Robustness of Score Normalization in Multibiometric Systems

Radhey Shyam(✉) and Yogendra Narain Singh

Department of Computer Science and Engineering,
Institute of Engineering and Technology, 226 021 Lucknow, India
{shyam0058,singhyn}@gmail.com

Abstract. This paper presents an evaluation of normalization techniques of matching scores on the recognition performance of a multibiometric system. We present two score normalization techniques, namely modified-linear-tanh-linear (MLTL) and four-segments-double-sigmoid (FSDS) that are found to be robust in achieving the recognition performance to the optimum value. The techniques are tested in fusion of the two face recognition methods Fisherface and A-LBP on the dataset of uncontrolled environments. In particular, AT & T (ORL) face dataset is used in this experiment. The performance of the MLTL and FSDS score normalization techniques are compared with the existing normalization techniques, for instance min-max, tanh and linear-tanh-linear (LTL). The proposed normalization techniques show the significant improvement in the recognition performance of the multibiometric system over the known techniques.

Keywords: Face recognition · Multibiometric · Normalization · Identification

1 Introduction

The unibiometric system that is based on a single source of information suffers from the problems like lack of uniqueness, non-universality, and spoofing attacks. On the contrary, a multibiometric system harnesses relevant information obtained from multiple biometric cues. A strategic combination of these relevant information obtained from multiple biometric cues may overcome some of the problems of unibiometric systems [1–3].

Our concern is to combine several unibiometric systems to achieve a multibiometric system that meets the characteristics of a robust system i.e., optimum recognition accuracy and less falsifications [4–6]. In order to achieve these characteristics the matching scores obtained from different unibiometric systems need transformation and mapping before their fusion. The objective of transformation and mapping operations that refers the normalization process in the biometric terminology, is to supplement the information received at the matching score level of the biometric systems, so that the performance of the combined system improves. Therefore, score normalization is an intrinsic problem. It plays a

S. Jajodia and C. Mazumdar (Eds.): ICISS 2015, LNCS 9478, pp. 542–550, 2015.
DOI: 10.1007/978-3-319-26961-0_33

peculiar role in transforming and mapping the heterogeneous scores of distinct biometric cues into a homogeneous scale.

In literature, the normalization techniques has been found congenial in transforming the heterogeneous score to a homogeneous scale. An evaluation of normalization techniques of matching scores in multibiometric systems has been done by Singh and Gupta [7]. They reported the performance of linear-tanh-linear(LTL) and four-segments-piecewise-linear (FSPL) are better than min-max (MM), z-score and tanh normalization techniques. They also found that MM and z-score normalization techniques are susceptible to outliers. Therefore, it is needed to devise robust and efficient normalization technique that achieves optimum accuracy results.

In [7], let $O_k^T = \{r_{k_1}^T, r_{k_2}^T, ..., r_{k_N}^T\}$ be the set of true scores of N individuals and $O_k^I = \{r_{k_1}^I, r_{k_2}^I, ..., r_{k_n}^I\}$ be the set of impostor scores of those individuals where, $n = N \times (N-1)$ for biometric cue k. The composite set of matching scores is denoted as O_k (i.e., $O_k = O_k^T \cup O_k^I$ and $|O_k^T \cup O_k^I| = N + n = N^2$).

The distance scores (r'_{k_i}) of user i for biometric cue k can be converted into similarity scores in the typical scale, suppose it should be [0, 1] using the formula:

$$r_{k_i} = \frac{max(O_k^T, O_k^I) - r'_{k_i}}{max(O_k^T, O_k^I) - min(O_k^T, O_k^I)} \tag{1}$$

whereas r_{k_i} is the similarity scores of biometric cue k. Otherwise, if the distance scores lies in the range $[min(O_k), max(O_k)]$ then they are simply converted to similarity scores by subtracting them from $max(O_k)$ (e.g., $max(O_k - r'_{k_i})$). The precise summarization of these normalization techniques which transform the raw scores in the typical range of [0, 1], including double-sigmoid (DS), piecewise-linear (PL) are rendered in Table 1.

