A FUZZY-BASED TWO-STAGE BIOMETRIC SAMPLE QUALITY EVALUATION SYSTEM

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ABSTRACT

Performance of biometric systems is highly dependent on the quality of the input samples captured by the sensing device. Although measures are taken for capturing high quality images, but the authentication system mandates the analysis of captured images for selection of precise data. The benefit of such an analysis are two-fold; it helps to identify the best sample, and is useful for improving the sensor design, user interface for sample collection and providing data interchange standards. In this work, we propose to analyse the quality of the sample data by using a two-stage fuzzy quality evaluation system. The proposed work has been demonstrated on the iris images using $CASIA-3.0$ Interval, $CASIA-4.0$ Interval and $IIT\ Delhi$ iris database. We evaluate the quality of the images by classifying them into classes. The experimental results verify the efficacy of the proposed method.

Index Terms— Biometric Quality, Fuzzy System, Local Quality Feature, Global Quality Feature

1. INTRODUCTION

Regardless of all the efforts taken to capture high quality biometric samples, it becomes mandatory to analyse the quality of a scanned data for precise extraction of biometric features. It is because biometric recognition system's performance does not entirely depend on its recognition algorithm or sensor technology used but both. Recognition algorithm takes images as input and works accordingly with no tolerance to artefacts. While, the sensors only captures images without analyzing its quality. Therefore, for the recognition systems to work effectively biometric sample quality analysis is necessary. Further, this can also be benefiacial in improving the performance of spoof detection systems [1].

Traditional approaches to evaluate the performance of a biometric system generally focuses at the system level [2, 3]. Although these approaches have effectively evaluated emerging technologies, new biometric modalities, and algorithm revisions, but, the focus on system-level evaluations have overlooked the issues present at the ground level (that is, sample collection). To tackle the issues related to quality of biometric sample several concerted efforts have been made with respect to: a) global features and b) local features.

Daugman and Downing [4] analysed the effect of motion and image compression of iris sample and verified its performance for identification purposes. Hugo Proença in [5] proposes a method to assess the quality of visible wavelength (VW) iris samples using focus, motion, angle, occlusions, area, pupillary dilation, and levels of iris pigmentation as quality estimation factors. Chen et al. [6] used the strength of ridges as global features to evaluate the quality of fingerprint images. Automatic fingerprint matching approach was proposed in [7] by analysing the image quality. In the same line, face quality analysis helped in decreasing uncertainty of identity for a given sample. Further, quality analysis helped in prediction of relevant classes. Kalka et al. [8] carried out the measurement of various degradations known to affect iris recognition through quality analysis. Confidence of generating reliable matching scores from the user templates was also made possible through the quality analysis of *Knuckles* [9]. Besides, some authors proposed a general feature selection framework for identifying degree of extractability of features [10].

Although, the existing approaches help in estimating the quality of the complete image, but the overall computational complexity of the system becomes very high. Thus, to speed up this process it is necessary that the quality analysis is done in two stages. In the proposed approach we develop a *no-reference biometric quality prediction system* with low computational complexity. We propose a two step approach which classify the images on the basis of their quality. Efficacy of the proposed approach has been demonstrated by applying the proposed approach over iris sample data.

2. PROPOSED APPROACH

The performance of biometric systems suffer due to the usage of poor quality images which suppresses the effective features. The gap between collection of useful images and the extraction of effective features can be bridged if the quality of the captured images is analysed before feature extraction step.

As a feasible solution to the above-mentioned issue, we propose a quantitative quality assessment strategy which helps in selecting the useful images. The proposed approach assists in quick quality assessment of the scanned image, thereby helps in quick decision making of accepting or rejecting the sample.

In the preliminary screening, a quality score (global quality score) is calculated which is compared with the predefined threshold, t_{IQ}. If the quality score is greater than the threshold value then the scanned image is accepted otherwise rejected. An accepted image is further segmented to extract region of interest (ROI). The quality score (local quality score) of specific (precise) region is evaluated. Finally, based on the obtained quality score of sample, the image is categorized into classes.

3. EXPOSITION OF THE PROPOSED MECHANISM ON IRIS DATA

There are several factors that determine the quality of an iris image and when each of these factors is within a predefined threshold/range, the iris image can be said to be of high quality. The proposed quality evaluation methodology works in two stages: a) Pre-segmentation stage and b) Post-segmentation stage. The overview of the proposed quality evaluation approach is shown in 1.

