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Abstract. In a face authentication system, face image quality can significantly influence system performance. Designing an effective image quality measure is necessary to reduce the number of poor quality face images acquired during enrollment and authentication, thereby improving system performance. Furthermore, image quality scores can be used as weights in multimodal system based on weighted score level fusion. In this paper, the authors examined image quality factors, such as contrast, brightness, focus and illumination, and defined quality measure for these factors. The quality measure used template image's, or registration image's, quality as reference quality. Thus, the quality measure does not rely on any reference good quality and criteria to evaluate how good a face image is. The quality measure reflects difference in quality between a template image and a query image. Then, we proposed a face quality measure by combining these factors. Finally, we conducted experiments to evaluate the relationship between face authentication performance and individual image quality factors as well as the combined face quality measure.

Keywords: Face quality index · Face quality measure · Face authentication · Quality metrics

1 Introduction

In biometric systems, the surrounding environment can highly impact on the quality of the input biometric data so that it also affects the system performance [1]. Improving the matching performance does not rely on improving only the matching algorithm but the input biometric data. Poor quality data can decrease the efficiency of the biometric system. Thus, assessing the quality of the input biometric data prior to processing, can be beneficial in terms of improving matching performance.

Moreover, in multimodal systems, qualities of different input modals can play an important role in determining the weight of each modal in the weighted-based fusion scheme. For example, in a multimodal system of two modalities, including face and voice, in order to authenticate to the system, a user must present his face and voice. The system considers that the modality input with a better

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quality can have a better matching accuracy. Therefore, the system will rate the better-quality-input modality higher than the other. The final decision is also highly depended on the better one.

Image quality measures are typically modality specific. There are two categories of quality measures, including generic (used for any biometric modality) and specific (designed to address issues related to a specific biometric modality). However, it is hard to design a on-size-fits-all quality measure for all biometric modalities. Most researches define quality measure for specific modality such as iris [2], fingerprints [3] or faces [4–6]). For the face modality, based on two-dimensional (2D) visible images, generic image quality measures such as average image (AVI) [7], universal quality index (UQI) [8] and IQM [9] can be used. Biometric researchers have also developed modality-specific image quality assessment measures such as those based on redundant wavelets [10].

Several techniques have been proposed in the literature that discuss the benefits of using image quality factors for solving face recognition related problems. However, biometric systems are expected to determine which technique to use to compute a specific quality factor. For example, the sharpness factor can be assessed using several techniques [11,12]. The decision to select one technique over another is problem/application specific and often is made based on experience. However, such a heuristic decision making process becomes even more complicated when multiple image quality factors are considered (sharpness, illumination, focus etc.). Processing time can be saved and face recognition accuracy can benefit from having an alternative solution, that is, a unified technique for computing multiple image quality factors.

The main contributions of this work are: (i) evaluation of various image quality factors for face images, (ii) proposal of a new generic face quality measure.

The rest of the paper is organized as follows: Sect. 2 presents a number of quality factors for face images. Next, we propose a generic face quality measure in Sect. 3. Section 4 is the evaluation of our proposed measure. Conclusions and future works are discussed in Sect. 5.

2 Quality Factors for Face Images

In order to evaluate quality of a face images for authentication, we need to examine various factors, including image's features and posing positions. In scope of this paper, the posing position of face is frontal face. This assumption is quite acceptable in case of mobile authentication in which users have to face to the mobile's cameras. In this paper, we considered four popular image features including brightness, contrast, focus, and illumination.

2.1 Brightness

Brightness is defined as an attribute of a visual sensation according to which a given visual stimulus appears to be more or less intense [13]. The image brightness measure can be calculated as the average of the brightness component after converting it into the HSB color space [14]. HSL stands for hue, saturation, and brightness, and is also often called HSV (V for value)) or HSL (L for lightness).

