Results evaluation of max rule, min rule and product rule in score fusion multibiometric systems

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Abstract—**this paper discusses about unibiometric systems, multibiometric systems, product rule, max rule and min rule of score level fusion. Score level fusion is used to generate scores of a person. Min max normalization scheme is used for normalization which normalizes scores between 0 and 1. The proposed method also evaluates the results between product rule, min rule and max rule.**

Keywords-multimodal biometrics, score level fusion, product rule, min rule, max rule.

I. INTRODUCTION

Biometric authentication, or simply biometrics, offers a natural and reliable solution to the problem of identity determination by establishing the identity of a person based on "who he is", rather than "what he knows" or "what he carries". Biometric systems [1] automatically determine or verify a person's identity based on his anatomical and behavioral characteristics such as fingerprint, face, iris, voice and gait. Biometric traits constitute a strong and permanent "link" between a person and his identity and these traits cannot be easily lost or forgotten or shared or forged. Since biometric systems require the user to be present at the time of authentication, it can also determine users from making false repudiation claims. Moreover, only biometrics can provide negative identification functionality where the goal is to establish whether a certain individual is indeed enrolled in the system although the individual might deny it. Due to these reasons, biometric systems are being increasingly adopted in a number of government and civilian applications either as a replacement for or to complement existing knowledge and token-based mechanisms. A number of anatomical and behavioral body traits can be used for biometric recognition. Examples of anatomical traits include face, fingerprint, iris, palm print, hand geometry and ear shape. Gait, signature and keystroke dynamics are some of the behavioral characteristics that can be used for person authentication. There are some factors which affects the accuracy of a uni biometric system which are noisy sensor data, non-universality, inter user similarity, Lack of invariant representation etc. To overcome these types of problems multibiometric systems are used. Multibiometric systems [2] offer following advantages over unibiometric systems.

1. When several sources of information are combined it will definitely improve the performance of the biometric system. The presence of multiple sources also effectively increases the dimensionality of the feature space and reduces the overlap between the feature spaces of different individuals.
2. Multibiometric biometric systems reduce the problem of non universality and reduce the failure to enrol rate problem and failure to control rate problem.
3. Multibiometric systems also reduces the effect of noise data If the biometric sample obtained from one of the sources is not of sufficient quality during a particular acquisition, the samples from other sources may still provide sufficient discriminatory information to enable reliable decision-making.
4. In case of spoof attacks multibiometric systems are more efficient as compare to unibiometric systems because it difficult to spoof multiple biometric sources.
5. Multibiometric systems also provide a certain degree of flexibility in user authentication. Suppose a user enrols into the system using several different traits. Later, at the time of authentication, only a subset of these traits may be acquired based on the nature of the application under consideration and the convenience of the user. For example, consider a banking application where the user enrols into the system using face, voice and fingerprint. During authentication, the user can select which trait to present depending on his convenience. While the user can choose face or voice modality when he is attempting to access the application from his mobile phone equipped with a digital camera he can choose the fingerprint modality when accessing the same application from a public ATM or a network computer.
6. Multibiometric systems in presence of multiple biometric traits provide more security as compare to unibiometric systems.
7. Multibiometric systems also provide more reliability as compare to unibiometric systems.
8. Multibiometric systems have the capability to search the entire database in an efficient manner.

Rest of the paper as follows, I section introduces some aspects of unibiometric systems and multibiometric systems, section II discusses about score section, product rule is described in section III, max rule in IV and min rule in V, section VI explains example of score level fusion, section VII evaluate results and conclusion is drawn in section VIII.

II. SCORE FUSION

Score fusion [3] is commonly used in multibiometric systems which is sufficient to distinguish between a genuine and imposter scores. Firstly scores are obtained from a person, that scores can be either similarity scores or distance scores, it needs to convert these scores in a similar manner. In this paper these scores are converted into similar nature there are various schemes are available which is used to convert these scores in a similar nature. Min max normalization scheme is used in this paper for conversion and product rule based fusion is used for multiplication of raw scores, max rule takes maximum value of raw scores and min rule takes minimum value of raw scores. The normalized score by using min max normalization is calculated as

$$x' = x - Min(X) / Max (X)-Min(X)$$

X denotes the set of raw matching scores, the normalized score of x is denoted by x'. Normalization maps the raw matching scores between 0 and 1. Let xi be the feature vector [4] (derived from the input pattern X) presented to the ith matcher. Let the outputs of the individual matchers be $P(Wj \mid Xi)$, i.e., the posterior probability of the of class Wj given the feature vector Xi . Let c □ $\{w_1, w_2 \ldots\ldots w_m\}$ be the class to which the input pattern X is finally assigned. The following rules can be used to estimate c:

III. PRODUCT RULE

This rule is based on the assumption of statistical independence of the representations x_1, $x_{2\ldots}$ $x_{r.}$ The input pattern is assigned to class c such that

$$c = \text{argmax}_j\ \pi \text{ ranges from 1 to r } P(Wj \mid Xi)$$

In general, different biometric traits of an individual (e.g., face, fingerprint and hand geometry) are mutually independent. This allows us to make use of the product rule in a multimodal biometric system based on the independence assumption.