The factors contributing to the quality of an iris image before segmentation are called global quality features and those after segmentation are local quality features. In this work, the considered global quality features are *focus* [11], *interlacing* [12] and *blur* [13] whereas, local quality features consists of *occlusion* [14], *dilation* [15], *displacement* [16], *lighting variation* [8].

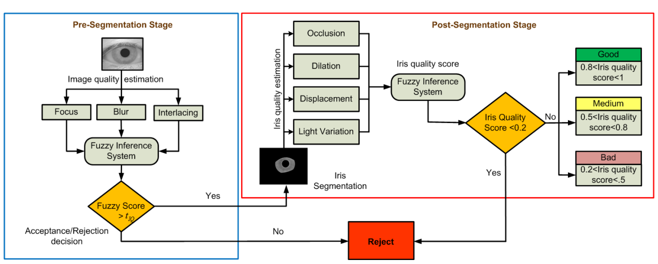


Fig. 1: Overview of the iris quality estimation and classification

3.1. Pre-segmentation stage

Quality of the iris images are analysed to evaluate the presence or absence of artefacts arising due to $defocus$, $blur$ or $interlacing$. The individual score of $focus$, $blur$ and $interlacing$ is taken in the range of 0 to 100 and are combined using fuzzy rules. Here, it is noteworthy to mention that the fuzzy sets of the considered variables follow triangular membership function.

For defining the ranges of fuzzy states for each quality parameter, we have used 50% of the database images and induced blur, defocus and interlace errors upon them. Thereafter, from these degraded images the considered quality parameters are evaluated. Using the evaluated parameters, quality score is calculated; and based on this score the fuzzy state is identified. Overview of the proposed fuzzy model for the pre-segmentation stage is shown in Figure 2.

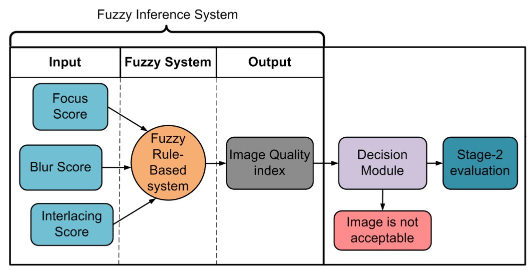


Fig. 2: Quality assessment in pre-segmentation stage

Input variables: The input variables ($i.e.$, $Focus(F)$, $Blur(B)$, $Interlace(I)$ are in the range of 0 to 100. All these variables are divided into four fuzzy states as shown in Table 1. It is worthy to note that, an image is said to be of good quality iff it has high focus score, low blur score and low interlace score.

Table 1: Pre-segmentation stage fuzzy input values

	Levels			
	Low (L)	Medium (M)	High (H)	Very High (VH)
Focus	[0 0 40]	[32 46 60]	[52 66 80]	[72 100 100]
Blur	[0 0 20]	[5 22 40]	[30 50 70]	[55 100 100]
Interlace	[0 0 20]	[5 22 40]	[30 50 70]	[55 100 100]

Fuzzy rule base: The details about the various rules involved in our proposed fuzzy system are tabulated in Table 2.

Table 2: Rule-base of pre-segmentation stage

S. No.	Input Features			Output
	Focus	Blur	Interlace	
1	L	-	-	Reject
2	H	L	L/M	Accept
3	H	L	H/VH	Reject
4	H	M	L	Accept
5	H	M	M/H/VH	Reject
6	M	L	L	Accept
7	M	L	M/H/VH	Reject
8	M	M	-	Reject
9	-	H/VH	-	Reject
10	VH	L	L/M	Accept
11	VH	L	H/VH	Reject
12	VH	M	L/M	Accept
13	VH	M	H/VH	Reject

Output: Output of the pre-segmentation fuzzy system gives decision regarding accepting or rejecting an image from further processing. The acceptable images first undergo the segmentation stage which is followed by the post-segmentation stage where images are classified into different classes.

3.2. Segmentation

From the acceptable images, the ROI is identified for the process of feature extraction. For this, the iris localization algorithm [17] is used which aims to find the centers and the radii of the two boundaries to isolate the annular iris region from the entire eye image.

