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Transformation of Biometrics through Unsupervised Tools and Fuzzy Logic

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Abstract

Biometrics is an emerging technology in the present era. It is one of the safest way as it does not need to remember any passwords or carry passports, driving license or other such things. It only requires what a person has in himself such as face, fingerprints, iris, veins, DNA, ear etc i.e. only behavioral and physical characteristics of a person. It has a numerous advantages above all other authentication processes used presently. In this paper, face, left finger and right finger prints are used as biometrics. Four normalization methods such as adaptive normalization, double sigmoid function normalization, z score normalization and mathematical function normalization are used to transform or normalize the matching scores and four unsupervised tools such as max rule, min rule, product rule and sum rule are applied to them. Then through fuzzy logic its membership output is determined.

Keywords: Biometrics, normalization, unsupervised tools, fuzzy logic, membership function.

Introduction

Biometrics refers to the identification of human beings on the basis of their physical and/or behavioral characteristics. It provides a great level of security and authentication. Now days, a wide variety of the biometric systems are available in the market which employ reliable and secure authentication methods to confirm the identity of person when he presents his/her identity to the system. Hence, it is possible to setup an identity by considering “who you are” rather than by “what you have” [1] such as identification cards and passwords. Security is one of the most favored applications of the biometrics. Some of the physiological and/or behavioral characteristics that are being used for the biometric recognition include face, retina, palm print, DNA, hand-geometry, ear, voice, finger print, gait, signature, key-stroke dynamics and iris [2]. In this paper, face, left index finger and right index finger are taken into consideration.

Fingerprint Recognition: In fingerprint recognition system an image of the fingerprint either using scanner or ink is taken. These images are then used to fetch the characteristics like loops, whorls, and arches patterns of ridges and minutiae. There are various encoding and decoding methods available for accumulating and processing these characteristics. When a person leaves his/her finger on the sensor, he/she can we identified or verified on basis of matching of previously saved templates. Fingerprint recognition system is very accurate and stable, and it can be used to enroll multiple fingers to increase the anti-spoofing property [3]. Some of the disadvantages of this method are that the sensor may get dirty and can give false result due to the presence of the residual of previous user. [4]

Facial Recognition: It is the most natural means of biometric identification [5]. The facial recognition mainly works on the principle of distance measurement between the nose, mouth, eyes, and jaw edges. These characteristic are then used to create the database/template. Hence for verification or identification of any person, an image of the person is taken using a camera and template is then compared to the characteristic of this image, which is already stored in the database.

Normalization

Normalization is a method to convert the matching scores obtained from the different matchers in a common domain [6]. In other words, normalization is used to unionize the database and to eliminate the inconsistency in the data. The matching scores obtained after normalization must be robust and efficient over the entire distribution. Robustness is necessary in case if outliers are present in the distribution and efficiency is required as to check the proximity of the estimated distribution [7]. But, the main issue is to select a technique which is robust and efficient in nature.

Z-Score Normalization: z-score normalization technique estimates mean and standard deviation of matching scores to normalize the entire distribution. If μ and σ are the mean and standard deviation of the given database then normalized scores are given as [6]:

$$s_k^{'} = \frac{s_k - \mu}{\sigma} \qquad \ldots(1)$$

Mathematical Functional Normalization:

A novel approach which employ a mathematical function which has two different forms; one is used for dissimilarity matching scores and other for the similarity matching scores. After normalization, the whole distribution spreads in the range of 0 and 1, i.e. the minimum values approaches toward 0 and maximum toward 1. If sk is the original matching score then normalized scores s k are given by [8].

$$s_k^{'} = \frac{1}{2}\left(1 - \frac{s_k}{\sqrt{s_k^2 + a}}\right) \text{ and } s_k^{'} = \left(\frac{s_k}{\sqrt{s_k^2 + a}}\right) \qquad \ldots(2)$$

Adaptive Normalization:

The errors of individual biometric matchers stem from the overlap of the genuine and impostor distributions. This region is characterized with its center c and its width w. To decrease the effect of this overlap on the fusion algorithm, we propose to use an adaptive normalization procedure that aims to increase the separation of the genuine and impostor distributions. [9]

$$n_{AD} = \frac{1}{(c-\frac{w}{2})} n_{MM}^2, n_{MM} \le (c-\frac{w}{2}),$$

$$n_{MM}, (c-\frac{w}{2}) < n_{MM<} (c+\frac{w}{2}) \text{ and}$$

$$(c+\frac{w}{2}) + \sqrt{(1-c-\frac{w}{2})(n_{MM} - c - \frac{w}{2})}, otherwise \ \ldots \qquad (3)$$

Where n_{MM} = normalized score by min max normalization.

