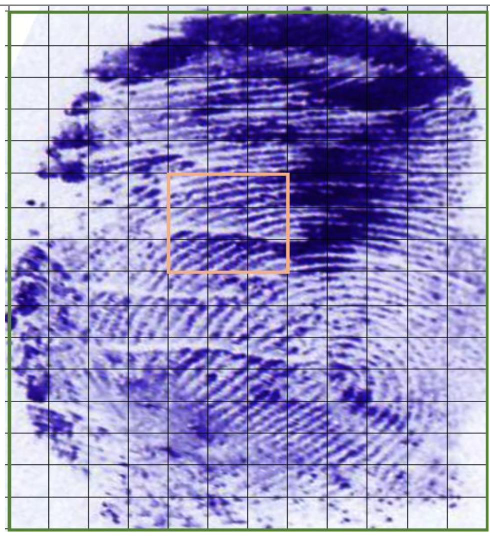
G_3	G_1
	

Table 6. Build matrix table I_3, by applying definition 2.1 and table 3.

	y_1	y_2	y_3
x_1	(0.8, 0.2)	(0.9, 0.1)	(0.8, 0.2)
x_2	(0.8, 0.2)	(0.8, 0.2)	(0.9, 0.1)
x_3	(0.9, 0.1)	(0.7, 0.3)	(0.8, 0.2)

(i) $(I_1 \cup I_2) \cup I_3 = I_1 \cup (I_2 \cup I_3)$

Left hand side

Table 7. $I_1 \cup I_2$

	y_1	y_2	y_3
x_1	(0.9, 0.1)	(0.9, 0.1)	(0.8, 0.2)
x_2	(0.9, 0.1)	(0.8, 0.2)	(0.9, 0.1)
x_3	(0.9, 0.1)	(0.8, 0.2)	(0.8, 0.2)

Table 8. $(I_1 \cup I_2) \cup I_3$

	y_1	y_2	y_3
x_1	(0.9, 0.1)	(0.9, 0.1)	(0.8, 0.2)
x_2	(0.9, 0.1)	(0.8, 0.2)	(0.9, 0.1)
x_3	(0.9, 0.1)	(0.8, 0.2)	(0.8, 0.2)

Right hand side

Table 9. $I_2 \cup I_3$

	y_1	y_2	y_3
x_1	(0.9, 0.1)	(0.9, 0.1)	(0.8, 0.2)
x_2	(0.9, 0.1)	(0.8, 0.2)	(0.9, 0.1)
x_3	(0.9, 0.1)	(0.8, 0.2)	(0.8, 0.2)

Table 10. $I_1 \cup (I_2 \cup I_3)$

	y_1	y_2	y_3
x_1	(0.9, 0.1)	(0.9, 0.1)	(0.8, 0.2)
x_2	(0.9, 0.1)	(0.8, 0.2)	(0.9, 0.1)
x_3	(0.9, 0.1)	(0.8, 0.2)	(0.8, 0.2)

Table 11. Analyze maximum by using Definition 2.6 and table 8 or 10.

	y_1	y_2	y_3	Max
x_1	(0.9, 0.1)	(0.9, 0.1)	(0.8, 0.2)	(0.9, 0.1)
x_2	(0.9, 0.1)	(0.8, 0.2)	(0.9, 0.1)	(0.9, 0.1)
x_3	(0.9, 0.1)	(0.8, 0.2)	(0.8, 0.2)	(0.9, 0.1)
Max	(0.9, 0.1)	(0.9, 0.1)	(0.9, 0.1)	(0.9, 0.1)

(i) = (0.9, 0.1) = Normal

(ii) $(I_1 \cap I_2) \cap I_3 = I_1 \cap (I_2 \cap I_3)$

Left hand side

Table 12. $I_1 \cap I_2$

	y_1	y_2	y_3
x_1	(0.8, 0.2)	(0.8, 0.2)	(0.8, 0.2)
x_2	(0.9, 0.1)	(0.7, 0.3)	(0.8, 0.2)
x_3	(0.8, 0.2)	(0.8, 0.2)	(0.7, 0.3)

