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Design and evaluation of photometric image quality measures for effective face recognition

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Abstract: The performance of an automated face recognition system can be significantly influenced by face image quality. Designing effective image quality index is necessary in order to provide real-time feedback for reducing the number of poor quality face images acquired during enrollment and authentication, thereby improving matching performance. In this study, the authors first evaluate techniques that can measure image quality factors such as contrast, brightness, sharpness, focus and illumination in the context of face recognition. Second, they determine whether using a combination of techniques for measuring each quality factor is more beneficial, in terms of face recognition performance, than using a single independent technique. Third, they propose a new face image quality index (FQI) that combines multiple quality measures, and classifies a face image based on this index. In the author's studies, they evaluate the benefit of using FQI as an alternative index to independent measures. Finally, they conduct statistical significance Z-tests that demonstrate the advantages of the proposed FQI in face recognition applications.

1 Introduction

The performance of biometric systems in operational environments can be impacted by several factors [1], including the quality of the input biometric data (e.g. face image). Poor quality data can cause efficiency loss 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.

Before we discuss our proposed approach let us first introduce some image-related notations and terminology that will be used through the remainder of this paper:

- *Quality factors* are image quality attributes such as contrast, brightness, sharpness, focus and illumination.
- *Quality measures* are techniques that are used to quantify quality factors. These measures can be arranged in an array called 'quality matrix'.
- *Quality index* is a single number that represents the overall image quality of a biometric modality (e.g. face image).

Image quality measures (IQMs) are typically modality specific. Two categories of quality measures can be distinguished: generic (can be used for any biometric modality) or specific (viz. designed to address issues related to a specific biometric modality such as iris [2], fingerprints [3] or faces [4–6]). For the face modality, based on two-dimensional (2D) visible images, generic IQMs 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].

Face-based quality factors can be categorised in many different ways. One such categorisation, based on ISO/IEC standards, is described as follows (see Table 1):

- Factors related to the digital formatting of face images such as spatial resolution and contrast of grey-scale images.
- Factors related to scenes where faces are present such as head rotation, illumination, eyes, glasses and mouth.
- Factors related to photographic clauses such as head position in the image, exposure, brightness, focus and sharpness.

Several techniques have been proposed in the literature that discuss the benefits of using image quality factors for solving various 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 [12, 13]. 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 could

Table 1 Face image requirements as per ISO/IEC-19794–5 [11]

Clause	Factor	Constraint
digital	resolution	inter-eye distance
	contrast	grey-scale range over facial area
scene	head rotation	yaw, roll and pitch angles
	background	texture uniformity and brightness
	illumination	uniformly illuminated/shadows
	eyes	open/closed
	glasses	flash reflections or tinted lens
	mouth	open/closed and visibility
photographic	head position	face centred in the image
	colour	brightness
	exposure	luminance distribution
	focus	clarity of image details

be saved and face recognition accuracy can benefit from having an alternative solution, that is, a unified technique for computing multiple image quality factors.

To the best of our knowledge, there is no comparative study among such techniques in the context of face recognition. Therefore, it is necessary to determine the single, most appropriate, technique for a given factor. Secondly, there are no established ways to consolidate quality measures corresponding to different factors into a single index value that characterises the quality of a query face image.

The contributions of this paper are as follows:

(1) Perform a comparative study of various techniques that have been used to measure quality factors such as contrast, brightness, focus, sharpness and illumination. In particular, we evaluate the correlation between the measure used and a known (manually adjusted or computed) degradation in image quality (see Section 4).
(2) Determine the most practical set of quality measures based on their correlation with systematic image degradation and computational speed.
(3) Propose an alternative face image quality index (FQI) to predict face matching performance (see Fig. 1).

For the purpose of this study, we utilised several face databases, viz. CASPL [14], YALE [15], FERET [16], MBGC [17], FOCS [18] and QFIRE [19]. The rest of this paper is organised as follows. Section 2 describes the databases used throughout this paper. Section 3 summarises some of the evaluation criteria for image quality assessment measures. Section 4 presents a study on the evaluation of various IQMs, followed by selection of the practical measures Section 5, and integration of the selected measures into a face quality index Section 6. Section 7 presents the results of applying our proposed image quality

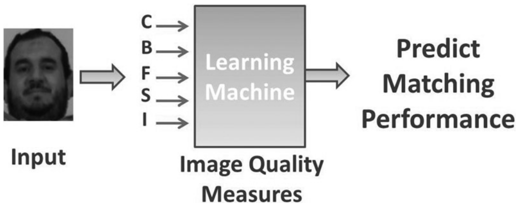

Fig. 1 *Neural network to integrate (C: contrast, B: brightness, F: focus, S: sharpness, I: illumination) quality measures into an unified quality index that is designed to predict the expected matching performance based on face image quality*

index to both real data as well as data in which different image quality factors were manually adjusted, that is, synthetically changed (in the rest of the paper such data will be called 'simulated' data), followed by a case study to show beneficial usage of the proposed quality index. Conclusions and future work are discussed in Section 8.