Double Sigmoid Function Normalization:

Cappelli et al. have used a *double sigmoid function* for score normalization in a multimodal biometric system that combines different fingerprint classifiers. The normalized score is given by where *t* is the reference operating point and *r*1 and *r*2 denote the left and right edges of the region in which the function is linear, i.e., the double sigmoid function exhibits linear characteristics in the interval (*t* − *r*1, *t* − *r*2). [10]

$$s_k^{'} = \frac{1}{1+\exp(-2((s_k - t)/r_1))} \text{ if } s_k < t \text{ and}$$

$$\frac{1}{1+\exp(-2((s_k - t)/r_2))} \text{ otherwise} \ \ldots. \qquad (4)$$

Unsupervised Method

In unsupervised methods of fusion there is no training process exist because learning rules are best suited for physical applications which works for pre-decided target marks. Some commonly followed unsupervised methods are as PRODUCT, MIN and MAX rules and weighted- SUM rule [11].

Sum Rule:

This is one of the productive rule because it eliminates the problem of equivocalness during classification. In sum rule, transformed scores of every class are added together to get the final score. Here, input pattern is delegated to the class c such that [12]:

$$c = \arg\max_j \sum_{i=1}^{R} PW_j \middle| \vec{X}_i$$

Product Rule:

The product rule provides a less intended results than sum rule because it is based on the statistical independence of the feature vectors. The input pattern delegated to the class c is given by [12]:

$$c = \arg\max_j \prod_{i=1}^{R} PW_j \Big| \vec{X}_i$$

Min Rule:

In this rule a minimum posterior probability is collected out of all classes. Hence, the input pattern delegated to the class c such that [12]:

$$c = \arg\max_j \min PW_j \Big| \vec{X}_i$$

Max Rule:

In max rule, the posterior probability is approximated by the maximum value of the input pattern. The input pattern delegated to the class c is given by [12]

$$c = \arg\max_j \max PW_j \Big| \vec{X}_i$$

Results

To evaluate the performance of the above said four normalization techniques with the various fusion rules the NIST- *Biometric Scores Set - Release 1 (*BSSR1), biometric database has been used. This database has a large amount of matching scores of face, left index finger and right index finger, specially derived for the fusion process. The matching scores have prepared for 6, 10 and 100 users. The normalized scores are calculated from the matching scores.

Following tables shows the results of the unsupervised tools.

Sum Rule	Threshold 6 users	Threshold 10 users	Threshold 100 users		6 users	10 users	100 users
Z Score	12.6780	4.4508	5.8439	GAR% FRR%	100 0	100 0	100 0
Mathematical	0.7889	0.7888	0.7992	GAR% FRR%	83.33 16.67	100 0	95 5
Adaptive	0.990847	0.712911	0.8271	GAR% FRR%	100 0	96 4	95 5
Double Sigmoid	0.013855	0.171454	0.287461	GAR% FRR%	100 0	100 0	99 1

Product Rule	Threshold 6 users	Threshold 10 users	Threshold 100 users		6 users	10 users	100 users
Z Score	24.8445	1.881	0.8047	GAR% FRR%	100 0	90 10	96 4
Mathematical	0.0049	0.0049	0.0039	GAR% FRR%	100 0	100 0	97 3
Adaptive	0.003267	0.00242	0.084646	GAR% FRR%	99 1	100 0	96 4
Double Sigmoid	0.023126	0.020715	0.043924	GAR% FRR%	100 0	100 0	99 1

Min Rule	Threshold 6 users	Threshold 10 users	Threshold 100 users		6 users	10 users	100 users
Z Score	1.2306	0.6549	0.1197	GAR% FRR%	83.33 16.67	90 10	95 5
Mathematical	0.0287	0.0287	0.0291	GAR% FRR%	100 0	100 0	94 6
Adaptive	0.017442	0.017442	0.04386	GAR% FRR%	96 4	90 10	100 0
Double Sigmoid	0.007855	0.179462	0.163617	GAR% FRR%	100 0	95 5	100 0

Max Rule	Threshold 6 users	Threshold 10 users	Threshold 100 users		6 users	10 users	100 users
Z Score	9.3541	2.6687	4.1582	GAR% FRR%	100 0	100 0	99 1
Mathematical	0.4642	0.4310	0.4300	GAR% FRR%	100 0	90 10	99 1
Adaptive	0.519481	0.406452	0.767544	GAR% FRR%	83.33 16.67	95 5	99 1
Double Sigmoid	0.014393	0.061144	0.018722	GAR% FRR%	100 0	100 0	99 1

Then finally the fuzzy logic implementation [13] is done and the membership output is determined.

GAR%	FRR%	REENTER%
91.3	0.3	8.4

Conclusion

In this paper the performance of a multimodal biometric system has been examined at matching score level fusion with various fusion rules and normalization methods. The purpose of analytical study is to investigate how multiple biometric modalities can together be made a more useful to create an effective authentication system. Four normalization method (Adaptive, Double Sigmoid Function, Z-Score and Mathematical normalizations) and four fusion rules (Sum, Product, Min and Max), have been examined. NIST BSSR release1 database has been used. The significant distinction between these methods has made on the basis of recognition rates (FRR and FAR).

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