Table 13. $(I_1 \cap I_2) \cap I_3$

	y_1	y_2	y_3
x_1	(0.8, 0.2)	(0.8, 0.2)	(0.8, 0.2)
x_2	(0.8, 0.2)	(0.7, 0.3)	(0.8, 0.2)
x_3	(0.8, 0.2)	(0.7, 0.3)	(0.7, 0.3)

Right hand side

Table 14. $I_2 \cap I_3$

	y_1	y_2	y_3
x_1	(0.8, 0.2)	(0.9, 0.1)	(0.8, 0.2)
x_2	(0.8, 0.2)	(0.8, 0.2)	(0.9, 0.1)
x_3	(0.9, 0.1)	(0.7, 0.3)	(0.8, 0.2)

Table 15. $I_1 \cap (I_2 \cap I_3)$

	y_1	y_2	y_3
x_1	(0.8, 0.2)	(0.8, 0.2)	(0.8, 0.2)
x_2	(0.8, 0.2)	(0.7, 0.3)	(0.8, 0.2)
x_3	(0.8, 0.2)	(0.7, 0.3)	(0.7, 0.3)

Table 16. Analyse maximum by using Definition 2.6 and table 13 or 15.

	y_1	y_2	y_3	Max
x_1	(0.8, 0.2)	(0.8, 0.2)	(0.8, 0.2)	(0.8, 0.2)
x_2	(0.8, 0.2)	(0.7, 0.3)	(0.8, 0.2)	(0.8, 0.2)
x_3	(0.8, 0.2)	(0.7, 0.3)	(0.7, 0.3)	(0.8, 0.2)
Max	(0.8, 0.2)	(0.8, 0.2)	(0.8, 0.2)	(0.8, 0.2)

(ii) = (0.8, 0.2) = sub-normal.

(iii) $(I_1 \cap I_2) \cup I_3 = (I_1 \cup I_3) \cap (I_2 \cup I_3)$

Left hand side

Table 17. $(I_1 \cap I_2) \cup I_3$

	y_1	y_2	y_3
x_1	(0.8, 0.2)	(0.9, 0.1)	(0.8, 0.2)
x_2	(0.9, 0.1)	(0.8, 0.2)	(0.9, 0.1)
x_3	(0.9, 0.1)	(0.8, 0.2)	(0.8, 0.2)

Right hand side

Table 18. $I_1 \cup I_3$

	y_1	y_2	y_3
x_1	(0.8, 0.2)	(0.9, 0.1)	(0.8, 0.2)
x_2	(0.9, 0.1)	(0.8, 0.2)	(0.9, 0.1)
x_3	(0.9, 0.1)	(0.8, 0.2)	(0.8, 0.2)

Table 19. $(I_1 \cup I_3) \cap (I_2 \cup I_3)$

	y_1	y_2	y_3
x_1	(0.8, 0.2)	(0.9, 0.1)	(0.8, 0.2)
x_2	(0.9, 0.1)	(0.8, 0.2)	(0.9, 0.1)
x_3	(0.9, 0.1)	(0.8, 0.2)	(0.8, 0.2)

Table 20. Analyze maximum by using Definition 2.6 and table 10 or 8.

	y_1	y_2	y_3	Max
x_1	(0.8, 0.2)	(0.9, 0.1)	(0.8, 0.2)	(0.9, 0.1)
x_2	(0.9, 0.1)	(0.8, 0.2)	(0.9, 0.1)	(0.9, 0.1)
x_3	(0.9, 0.1)	(0.8, 0.2)	(0.8, 0.2)	(0.9, 0.1)
Max	(0.9, 0.1)	(0.9, 0.1)	(0.9, 0.1)	(0.9, 0.1)

(iii) = (0.9, 0.1) = sub-normal

(iv) $(I_1 \cup I_2) \cap I_3 = (I_1 \cap I_3) \cup (I_2 \cap I_3)$

Left hand side

Table 21. $(I_1 \cup I_2) \cap I_3$

	y_1	y_2	y_3
x_1	(0.8, 0.2)	(0.9, 0.1)	(0.8, 0.2)
x_2	(0.8, 0.2)	(0.8, 0.2)	(0.9, 0.1)
x_3	(0.9, 0.1)	(0.7, 0.3)	(0.8, 0.2)