Another approach is to use YUV color space instead of HSB. Y stands for the luminance component (the brightness) and U and V are the chrominance (color) components. YUV is a color space which encodes a color image taking human perception into account. In our experiments, we calculated image brightness under both HSB and YUV color space. The results showed that image brightness under YUV color space has a higher correlation to the authentication performance. Thus, we calculated image brightness based on YUV color space.

$$B = \frac{\sum_{x=1}^{M} \sum_{y=1}^{N} Y(x,y)}{M.N} \ . \tag{1}$$

where $Y(x, y)$ is the luminance (the brightness) component of a pixel (x, y). The size of image is M × N.

Y is computed from RGB as follows:

$$Y = 0.299R + 0.587G + 0.114B \ . \tag{2}$$

2.2 Contrast

Image contrast is the difference in color intensities of the object and other objects within the same field of view. In face images, contrast shows how a face object distinguishes from the background. A simple way to calculate image contrast is the Michelson contrast equation [15,16]:

$$C = \frac{I_{max} - I_{min}}{I_{max} + I_{min}} \ . \tag{3}$$

where I_{min}, and I_{max} are the minimum and maximum intensity values of the face image.

Another technique to calculate image contrast is the Root Mean Square (RMS) equation [11,17]:

$$C = \sqrt{\frac{\sum_{x=1}^{M} \sum_{y=1}^{N} (I(x,y) - \mu)^2}{M.N}} \ . \tag{4}$$

where μ is the mean intensity value of the face image $I(x, y)$ of size $N \times M$.

Michelson contrast measure does not represent the image contrast factor well due to the fact that it depends only on the maximum and minimum intensity values of the image. Therefore, we used the RMS equation for image contrast. In the experiment, raw images are converted to gray-scale images before calculating contrast values so $I(x, y)$ is in range [0, 256]. The image size is 108 × 108.

2.3 Focus

Image focus refers to the degree of blurring of face images. Image focus can be computed from the energy of the Laplacian which is defined as follows [18]:

$$F = \sum_{x=1}^{M}\sum_{y=1}^{N}(|G_{xx}(x,y)| + |G_{yy}(x,y)|)^2 \ . \tag{5}$$

where G_{xx} and G_{yy} are the second derivatives of the image gradient in the horizontal and vertical directions, respectively.

2.4 Illumination

Luminance distortion is one of the measures of the image factor related to illumination. The term luminance is used to describe the amount of light that passes through or is emitted from a particular area of the image [20]. Image illumination measure is calculated as the weighted sum of the mean intensity values of the image divided into (4–4) blocks [21].

$$I = \sum_{i=1}^{4}\sum_{j=1}^{4} w_{ij}.\bar{I}_{ij} \ . \tag{6}$$

where w_{ij} is the weight factor, and $\bar{I}_{ij}$ is the average intensity value of each block. In a face image, list of weight factors are defined in [21]. The weights are designed so that the middle of image is more considerable than the area near the edge.

3 Proposed Face Quality Measure

A face quality measure should show how good a face image is for an authentication process. In our approach, an image has a good quality if it is taken under a similar condition with the template image. The condition includes brightness factor, contrast factor, focus factor and illumination factor of the image. It means that we compare the conditions in which the two images, e.g. template image and query image, are taken in order to conclude the quality of the query image.

Firstly, we calculated the quality of each factor. Then, we combine them into a single face quality measure.

3.1 Individual Quality Factor Measure

In this section, we used brightness factor for illustration. The other factors work in the same scheme.

Let $B_{template}, B_{query}$ be the brightness values of the template and query images and D_B be the distance of these images.

$$D_B = |B_{template} - B_{query}| \ . \tag{7}$$

The smaller the D_B value is, the better quality is, and vice versa. Then, we normalized the distance in the range [0, 1], where '0' corresponds to bad quality and '1' corresponds to good quality, by using min-max normalization technique. The normalized distance is also the brightness quality measure Q_B.

$$Q_B = 1 - \frac{D_B - D_{Bmin}}{D_{Bmax} - D_{Bmin}} \,. \tag{8}$$

Similarly, contrast quality Q_C, focus quality Q_F and illumination quality measure Q_I are defined.

3.2 Face Quality Measure

We proposed a quality measure for face images which combines individual quality factors in the previous section. Several methods are introduced to combine 'normalized' quality scores [22,23].