3.3. Post-segmentation stage

Here, we identify whether the iris features can be effectively extracted from the ROI. The quality features, namely, $occlusion$, $dilation$, $displacement$ and $lighting\ variation$ are evaluated and the overall scores obtained from them is used to classify the images amongst the four classes as $good$, $medium$, bad or $worst$. Overview of the post-segmentation stage is diagrammatically shown in Fig 3.

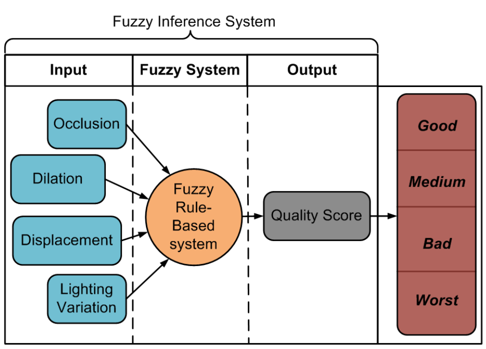


Fig. 3: Quality assessment in post-segmentation stage

Input: The considered input variables ($i.e.$, $occlusion$, $dilation$, $displacement$ and $lighting\ variation$) are in the range of *0* to *100*. They are divided into four fuzzy states: low(L) (0 0 30), medium(M) (20 35 50), high(H) (40 55 70), very high(VH) (60 100 100).

Fuzzy rule base: The various fuzzy rules involved to classify images in the post-segmentation stage are tabulated in Table 3.

Output: Output of the fuzzy model classifies the images into one of the four classes based on how effectively the identifying features can be extracted from the images.

4. EXPERIMENT

4.1. Experimental setup

All image categorization and matching (inter/intra class) experiments are performed using Matlab *2016a* on a PC having an Intel *i5* processor (3.20 GHz), 4 GB memory. Three iris databases namely, *CASIA 3.0* [18], *CASIA 4.0* [19] and *IIT Delhi Iris Database* [20] have been used for performing the experiments. Details about the databases are given in Table 4.

Table 3: Rule-base of post-segmentation stage

S. No.	Input Features				Output
	Occlusion	Dilation	Displacement	Lighting Variation	
1	L	L	L/M	-	Good
2	L	L	H/VH	-	Medium
3	L	M	L		Good
4	L	M	M		Medium
5	L	M	H	L/M	Medium
6	L	M	H	H/VH	Bad
7	L	M	VH	L/M	Medium
8	L	M	VH	H/VH	Bad
9	L	H	-	-	Bad
10	-	VH	-	-	Worst
11	M	L	L		Good
12	M	L	M		Medium
13	M	L	H	L/M	Medium
14	M	L	H	H/VH	Bad
15	M	L	VH	L/M	Medium
16	M	L	VH	H/VH	Bad
17	M	M	L/M	-	Medium
18	M	M	H/VH	-	Bad
19	M	H	-	-	Bad
20	H	M	-	-	Bad
21	H	H	-	-	Worst
22	VH	-	-	-	Worst

Table 4: Iris datasets used in experiments

Database	Version	Total Images	Total Subjects	Training Images	Testing Images	Band	Resolution
CASIA	V 3.0-Interval [18]	2639	249 (×2)	1320 (1-116L)	1319 (116R-249)	NIR	320 × 280
CASIA	V 4.0-Interval [19]	2639	249 (× 2)	1320 (1-116L)	1319 (116R-249)	NIR	320 × 280
IITD [20]	V 1.0	2240	224 (× 2)	1120 (1-112)	1120 (113-224)	NIR	320 × 240

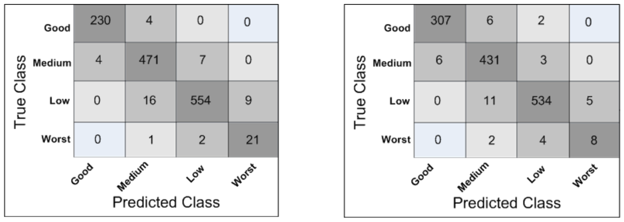
5. RESULT AND DISCUSSION

The efficacy of the proposed approach has been verified by testing it on the mentioned databases (refer 4.1). Based on the obtained results, the classification accuracy has been analyzed.