2 Databases used

We evaluated a set of established IQMs using the following face databases: CASPL [14], Yale [15], FERET [16], MBGC [17], good–bad–ugly [18] and QFIRE [19]. Several face data sets, generated from the aforementioned databases, were evaluated:

- *CASPL:* CASPEAL database [14] contains 99 594 face images of 1040 individuals (595 males and 445 females) of variable pose, expression, accessories and lighting (PEAL).
- *Yale:* 38 gallery images from Yale [15] database where the light source direction with respect to the camera axis is at 0° azimuth and 0° elevation; and several probes data sets with illumination changes azimuth or elevation with respect to the camera axis.
- *FTMC:* A set of 238 subjects from FERET [16] and 107 from MBGC [17] databases forming 345 gallery images and 345 corresponding probes.
- *Good–ugly:* 1085 image pairs from the good set and 1085 image pairs from the face and ocular challenge series (FOCS) database [18] were used.
- *QFIRE:* A set of 90 subjects from QFIRE [19] database were used: (i) 1800 face images from the normal setting images; (ii) 1080 face images extracted randomly from videos captured at 5, 15 and 25 feet while adjusting the focal plane of the camcorder across the full range; and (iii) 3240 face images extracted randomly from videos captured at three different illumination settings, that is, low, medium and high.

3 Quality measure evaluation criteria

Sheikh *et al.* [20] defined the goal of quality assessment measures to be: 'objective evaluation of quality in a way that is consistent with subjective human evaluation'. However, in the field of biometrics, this objective is consistent with matching or recognition accuracy. Table 2 summarises some of the evaluation criteria for image quality assessment measures. To the best of our knowledge, Hsu *et al.* [4] presented the only face quality assessment measure that is driven by face-based matching scores.

Other similar case studies for image quality assessment include:

Table 2 Classification of image quality assessment measures based on evaluation criteria

Method	Evaluation criteria
IQM algorithm [9]	quality evaluation by human participants
pose estimation, sharpness, brightness and spatial resolution [21]	quality-based rankings compared with human rankings
focus [22]	synthesised degradation using Gaussian noise
illumination [12]	using various illuminated data from 'Yale database'

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- Yao *et al.* [13], measure the sharpness of face images, where the authors first, enhanced these images and, then, they performed FR before, finally comparing it to using un-enhanced images.
- Poh *et al.* [23], use a fusion algorithm that attempts to select a subset of biometric modalities/systems in order to achieve the maximal generalisation performance. In [24], Poh *et al.* normalised the quality-based score, and, then, FR performance was compared with linear normalisation.
- Vatsa *et al.* [10] fused the quality-based score, and then FR performance was compared with linear normalisation.
- Bhatt *et al.* [25] proposed a framework for quality-based classifier selection, and, then, recognition performance was performed to regular fusion cases.
- Kryszczuk and Drygajlo [26] used signal quality measures and classifier scores to improve performance in uni- and multi-modal scenarios.

4 Quality factors and measures for face images

Various IQMs have been reported in the literature that were used for face recognition. The most frequently used ones are those measuring the following quality factors [11]: (a) brightness, (b) contrast, (c) focus, (d) sharpness and (e) illumination. As discussed in the introduction, for each of the aforementioned factor, multiple measures are available in the literature. In this paper, our goal is to design, develop and evaluate a unified technique that combines various IQMs and generates a single value that can be used to represent the level of overall quality of query face images when used in practical face recognition scenarios.

4.1 Contrast

Image contrast is the difference in colour intensities that makes an object (face) distinguishable. The face image contrast [12] can be measured using the following equation

$$C_{\mathrm{RMS}} = \sqrt{\frac{\sum_{x=1}^{M}\sum_{y=1}^{N}[I(x,y)-\mu]^2}{MN}} \quad (1)$$

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

Another technique for image contrast is the Michelson contrast measure [27]

$$C_{\mathrm{Mic}} = \frac{I_{\max} - I_{\min}}{I_{\max} + I_{\min}} \quad (2)$$

where $I_{\min}$, and $I_{\max}$ are the minimum and maximum intensity values of the test face image I (Fig. 2).