Right hand side

Table 22. $I_1 \cap I_3$

	y_1	y_2	y_3
x_1	(0.8, 0.2)	(0.8, 0.2)	(0.8, 0.2)
x_2	(0.8, 0.2)	(0.7, 0.3)	(0.8, 0.2)
x_3	(0.8, 0.2)	(0.7, 0.3)	(0.7, 0.3)

Table 23. $(I_1 \cap I_3) \cup (I_2 \cap I_3)$

	y_1	y_2	y_3
x_1	(0.8, 0.2)	(0.9, 0.1)	(0.8, 0.2)
x_2	(0.8, 0.2)	(0.8, 0.2)	(0.9, 0.1)
x_3	(0.9, 0.1)	(0.7, 0.3)	(0.8, 0.2)

Table 24. Analyze maximum by using Definition 2.6 and table 21 or 23.

	y_1	y_2	y_3	Max
x_1	(0.8, 0.2)	(0.9, 0.1)	(0.8, 0.2)	(0.9, 0.1)
x_2	(0.8, 0.2)	(0.8, 0.2)	(0.9, 0.1)	(0.9, 0.1)
x_3	(0.9, 0.1)	(0.7, 0.3)	(0.8, 0.2)	(0.9, 0.1)
Max	(0.9, 0.1)	(0.9, 0.1)	(0.9, 0.1)	(0.9, 0.1)

(iv) = (0.9, 0.1) = normal

Hence definition 2.5 satisfied

Result:

From above analysis of projection of IFR is subnormal. Because the results are less than 1.

Conclusion

Fingerprint biometric will be uses in many fields to identify a person like Aadhar card, government office, attendance, mobile phones, etc. From the above method we compare 25 family fingerprint and get the result with help of fuzzy relation. Then, we conclude that the three generation fingerprints have some similarity.

References

[1] A. Kaufmann, Introduction to the Theory of Fuzzy Subsets, United Kingdom Edition, Academic Press, Inc, London, 1973.

[2] D. Maltoni, D. Maio, A.K. Jain, Salil Prabhakar, Handbook of Fingerprint Recognition, 2nd edition, Springer, 2009.

[3] D. Wan, J. Zhou, Fingerprint Recognition Using Model-Based Density Map, IEEE Transactions on Image Processing, 15(6) (2006) pp.1690-1696.

[4] E. Szmidt, Distances and Similarities in Intuitionistic Fuzzy Sets, Studies in Fuzziness and Soft Computing, Springer, 2014.

[5] G.J. Klir, B. Yuan, Fuzzy Sets and Fuzzy Logic: Theory and Applications", Prentice Hall P T R, New Jersey, 1996.

[6] H.J. Zimmermann, Fuzzy Set Theory and its applications, 3rd edition, Kluwer Academic Publishers, London, 1996.

[7] K. Hur, S.Y. Jang, Y.S. Ahn, Intuitionistic Fuzzy Equivalence Relations, Honam Mathematical Journal, 27(2) (2005) pp.163-181.

[8] M. Kaur, M. Singh, A. Girdhar, P.S. Sandhu, Fingerprint Verification System using Minutiae Extraction Technique, International Journal of Computer and Information Engineering, 2(10) (2008) pp.3405-3410.

[9] N. Kaushal, P. Kaushal, Human Identification and Fingerprints, Journal of Biometrics and Biostatistics, 2 (2011) pp.1-5.

[10] P.A. Ejegwa, A.J. Akubo, O.M. Joshua, Intuitionistic fuzzy set and its application in career determination via normalized Euclidean distance method, European scientific journal, 10(15) (2014) pp.529-536.

[11] S. Kavitha, D. Vidhya, Fingerprint Matching Based on Fuzzy Astribution, AIP Conference Proceedings, 2277(1) (2020) pp.090016.

[12] W.L. Hung, J.S. Lee, C.D. Fuh, Fuzzy Clustering based on Intuitionistic Fuzzy Relations, International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, 12(4) (2004) pp.513-529.