This paper proposes two new normalization techniques and evaluated their performance by fusing two face recognition methods in uncontrolled environments, namely Fisherface and augmented local binary pattern (A-LBP) [8–13]. The description of techniques are given in Sect. 2. A short discussion of fusion techniques is found in Sect. 3. The effect of normalization techniques on recognition performance achieved by a multibiometric system is reported in Sect. 4. Finally, the conclusions are outlined in Sect. 5.

2 Proposed Score Normalization Techniques

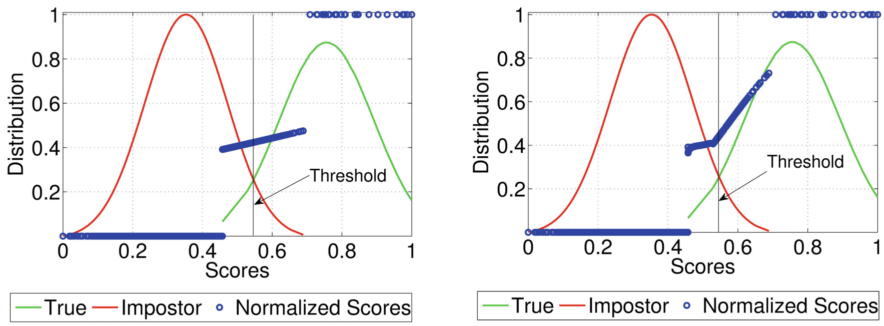
This section proposes two new normalization techniques that transform heterogeneous scores to homogeneous scores. The new formulations of normalizing the matching scores are named as: (i) Modified-linear-tanh-linear (MLTL) which is formulated over tanh and linear-tanh-linear (LTL) normalization techniques along with the conversion of linear function into sigmoid function and (ii) Four-segments-double-sigmoid (FSDS) cleaves the regions of true and impostor scores into four segments and map each segment using piecewise sigmoid functions.

Table 1. Summary of the existing normalization techniques

Normalization Technique	**Formula**
Min-max(MM)	$n_{k_i} = \dfrac{r_{k_i} - min(O_k)}{max(O_k) - min(O_k)}$
Z-score	$n_{k_i} = \dfrac{r_{k_i} - \mu O_k}{\sigma O_k}$
DS	$n_{k_i} = \begin{cases} \frac{1}{1+exp\left(-2\left(\frac{r_{k_i}-t_k}{t_{k_L}}\right)\right)} & \text{if } r_{k_i} < t_k, \\ \frac{1}{1+exp\left(-2\left(\frac{r_{k_i}-t_k}{t_{k_R}}\right)\right)} & \text{otherwise.} \end{cases}$
Tanh	$n_{k_i} = \frac{1}{2} * \left[tanh\left\{0.01 * \left(\frac{r_{k_i} - \mu_{O_k^T}}{\sigma_{O_k^T}}\right)\right\} + 1\right]$
PL	$n_{k_i} = \begin{cases} 0 & \text{if } r_{k_i} \leq min(O_k^T), \\ 1 & \text{if } r_{k_i} \geq max(O_k^I), \\ \frac{r_{k_i}-min(O_k^T)}{max(O_k^I)-min(O_k^T)} & \text{otherwise.} \end{cases}$
LTL	$n_{k_i} = \begin{cases} 0 & \text{if } r_{k_i} \leq min(O_k^T), \\ 1 & \text{if } r_{k_i} \geq max(O_k^I), \\ \frac{1}{2} * \left[tanh\left\{0.01 * \left(\frac{r_{k_i} - \mu_{O_k^T}}{\delta_{O_k^T}}\right)\right\} + 1.5\right] & \text{otherwise.} \end{cases}$
FSPL	$n_{k_i} = \begin{cases} 0 & \text{if } r_{k_i} \leq min(O_k^T), \\ \dfrac{r_{k_i} - min(O_k^T)}{t_k - min(O_k^T)} & \text{if } min(O_k^T) < r_{k_i} \leq t_k, \\ 1 + \dfrac{r_{k_i} - t_k}{max(O_k^I) - t_k} & \text{if } t_k < r_{k_i} \leq max(O_k^I), \\ 2 & \text{if } r_{k_i} > max(O_k^I). \end{cases}$