- Minimum: $\bar{q} = min(q_1, q_2)$
- Geometric mean: $\bar{q} = \sqrt{q_1.q_2}$
- Difference: $\bar{q} = |q_1 - q_2|$
- Mean: $\bar{q} = \frac{q_1+q_2}{2}$

However, the two quality scores q_1, q_2 may have different effects on the authentication performance. For example, in face authentication, system performance of Principle Component Analysis (PCA) technique [24], which is a common technique to extract feature vectors, is highly affected by brightness. In the evaluation section, the correlation value of brightness is much higher than the correlation values of the other factors. Therefore, to combine quality scores of individual quality factors, we used a weighted average scheme in which correlation values are weights for each quality factors. Correlation value or correlation coefficient reflect relationship between distance of quality and distance of feature vectors from a same person's images. The details of the calculation of correlation coefficients are presented in Sect. 4 (Evaluation).

Let w_B, w_C, w_F, w_I be correlation values of quality factors brightness, contrast, focus, and illumination respectively. We defined a face image quality score Q which is a combination of quality factors as follows:

$$Q = \frac{w_B.Q_B + w_C.Q_C + w_F.Q_F + w_I.Q_I}{w_B + w_C + w_F + w_I} \,. \tag{9}$$

The face image quality measure Q is also in the range [0, 1] where '0' corresponds to bad quality and '1' corresponds to good quality. This proposed quality measure differently treats quality factors of a single biometric feature depending on their correlation values with the authentication performance.

4 Evaluation

In this section, we present various experiments to evaluate: (i) the relationship between individual face quality factor and face authentication performance, and (ii) the effect of the proposed face quality measure to face authentication performance. In our experiments, the face authentication performance is represented by the distance between the template feature vector which is used for registration and the query feature vector which is used for authentication. In general, the expected results of these experiments should confirm that for images from a same person, the better quality score is (e.g. the closer to zero the quality score is), the smaller the distance between template and query feature vectors is (e.g. the higher the authentication performance is).

The algorithm to extract feature vectors from face images is Principle Component Analysis (PCA) [24].

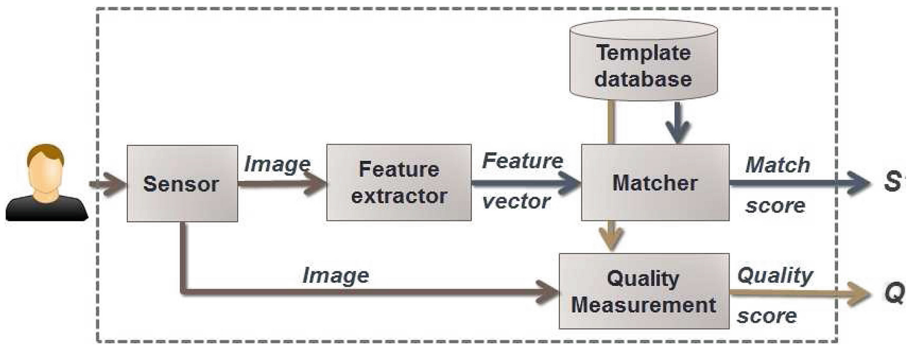

Fig. 1. The evaluation process for face quality

The evaluation process for face quality is carried out as follows:

The first stage: Registration

1- A user registers to the system by supplying his template image. Feature vector is extracted and saved in the template database with user ID.
2- The system calculates quality score of each factor (brightness, contrast, focus, illumination) from the template image and also saves them in the template database.

The second stage: Authentication and Quality Measurement

1- The user presents a query image to the system to authentication. The feature vector of query image is extracted and compared with the feature vector of template image to get match score (the distance between the two feature vectors).
2- The system calculates quality score of each factor (brightness, contrast, focus, illumination) from the query image. Then, the system produces the generic quality measure for the query image by comparing quality scores of the query image to quality scores of the template image.

We repeated the above process for each pair of images of a same person in the face database and then evaluate the correlation coefficient value between the face quality measure and the face authentication performance (Fig. 1).