5.1. Accuracy of classification

Biometric quality metrics are used for predicting the matching performance of the biometric sample. In this work, the d-prime index has been calculated to predict the matching performance. The formula of d-prime index [16, 21] for estimating the overall quality (QS_X) of a sample X is given in Eq. 1

$$QS_X = \frac{m(Imp.Scores)_X - m(Gen.Scores)_X}{var(Imp.Scores)_X + var(Gen.Scores)_X} \quad (1)$$



(a) (b)

Fig. 4: Confusion matrix for (a) CASIA-4.0-Interval and (b) CASIA-3.0-Interval database

where, $m(.)_X$ and $var(.)_X$ are the mean and variance of genuine and imposter scores formed by involving the sample X. The accuracy of the proposed quality estimation technique with respect to d-prime index is shown with the help of confusion matrices (refer Fig. 4 and 5).

Fig. 5: Confusion matrix for IITD database

Next, we perform the matching operation for every class and evaluate the EER using Gabor Energy features [22] to indicate the overall performance of the biometric system. The system performance is considered to be more accurate if it gives a lower EER value (see Table 5). To calculate EER, we have evaluated *False Non-Match Rate* (FNMR) and *False Match Rate* (FMR) and plotted them separately for each database to obtain the respective *Detection Error Tradeoff* (DET) curves.

Table 5: EER of different classes of images over different databases

Database	**EER (in %)**			
	Good	**Medium**	**Low**	**Worst**
CASIA 3.0-Interval [18]	0.01605	0.09534	0.1208	0.173
CASIA 4.0-Interval [19]	0.00263	0.0913	0.0624	0.105
IITD [20]	0.00437	0.0455	0.0810	0.255

From the plotted DET graphs, it can be noted that for all databases the EER for *good* quality images is quite low and subsequently the EER increases as the image quality decreases (refer Fig. 8). From the obtained result, it is quite prominent that for recognition, evaluation of image quality is necessary for effective performance of the system.

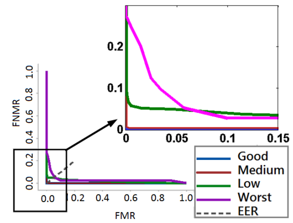
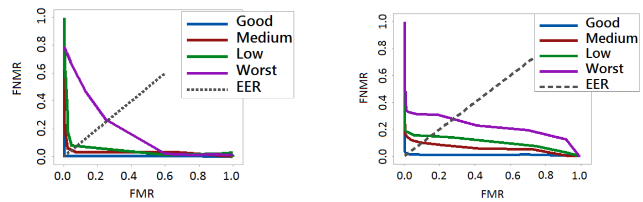


Fig. 6: DET curve of CASIA-4.0-Interval database



(a) (b)

Fig. 7: DET curve of (a) CASIA-3.0-Interval and (b) IITD database

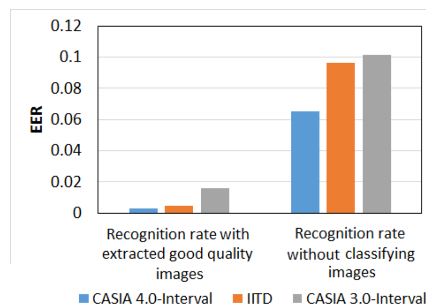


Fig. 8: Bar chart representing EER for classified and non-classified images

6. CONCLUSION

Now-a-days biometric imaging sensors are being widely used by several organizations to increase the level of security and also to protect their data and copyrights. However, quality measurement of the captured images are an operationally important and difficult problem that is nevertheless massively under researched in comparison to the primary feature extraction and pattern recognition tasks. In this paper, we enumerated a technique for easy and fast computation of quality score from a sample. We propose a two stage fuzzy approach to make a quantitative assessment of iris images. The proposed work is believed to show high potential for selection of best quality images for improving performance of iris recognition systems. Future work will focus on improving the estimation techniques for the described quality factors and experimenting with the new measures of quality scores.

7. REFERENCES

[1] Murilo Varges da Silva, Aparecido Nilceu Marana, and Alessandra Aparecida Paulino, "On the importance of using high resolution images, third level features and sequence of images for fingerprint spoof detection," in *Acoustics, Speech and Signal Processing (ICASSP), 2015 IEEE International Conference on*. IEEE, 2015, pp. 1807–1811.