2.1 Modified-Linear-Tanh-Linear (MLTL)

This normalization technique reinforce the strength of the characteristic resulted from tanh and linear-tanh-linear (LTL) function as illustrated in Fig. 1(a). Normalization function of it corresponds the non overlap region of the impostor scores to a constant value 0 and non overlap region of the true scores to a constant value 1. The overlapped region between O_k^I and O_k^T is mapped to a sigmoid function using tanh and LTL evaluator as,



(a) (b)

Fig. 1. Proposed score normalization techniques (a) Modified-linear-tanh-linear (MLTL), and (b) Four-segments-piecewise-sigmoid (MSPS).

$$n_{k_i} = \begin{cases} 0 & \text{if } r_{k_i} < min(O_k^T), \\ 1 & \text{if } r_{k_i} > max(O_k^I), \\ \dfrac{1}{(1+\exp(-2*(0.1*z)))} & \text{otherwise.} \end{cases} \tag{2}$$

where $z = \dfrac{r_{k_i} - \mu O_k^T}{\delta O_k^T}$; and $\mu_{O_k^T}$, $\sigma_{O_k^T}$ are respectively the mean and standard deviation of the true matching scores of biometric cue k. The n_{k_i} is the normalized scores of biometric cue k.

2.2 Four-Segments-Double-Sigmoid (FSDS)

FSDS normalization technique cleaves the regions of true and impostor scores into four segments and map each segment using piecewise sigmoid functions as illustrated in Fig. 1(b). A reference point t_k is chosen between the overlapping regions of O_k^T and O_k^I. The scores between two extremities of the overlap region are mapped using two sigmoid functions separately in the range of [0, 1] towards left and right of t_k accordingly as,

$$n_{k_i} = \begin{cases} 0 & \text{if } r_{k_i} < min(O_k^T), \\ \dfrac{1}{(1+\exp(-2*(0.1*z)))} & min(O_k^T) \leq r_{k_i} \leq t_k, \\ \dfrac{1}{(1+\exp(-2*(0.5*p)))} & t_k < r_{k_i} \leq max(O_k^I), \\ 1 & \text{if } r_{k_i} > max(O_k^I) \end{cases} \tag{3}$$

where $z = \dfrac{r_{k_i} - \mu O_k^T}{\delta O_k^T}$ and $p = 2 * \left(\dfrac{r_{k_i} - min(O_k^T)}{max(O_k^I) - min(O_k^T)} \right) - 1$, the t_k is the threshold of biometric cue k.

3 Fusion Techniques

Kittler *et al.* [14], have developed a theoretical framework for reconciling the evidence achieved from more than one classifier schemes. These fusion rules are, such as sum, max, min, and product. Two more different fusion strategies namely strategy A and strategy B have been evaluated by Singh and Gupta in their studies [7]. In order to use these schemes, the matching scores are converted into posteriori probabilities conforming to a true user and an impostor. They consider the problem of classifying an input pattern Z into one of m possible classes based on the evidence presented by R different classifiers. Let $\boldsymbol{x_i}$ be the feature vector provided to the i^{th} classifier. Let the outputs of the respective

Table 2. Summary of the existing fusion techniques

Fusion Rule	Formula
Sum	$c = \underset{j}{\operatorname{argmax}} \sum_{i=1}^{R} p(w_j \mid \boldsymbol{x_i})$
Max	$c = \underset{j}{\operatorname{argmax}} \max_{i} p(w_j \mid \boldsymbol{x_i})$
Min	$c = \underset{j}{\operatorname{argmax}} \min_{i} p(w_j \mid \boldsymbol{x_i})$
Product	$c = \underset{j}{\operatorname{argmax}} \prod_{i=1}^{R} p(w_j \mid \boldsymbol{x_i})$
Fusion Strategy A [7]	$w_k = \left(\sum_{k=1}^{t} \frac{1}{e_k} \right)^{-1} * \frac{1}{e_k}$
Fusion Strategy B [7]	$d_k = \frac{\mu_{O_k^T} - \mu_{O_k^I}}{\sqrt{\left(\sigma_{O_k^T}\right)^2 + \left(\sigma_{O_k^I}\right)^2}}$ and $w_k = \left(\sum_{k=1}^{t} d_k \right)^{-1} * d_k$ where the fused score f_i for user i is computed as follows: $f_i = \sum_{k=1}^{t} w_k * n_{k_i}; (\forall i)$ where, $0 \leq w_k \leq 1$, $(\forall k)$; $\sum_{k=1}^{t} w_k = 1$.

classifiers be $p(w_j|\boldsymbol{x_i})$, *i.e.*, the posteriori probability of the pattern Z belonging to class w_j given the feature vector $\boldsymbol{x_i}$. Let $c \in \{1, 2, ..., m\}$ be the class to which the input pattern Z is finally assigned. Whereas in verification (one to one map) the value of m is 2 and in identification (one to many) the value of m is $n - 1$. The following fusion rules have been simplified by Jain *et al.* [15] for computing the value of class c that are given Table 2.