IV. MAX RULE

The max rule approximates the mean of the posteriori probabilities by the maximum value. In this case, we assign the input pattern to class c such

$$c = \text{argmax}_j \max_i P(Wj \mid Xi)$$

V. MIN RULE

The min rule is derived by bounding the product of posteriori probabilities. Here, the input pattern is assigned to class *c* such that

$$c = \text{argmax}_j \min_i P(Wj \mid Xi)$$

VI. EXAMPLE OF SCORE FUSION

Example [5] shows a fusion of left fingerprint and right fingerprint scores. Suppose that there are 7 persons, and the images captured are of their left fingerprint and right fingerprint (2 images per finger per person). After that their images are compared and the genuine and impostor scores are shown in Tables given below

Left fingerprint								
	Image 1							
Image 2	person	a	b	c	d	e	f	g
	a	28	12	7	32	36	5	24
	b	2	5	2	5	8	4	3
	c	4	3	8	3	5	3	2
	d	9	5	8	6	4	2	3
	e	3	7	5	5	3	3	2
	f	3	6	4	4	3	3	5
	g	6	5	4	4	6	3	4

Table 1 genuine and imposter scores of a person for left fingerprint.

Right fingerprint								
	Image 1							
Image 2	person	a	b	c	d	e	f	g
	a	43	24	4	17	23	24	25
	b	3	4	2	6	3	3	2
	c	14	7	9	6	3	3	4
	d	2	3	3	3	9	7	3
	e	5	8	6	2	3	4	8
	f	6	9	5	2	4	5	9
	g	7	10	6	4	3	4	8

Table 2 genuine and imposter scores of a person for right fingerprint

In the table given above it is assumed that scores that are at the right hand side of the first row and first column are genuine scores and the rest are imposter scores. For the left fingerprint the maximum score is 36 and minimum score is 2. For right fingerprint maximum score is 43 and minimum score is 2. Now in next step normalization is done by min max normalization scheme to arrange them in the range of 0 and 1. After applying min max normalization scheme table 1 and table 2 look like this

left fingerprint								
		Image 1						
Image 2	person	a	b	c	d	e	f	g
	a	.764705	.294117	.147058	.882352	1	.088235	.647058
	b	0	.382352	0	.088235	.176470	.058823	.029411
	c	.058823	.029411	.176470	.029411	.088235	.029411	0
	d	.205882	.088235	.176470	.117647	.058823	0	.02944
	e	.029411	.147058	.088235	.088235	.029411	.029411	0
	f	.029411	.117647	.058823	.058823	.029411	.029411	.088235
	g	.117647	.088235	.058823	.058823	.117647	.029411	.058823

Table 3 normalized data after min max normalization

Right fingerprint								
		Image 1						
Image 2	person	a	b	c	d	e	f	g
	a	1	.536585	.048780	.365853	.512195	.536585	.560975
	b	.024390	.048780	0	.097560	.024390	.024390	0
	c	.292682	.121951	.170731	.097560	.024390	.024390	.048780
	d	0	.024390	.024390	.024390	.170731	.121951	.024390
	e	.073170	.146341	.097560	0	.024390	.048780	.146341
	f	.097560	.170731	.073170	0	.048780	.073170	.170731
	g	.121951	.235294	.097560	.048780	.024390	.048780	.146341

Table 4 normalized data after min max normalization

At this stage normalized scores are available for further processing. Now product rule, max rule and min rule is applied to above scenario.

person	a	b	c	d	e	f	g
a	.764705	.157818	.007173	.322811	.512195	.047345	.362983
b	0	.018651	0	.008608	.004304	.001431	0
c	.017216	.003586	.030128	.002869	.002152	.007173	0
d	0	.002152	.004304	.002869	.010042	0	.007180
e	.002152	.021520	.005738	0	.000717	.001434	0
f	.002869	.020085	.043040	0	.001434	.002152	.015064
g	.014347	.020761	.005738	.002869	.002869	.001434	.008608