The face database used for evaluation consists of 1050 frontal face images from 10 people each of whom has 105 images and 44 frontal face images from other people to generate eigen-vectors. In order to evaluate the effects of quality factors to authentication performance, each person is asked to take pictures in a variety of conditions using his/her mobile device.

Fig. 2. Some sample images in the testing database

We supposed that a "good" quality measure in authentication should reflect the following assumption: *"For a same person, a query image is classified"* *good for authentication* *"if the distance of template and query feature vectors is closed enough to conclude a positive result. Further more, the result should be independent of the algorithm which is used to extract the feature vectors"* (Fig. 2).

In the experiment, for every person, for every pair of his/her images, we calculated a pair of the quality score and the distance of feature vectors. Then we used Pearson correlation coefficient to measure the correlation between the quality scores and the distance of feature vectors. The above process is carried out for all quality factors to get correlation coefficient values. The below table shows correlation coefficient values of brightness, contrast, focus, and illumination factor.

According to these correlation coefficient values, using the PCA algorithm, the brightness factor has the highest impact to the authentication system, while focus and illumination factor have less impact. Please note that, these correlation coefficient values may be changed if the authentication system uses another algorithm to generate feature vectors. These individual quality factor scores become weights in the Eq. 9.

Table 1. Correlation coefficient values of quality measures

Quality measure	Correlation coefficient value
Brightness	0.824
Contrast	0.484
Focus	0.071
Illumination	0.106
Generic face quality measure: mean	0.749
Generic face quality measure: geometric mean	0.605
Generic face quality measure: weighted mean	0.836

Next, we conducted an experiment to evaluate the relationship between the generic face quality measure and face authentication performance in the same way for individual factors. We examined three methods to combine quality factors, including mean, geometric mean and weighted mean (our proposed method). The correlation coefficient values of generic face quality measure are also shown in Table 1. Our proposed quality measure has a highest correlation coefficient values (**0.836**). This result confirms a high correlation between the proposed face quality measure and face authentication performance. Further more, we can conclude that our face quality measure is practical and can be applied in reality.

5 Conclusions and Future Works

This paper presented quality factors for face images and proposed a face quality measure for authentication. The authors' approach is different from previous researches. The proposed quality measure does not rely on any predefined good quality criteria or any reference good images. The face authentication systems, especially mobile face authentication systems, can be deployed in various environments and used different feature extraction algorithms. Therefore, it is hard to define good quality criteria and select a set of reference good images that fit all cases. We used a template image, which a user register to the authentication system, as a reference image to evaluate the quality of the query images from that user. Thus, every user has his/her own reference image. In other words, a query image has a good quality if it is taken under a similar condition with the template image.

In general, our quality measure can be applied for other biometric trails, such as voice, fingerprint, iris, and so on. Thus, the next work is to conduct more experiments on the other biometric trails to confirm the *practical* and *correctness* properties of the proposed quality measure.

After that, we will design a quality-based fusion solution for multi-modal system. The fusion solution will consider quality score of each biometric trail as weighted factor.