4 Experimental Results

The efficacy of the proposed normalization techniques are tested on fusion of the two face recognition methods in uncontrolled environments on AT & T (ORL) face dataset [16]. The images of this dataset suffers from the variations, such as pose, facial expression, and eye glasses. A total of 400 images are used to recognize 40 distinct individuals from the dataset. The system is trained for independent dataset composed of 40 true scores and 40×39 (i.e., 1560) impostor scores, whereas the test image is selected randomly from the given images for each individual and the performance is computed. The threshold value t_k is computed as the median of overlapped true and impostor scores. The performance of the proposed normalization technique is analyzed using equal error rate that is an error where the likelihood of acceptance is assumed to be same as to the likelihood of rejection of the people who should be correctly verified. This error is subtracted from 100 to compute the recognition accuracy. The performance of the proposed normalization techniques are also verified by the receiver operating characteristic (ROC) curves. The ROC curve is a two dimensional measure of classification performance that plots the likelihood of the true acceptance rate (TAR) against the likelihood of the false acceptance rate (FAR).

The recognition accuracies achieved by the score normalization techniques are rendered in Table 3. The accuracy values (%) for our proposed score normalization techniques i.e., FSDS (MLTL) are found better than other existing normalization techniques. For example, these values are 99.62(98.11), 97.21(96.89),

Table 3. Performance accuracies (%) of normalization techniques under different fusion criterions on AT & T (ORL) face dataset.

Methods	Normalization techniques	Accuracies(%)					
		Fusion techniques					
		Sum	Max	Min	Product	Strategy A	Strategy B
Fisherface + A-LBP	Min-max	97.95	97.50	97.50	97.92	97.98	97.98
	Tanh	98.01	96.86	97.50	98.01	97.92	97.98
	LTL	95.64	96.86	96.31	96.31	97.50	97.47
	MLTL	**98.11**	**96.89**	**97.56**	**98.11**	**97.98**	**98.11**
	FSDS	**99.62**	**97.21**	**97.79**	**99.62**	**99.55**	**99.65**