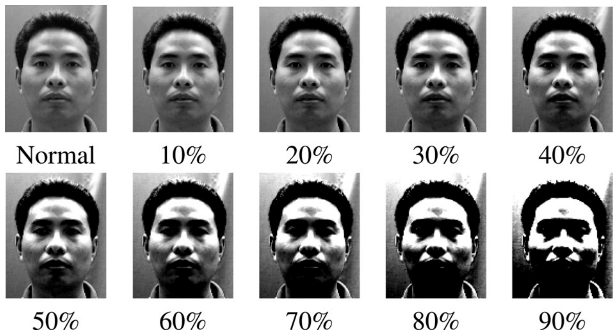

Fig. 2 *Contrast changes, where percentage of the face image intensity values are saturated (images from CASPL [14])*

4.2 Brightness

Wyszecki and Stiles [28] define brightness as an attribute of a visual sensation according to which a given visual stimulus appears to be more or less intense; or, according to which the area in which the visual stimulus is presented appears to emit more or less light, and range variation in brightness from ‘bright’ to ‘dim’ [29].

The face image brightness measure (let us denote it by B_1) can be calculated as the average of the brightness component after converting it into the HSB (hue, saturation and brightness) domain [29]. To convert from RGB (red, green and blue) colours to HSB range, each component is first normalised to the [0, 1] range as follows

$$\begin{bmatrix} r \\ g \\ b \end{bmatrix} = \frac{1}{255} \times \begin{bmatrix} \mathrm{R} \\ \mathrm{G} \\ \mathrm{B} \end{bmatrix}$$

$$B_1 = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}[\max(r, g, b)] \quad (3)$$

Bezryadin *et al.* [29] suggested another image brightness measure

$$B_2 = \sqrt{D^2 + E^2 + F^2} \quad (4)$$

$$\begin{bmatrix} D \\ E \\ F \end{bmatrix} = \begin{bmatrix} 0.2053 & 0.7125 & 0.4670 \\ 1.8537 & -1.2797 & -0.4429 \\ -0.3655 & 1.0120 & -0.6104 \end{bmatrix} \times \begin{bmatrix} X \\ Y \\ Z \end{bmatrix}$$

where X, Y and Z are the tristimulus values. To convert from RGB colours to XYZ range, each component is first normalised to the [0–1] range

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.4124 & 0.3576 & 0.1805 \\ 0.2126 & 0.7152 & 0.0722 \\ 0.0193 & 0.1192 & 0.9505 \end{bmatrix} \times \begin{bmatrix} r \\ g \\ b \end{bmatrix}$$

4.3 Focus and sharpness

Image focus refers to the degree of blurring of face images. For a thin lens, given an object (face) at distance O_d, and the image is formed at distance I_d; the focal distance of the lens f is given by: $1/f = 1/O_d + 1/I_d$. If the face is displaced from O_d, the energy from the face through the camera lens is distributed over a circular patch on the image plane, thus will form a blurred face image [22].

Yap and Raveendran [22] presented several image focus measures such as the L_1-norm of the image gradient, and the energy of the Laplacian. The L_1-norm of the image is defined as

$$F_{L_1} = \sum_{x=1}^{M}\sum_{y=1}^{N}|G_{xx}(x,y)| + |G_{yy}(x,y)| \quad (5)$$

and the energy of the Laplacian of the image as

$$F_{\mathrm{EL}} = \sum_{x=1}^{M}\sum_{y=1}^{N}[G_{xx}(x, y) + G_{yy}(x, y)]^2 \qquad (6)$$

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

Image sharpness describes the clarity of detail in a face image, and it refers to the degree of clarity in both coarse and fine details [12]. Several image sharpness measures have been proposed in the literature. Kryszczuk and Drygajlo [7] defined image sharpness measure as

$$S_1 = \frac{1}{2}\left[\frac{1}{(N-1)M}\sum_{x=1}^{M}\sum_{y=1}^{N-1}|I_{x,y} - I_{x,y+1}| + \frac{1}{(M-1)N}\sum_{x=1}^{M-1}\sum_{y=1}^{N}|I_{x,y} - I_{x+1,y}|\right] \qquad (7)$$

Gao *et al.* [12] defined the image sharpness measure as

$$S_2 = \sum_{x=1}^{M-2}\sum_{y=1}^{N-2}G(x, y) \qquad (8)$$

where $G(x, y)$ is the gradient value at (x, y).

The Tenengrad sharpness measure is defined as

$$\begin{aligned} S_3 &= \sum_{x=1}^{M}\sum_{y=1}^{N}(L_x \cdot I_x^2 + L_y \cdot I_y^2) \\ L_x(x, y) &= [I(x+1, y) - I(x-1, y)]^P \\ L_y(x, y) &= [I(x, y+1) - I(x, y-1)]^P \end{aligned} \qquad (9)$$

where L_x, L_y are the weights in the horizontal and vertical directions, and I_x, I_y are the horizontal and vertical gradients obtained by applying the Sobel filter.