References

1. Jain, A., Ross, A., Nandakumar, K.: Introduction to Biometrics. Springer, New York (2011)
2. Zuo, J., Schmid, N.: Adaptive quality-based performance prediction and boosting for iris authentication: methodology and its illustration. IEEE Trans. Inf. Forensics Sec. **2013**(8), 1051–1060 (2013)
3. Merkle, J., Schwaiger, M., Breitenstein, M.: Towards improving the NIST fingerprint image quality (NFIQ) algorithm. In: International Conference on Biometrics Special Interest Group (BIOSIG), Darmstadt, Germany (2010)
4. Hsu, R.L.V., Shah, J., Martin, B.: Quality assessment of facial images. In: Biometric Consortium Conference (BCC), Baltimore, MD, USA (2006)
5. Bhattacharjee, D., Prakash, S., Gupta, P.: No-reference image quality assessment for facial images. In: Huang, D.-S., Gan, Y., Gupta, P., Gromiha, M.M. (eds.) ICIC 2011. LNCS (LNAI), vol. 6839, pp. 594–601. Springer, Heidelberg (2012). doi:10.1007/978-3-642-25944-9_77
6. Wong, Y., Chen, S., Mau, S., Sanderson, C., Lovell, B.: Patch-based probabilistic image quality assessment for face selection and improved video-based face recognition. In: IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), Colorado Springs, CO, USA, 2011, pp. 74–81 Won+11, KrD06, WaB02, AdD06, VSN08, Gao+07, Yao+08 (2011)
7. Kryszczuk, K., Drygajlo, A.: On combining evidence for reliability estimation in face verification. In: European Signal Processing Conference (EUSIPCO), Florence, Italy (2006)
8. Wang, Z., Bovik, A.C.: A universal image quality index. IEEE Sig. Process. Lett. **2002**(9), 81–84 (2002)
9. Adler, A., Dembinsky, T.: Human vs. automatic measurement of biometric sample quality. In: IEEE Canadian Conference on Electrical and Computer Engineering (CCECE), Ottawa, Canada (2006)
10. Vatsa, M., Singh, R., Noore, A.: SVM-based adaptive biometric image enhancement using quality assessment. In: Prasad, B., Prasanna, S. (eds.) Speech, Audio, Image and Biomedical Signal Processing using Neural Networks. SCI, vol. 83, pp. 351–367. Springer, Heidelberg (2008)
11. Gao, X., Li, S.Z., Liu, R., Zhang, P.: Standardization of face image sample quality. In: Lee, S.-W., Li, S.Z. (eds.) ICB 2007. LNCS, vol. 4642, pp. 242–251. Springer, Heidelberg (2007)
12. Yao, Y., Abidi, B.R., Kalka, N.D., Schmid, N.A., Abidi, M.A.: Improving long range and high magnification face recognition: database acquisition, evaluation, and enhancement. Comput. Vis. Image Underst. **2008**(111), 111–125 (2008)
13. Wyszecki, G., Stiles, W.S.: Color science, Concepts and Methods, Quantitative Data and Formulae. Wiley, New York (2000)
14. Bezryadin, S., Bourov, P., Ilinih, D.: Brightness calculation in digital image processing. In: International Symposium on Technologies for Digital Fulfillment, Las Vegas, NV, USA (2007)
15. Michelson, A.: Studies in Optics. University of Chicago Press, Chicago (1927)
16. Bex, P.J., Makous, W.: Spatial frequency, phase, and the contrast of natural images. J. Opt. Soc. Am. A **19**(6), 1096–1106 (2002)
17. Peli, E.: Contrast in complex images. J. Opt. Soc. Am. A **7**(10), 2032–2040 (1990)
18. Yap, P.-T., Raveendran, P.: Image focus measure based on Chebyshev moments. IEEE Proc. Vis. Image Sig. Process. **151**(2), 128–136 (2004)

19. Pertuz, S., Puig, D., Garcia, M.A.: Analysis of focus measure operators for shape-from-focus. Pattern Recogn. **46**(5), 1415–1432 (2013)
20. Abaza, A., Harrison, M.A., Bourlai, T., Ross, A.: Design and evaluation of photometric image quality measures for effective face recognition. IET Biometrics **3**(4), 314–324 (2014)
21. Abdel-Mottaleb, M., Mahoor, M.: Application notes algorithms for assessing the quality of facial images. IEEE Comput. Intell. Mag. **2**, 10–17 (2007)
22. Grother, P., Tabassi, E.: Performance of biometric quality measures. IEEE Trans. Pattern Anal. Mach. Intell. **29**, 531–543 (2007)
23. Kryszczuk, K., Richiardi, J., Drygajlo, A.: Impact of combining quality measures on biometric sample matching. In: IEEE International Conference on Biometrics: Theory Applications and Systems (BTAS), Washington, DC, USA (2009)
24. Turk, M., Pentland, A.: Eigenfaces for recognition. J. Cogn. Neurosci. **3**, 71–86 (1991)