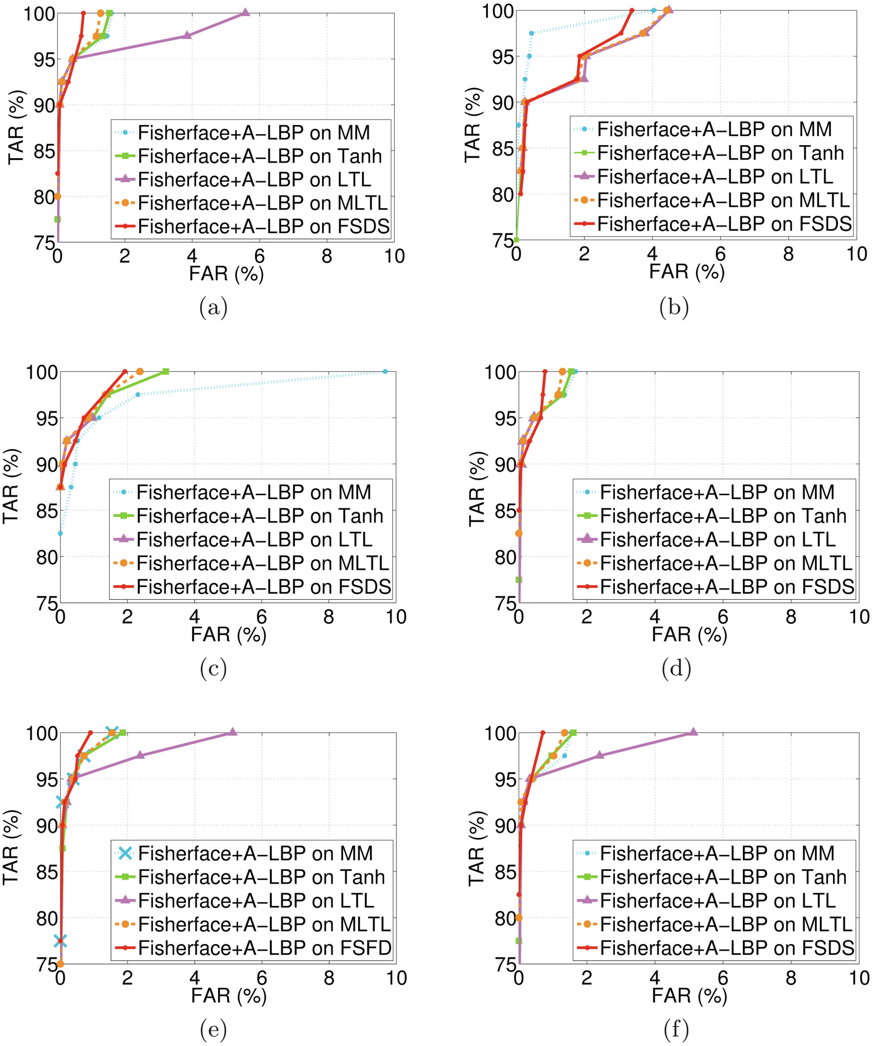


Fig. 2. Receiver operating characteristic curves show the performance of different normalization techniques of matching scores obtained from Fisherfaces and A-LBP methods using different fusion criterions on AT & T (ORL) face dataset.

97.79(97.56), 99.62(98.11), 99.55(97.98), 99.65(98.1), respectively for the fusion techniques, such as sum, max, min, product, strategy A and strategy B.

The receiver operating characteristic curves of the proposed score normalization techniques are plotted in accordance with their fusion techniques i.e., sum, max, min, product, strategy A, and strategy B as shown in Fig. 2. For example using sum rule, the proposed techniques FSDS (MLTL) render the TAR value of 80 % (83 %) at 0 % of FAR. The TAR value reaches to 100 % at 0.5 % (1.2 %)

of FAR for FSDS (MLTL) normalization technique. These values of TAR are far better than the other existing score normalization techniques as shown in Fig. 2(a). Next, under max rule of fusion the proposed technique FSDS (MLTL) shows the TAR value of 80 % (83 %) at 0.2 % of FAR. The TAR value reaches to 100 % at 3.3 % (4.4 %) of FAR for FSDS (MLTL) normalization technique. These values of TAR are better than the other existing normalization techniques as shown in Fig. 2(b).

Similarly, using min rule of fusion the proposed technique FSDS (MLTL) renders the TAR of 83 % (87 %) at 0 % of FAR. The TAR value reaches to 100 % at 1.9 % (2.1 %) of FAR for FSDS (MLTL) normalization technique. These values of TAR are far better than the other existing normalization techniques as shown in Fig. 2(c). The proposed technique FSDS (MLTL) shows the TAR value of 85 % (83 %) at 0 % of FAR using product rule of fusion. The TAR value reaches to 100 % at 0.9 % (1.4 %) of FAR for FSDS (MLTL) normalization technique. The reported values of TAR are better than the other existing normalization techniques using product rule as shown in Fig. 2(d).

For fusion strategy A, the normalization technique FSDS (MLTL) shows the TAR of 77 % (75 %) at 0 % of FAR. The TAR value reaches to 100 % at 0.8 % (1.7 %) of FAR for FSDS (MLTL) normalization technique. These values of TAR are better than the other normalization techniques as shown in Fig. 2(e). Same results are also reported for fusion strategy B e.g., the FSDS (MLTL) normalization technique reported the TAR of 83 % (80 %) at 0 % of FAR. The TAR reaches to 100 % at 0.7 % (1.3 %) of FAR for FSDS (MLTL). The reported values of TAR are found better than the other normalization techniques using the fusion strategy B as shown in Fig. 2(f).

The recognition accuracy results of the suggested techniques i.e., MLTL and FSDS indicate that these score normalization techniques can contribute a peculiar role in the design of a robust multibiometric system.