Table 5 genuine and imposter scores of a person after product rule based fusion

person	a	b	c	d	e	f	g
a	1	.536585	.147058	.882352	1	.536585	.647058
b	.024390	.382352	0	.097560	.176470	.058823	.029411
c	.292682	.121951	.176470	.097560	.088235	.029411	.048780
d	.025882	.088235	.176470	.117647	.170731	.121951	.02944
e	.073170	.147058	.097560	.088235	.029411	.048780	.146341
f	.097560	.170731	.073170	.058823	.048780	.073170	.170731
g	.121951	.235294	.097560	.058823	.117647	.048780	.146341

Table 6 genuine and imposter scores of a person after max rule based fusion

person	a	b	c	d	e	f	g
a	.764705	.294117	.048780	.365853	.512195	.088235	.560975
b	0	.048780	0	.097560	.024390	.024390	0
c	.058823	.029411	.170731	.029411	.024390	.024390	0
d	0	.024390	.024390	.024390	.058823	0	.024390
e	.029411	.146341	.088235	0	.024390	.029411	0
f	.029411	.117647	.058823	0	.029411	.029411	.088235
g	.117647	.088235	.058823	.048780	.024390	.029411	.058823

Table 7 genuine and imposter scores of a person after min rule based fusion

VII. RESULTS EVALUATION

Now result is calculated by each rule. As already discussed that some genuine scores are assumed at first row, therefore in case of table 5 genuine scores have 7 values. Suppose in case of product rule a threshold is .0473 then there are 6 values which are greater than .0473 therefore GAR (genuine acceptance rate) is 6/7=.857=85.7% and FAR is 0, GAR specifies the accuracy of the system, FAR is false acceptance rate which specifies number of false users in system. But if a threshold is considered which is .00717 the GAR becomes 100% but problem occurs in case of FAR it becomes 30%.

However in case of table 6 which is of max rule if a threshold is .536 then GAR is 6/7=.857=85.7% and FAR is 0, but if threshold is .147 then GAR is 100% but FAR is 23.8%. In case of table 7 which is of min rule if a threshold is .294 then GAR is 5/7 =.714=71.4% and FAR is 0, but if threshold is .048 then GAR is 100% but FAR becomes 42.8%.

So it is clear from the above results that when some threshold is assumed it should be kept in mind that FAR should be as minimum as possible. As shown above that in all three rules when GAR is 85.7, 85.7 and 71.7 then FAR is 0 but when GAR becomes 100% then FAR also increases. Normally FAR should be kept as minimum as possible. Therefore results obtained initially when GAR is 85.7%, 85.7% and 71.7% is better as compared to 100%.

ROC curve for above results shown below

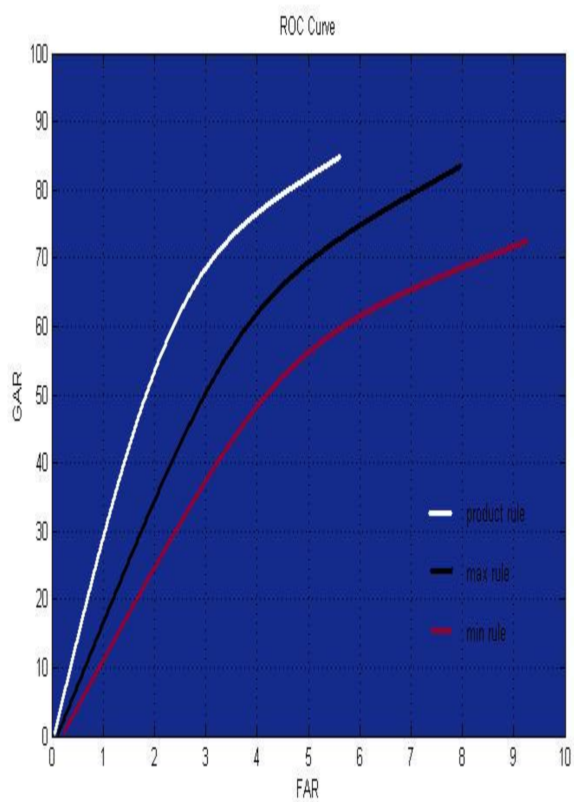

Fig.1 ROC curve for GAR and FAR

Figure 1 shows receiver operating characteristics curve for product rule, max rule and min rule, white line indicates product rule, black line indicates max rule and red line indicates min rule all these lines shows that as FAR is decreased GAR is increased.

VIII. CONCLUSION

This paper discusses about three rules which are product rule, max rule and min rule, an example is considered and all rules is applied on that example, results shows that FAR should be as minimum as possible and GAR should be as maximum as possible.

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