[2] Mingxing He, Shi-Jinn Horng, Pingzhi Fan, Ray-Shine Run, Rong-Jian Chen, Jui-Lin Lai, Muhammad Khurram Khan, and Kevin Octavius Sentosa, "Performance evaluation of score level fusion in multimodal biometric systems," *Pattern Recognition*, vol. 43, no. 5, pp. 1789–1800, 2010.

[3] Patrick Bours and Soumik Mondal, "Performance evaluation of continuous authentication systems," *IET Biometrics*, vol. 4, no. 4, pp. 220–226, 2015.

[4] John Daugman and Cathryn Downing, "Effect of severe image compression on iris recognition performance," *IEEE Transactions on information Forensics and Security*, vol. 3, no. 1, pp. 52–61, 2008.

[5] Hugo Proença, "Quality assessment of degraded iris images acquired in the visible wavelength," *IEEE Transactions on Information Forensics and Security*, vol. 6, no. 1, pp. 82–95, 2011.

[6] Tai Pang Chen, Xudong Jiang, and Wei-Yun Yau, "Fingerprint image quality analysis," in *Image Processing, 2004. ICIP'04. 2004 International Conference on*. IEEE, 2004, vol. 2, pp. 1253–1256.

[7] Patrick Grother and Elham Tabassi, "Performance of biometric quality measures," *IEEE transactions on pattern analysis and machine intelligence*, vol. 29, no. 4, pp. 531–543, 2007.

[8] Nathan D Kalka, Jinyu Zuo, Natalia A Schmid, and Bojan Cukic, "Estimating and fusing quality factors for iris biometric images," *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, vol. 40, no. 3, pp. 509–524, 2010.

[9] Ajay Kumar and David Zhang, "Improving biometric authentication performance from the user quality," *IEEE transactions on instrumentation and measurement*, vol. 59, no. 3, pp. 730–735, 2010.

[10] Norman Poh and Josef Kittler, "A unified framework for biometric expert fusion incorporating quality measures," *IEEE transactions on pattern analysis and machine intelligence*, vol. 34, no. 1, pp. 3–18, 2012.

[11] John Daugman, "How iris recognition works," *IEEE Transactions on circuits and systems for video technology*, vol. 14, no. 1, pp. 21–30, 2004.

[12] Kevin W Bowyer and Mark J Burge, *Handbook of iris recognition*, Springer, 2016.

[13] Frederique Crete, Thierry Dolmiere, Patricia Ladret, and Marina Nicolas, "The blur effect: perception and estimation with a new no-reference perceptual blur metric.," in *Human vision and electronic imaging*, 2007, vol. 12, p. 64920.

[14] Ankita Satish Adhau and DK Shedge, "Iris recognition methods of a blinked eye in nonideal condition," in *Information Processing (ICIP), 2015 International Conference on*. IEEE, 2015, pp. 75–79.

[15] Jinyu Zuo and Natalia A Schmid, "Global and local quality measures for nir iris video," in *Computer Vision and Pattern Recognition Workshops, 2009. CVPR Workshops 2009. IEEE Computer Society Conference on*. IEEE, 2009, pp. 120–125.

[16] N Schmid, Jinyu Zuo, Francesco Nicolo, and Harry Wechsler, "Iris quality metrics for adaptive authentication," in *Handbook of Iris Recognition*, pp. 101–118. Springer, 2016.

[17] Farmanullah Jan, "Segmentation and localization schemes for non-ideal iris biometric systems," *Signal Processing*, vol. 133, pp. 192–212, 2017.

[18] "Note on CASIA-IrisV3," `http://biometrics.idealtest.org/dbDetailForUser.do?id=3`, 2010, Online; accessed 13 September 2017.

[19] "Note on CASIA-IrisV4," `http://http://biometrics.idealtest.org/dbDetailForUser.do?id=4`, 2010, Online; accessed 13 September 2017.

[20] "IIT Delhi Iris Database (Version 1.0)," `http://http://www4.comp.polyu.edu.hk/~csajaykr/IITD/Database_Iris.htm`, 2007, Online; accessed 13 September 2017.

[21] Thomas D Wickens, *Elementary signal detection theory*, Oxford University Press, USA, 2002.

[22] Somnath Dey and Debasis Samanta, "Iris data indexing method using gabor energy features," *IEEE Transactions on Information Forensics and Security*, vol. 7, no. 4, pp. 1192–1203, 2012.