5 Conclusion

This paper has presented two novel techniques of score normalization namely, modified-linear-tanh-linear (MLTL) and four-segments-double-sigmoid (FSDS). The performance of these proposed score normalization techniques has been evaluated and the fusion of face recognition methods Fisherface and A-LBP. The performance of the proposed score normalization techniques have found better than the existing min-max, tanh and linear-tanh-linear (LTL) normalization techniques. This evaluation of score normalization techniques of matching scores insinuates that the proposed techniques may play an important role in evaluating the performance of a multibiometric system.

Acknowledgements. The authors acknowledge the Institute of Engineering and Technology (IET), Lucknow, Uttar Pradesh Technical University (UPTU), Lucknow for their partial financial support to carry out this research under the Technical Education Quality Improvement Programme (TEQIP-II) grant.

References

1. Jain, A.K., Ross, A.: Multibiometric systems. Commun. ACM **47**(1), 34–40 (2004)
2. Snelick, R., Uludag, U., Mink, A., Indovina, M., Jain, A.: Large scale evaluation of multimodal biometric authentication using state-of-the-art systems. IEEE Trans. Pattern Anal. Mach. Intell. **27**(3), 450–455 (2005)
3. Bolle, R.M., Ratha, N.K., Pankanti, S.: Error analysis of pattern recognition systems the subsets bootstrap. Comput. Vis. Image Underst. **93**(1), 1–33 (2004)
4. Shyam, R., Singh, Y.N.: Identifying individuals using multimodal face recognition techniques. Procedia Comput. Sci. Elsevier **48**, 666–672 (2015)
5. Singh, Y.N., Singh, S.K., Gupta, P.: Fusion of electrocardiogram with unobtrusive biometrics: an efficient individual authentication system. Pattern Recogn. Lett. Elsevier **33**(11), 1932–1941 (2012)
6. Singh, Y.N.: Human recognition using fisher's discriminant analysis of heartbeat interval features and ECG morphology. Neurocomputing Elsevier **167**(2015), 322–335 (2015)
7. Singh, Y.N., Gupta, P.: Quantitative evaluation of normalization techniques of matching scores in multimodal biometric systems. In: Lee, Seong-Whan, Li, Stan Z. (eds.) ICB 2007. LNCS, vol. 4642, pp. 574–583. Springer, Heidelberg (2007)
8. Shyam, R., Singh, Y.N.: A taxonomy of 2D and 3D face recognition methods. In: Proceedings of 1st International Conference on Signal Processing and Integrated Networks (SPIN 2014), pp. 749–754. IEEE, February 2014
9. Shyam, R., Singh, Y.N.: Evaluation of eigenfaces and fisherfaces using bray curtis dissimilarity metric. In: Proceedings of 9th IEEE International Conference on Industrial and Information Systems (ICIIS 2014), pp. 1–6. IEEE, Gwalior, December 2014
10. Shyam, R., Singh, Y.N.: Face recognition using augmented local binary patterns and bray curtis dissimilarity metric. In: Proceedings of 2nd International Conference on Signal Processing and Integrated Networks (SPIN 2015), pp. 779–784. IEEE, Noida, February 2015
11. Shyam, R., Singh, Y.N.: Analysis of local descriptors for human face recognition. In: Smart Innovation, Systems and Technologies, vol. 43, pp. 263–269. Springer, October 2015
12. Shyam, R., Singh, Y.N.: Automatic face recognition in digital world. Adv. Comput. Sci. Inf. Technol. (ACSIT) **2**(1), 64–70 (2015)
13. Shyam, R., Singh, Y.N.: Recognizing individuals from unconstrained facial images. Adv. Intell. Syst. Comput. Ser. Springer **384**, 383–392 (2015)
14. Kittler, J., Hatef, M., Duin, R., Matas, J.: On combining classifiers. IEEE Trans. Pattern Anal. Mach. Intell. **20**(3), 226–239 (1998)
15. Jain, A., Nandakumar, K., Ross, A.: Score normalization in multimodal biometric systems. Pattern Recogn. **38**(12), 2270–2285 (2005)
16. Samaria, F., Harter, A.: Parameterisation of a stochastic model for human face identification. In: Proceedings of 2nd IEEE Workshop on Applications of Computer Vision, Sarasota, FL, December 1994