The adaptive Tenengrad sharpness measure [13] is defined as

$$\begin{aligned} S_4 &= \sum_{x=1}^{M}\sum_{y=1}^{N}L(x, y)[I_x^2 + I_y^2] \\ L(x, y) &= [I(x-1, y) + I(x+1, y) \\ &\quad - I(x, y-1) - I(x, y+1)]^P \end{aligned} \qquad (10)$$

where $L(x, y)$ is the non-separable weight, and P is a power index that can define the degree of noise suppression.

4.4 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. The UQI is a combination of three main factors: loss of correlation, luminance distortion and contrast distortion. The luminance distortion is defined as

$$I_1 = \frac{2\sigma_{rt}\bar{r}\bar{t}}{[\bar{r}^2 + \bar{t}^2]} \qquad (11)$$

where $\bar{r}$ and $\bar{t}$ are the variances of the reference (r) and test image (t), respectively, and σ_{rt} is the covariance of (r) and (t).

Another image illumination measure [30] is calculated as the weighted sum of the mean intensity values of the image divided into (4 × 4) blocks

$$\begin{aligned} I_2 &= \sum_{i=1}^{4}\sum_{j=1}^{4}w_{ij}.\bar{I}_{ij} \\ \bar{I}_{ij} &= \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}I(x, y) \end{aligned} \qquad (12)$$

where w_{ij} is the weight factor of each block. Abdel-Mottaleb and Mahoor [30] defined a Gaussian mask to add weights to various blocks of the face. This has the effect of assigning large weights to the blocks in the middle of the image and small weights to image boarders.

5 Selection of quality measures

In this work, in order to evaluate the performance of various face quality measures, face images from CASPL [14] and Yale [15] databases were used. We synthetically change CASPL images by adjusting the contrast, brightness and blurriness. What follows is a description of the process we used to asses the performance of each quality measure, by calculating the correlation coefficient:

Contrast: The CASPL face images were saturated at low and high intensities (see Table 3, and Fig. 6), in a step of 10%. For example, for the 10%, the values in intensity image I, range [$\mathrm{LOW_{IN}} = 0$, $\mathrm{HIGH_{IN}} = 1$], are mapped to new values [$\mathrm{LOW_{OUT}} = 0.05$, $\mathrm{HIGH_{OUT}} = 0.95$]. Values below $\mathrm{LOW_{IN}}$ and above $\mathrm{HIGH_{IN}}$ are clipped; that is, values below $\mathrm{LOW_{IN}}$ map to $\mathrm{LOW_{OUT}}$, and those above $\mathrm{HIGH_{IN}}$ map to $\mathrm{HIGH_{OUT}}$. C_{RMS}, corr = 0.996, represents the face image contrast factor better than the Michelson contrast measure (C_{Mic}, corr = 0.684). Michelson contrast measure does not represent the image contrast factor well, we return this to the fact that Michelson contrast measure depends only on the maximum and minimum values of the image. Hence, we denote the selected contrast measure by $C = C_{\mathrm{RMS}}$.

Brightness: The image brightness was artificially adjusted via the 'gamma' parameter, shown in Table 3 and Fig. 3, in 10% steps. Gamma specifies the shape of the curve describing the relationship between the values in input and output images. Both face image brightness measures (B_1 and B_2) achieve

Table 3 Contrast and the brightness measures, where the face image intensity values were mapped to new values in the output image, and time in milliseconds

Contrast			Brightness		
CASPL	C_{RMS}	C_{Mic}	CASPEAL	B_1	B_2
normal	**0.4284**	**0.9277**	$\gamma = 0.5$	0.6135	0.6824
10%	0.4735	0.976	$\gamma = 0.6$	0.5382	0.6417
20%	0.5151	0.9931	$\gamma = 0.7$	0.4756	0.6054
30%	0.5578	0.9986	$\gamma = 0.8$	0.4226	0.5724
40%	0.6047	0.9999	$\gamma = 0.9$	0.3774	0.5424
50%	0.6564	1	**normal**	**0.3133**	**0.5148**
60%	0.7119	1	$\gamma = 1.1$	0.3045	0.4893
70%	0.7731	1	$\gamma = 1.2$	0.2753	0.466
80%	0.8393	1	$\gamma = 1.3$	0.2497	0.4444
90%	0.9085	1	$\gamma = 1.4$	0.2271	0.4243
corr	0.996	0.684	**corr**	0.974	0.993
time, ms	4.1	11.3	**time, ms**	230	11

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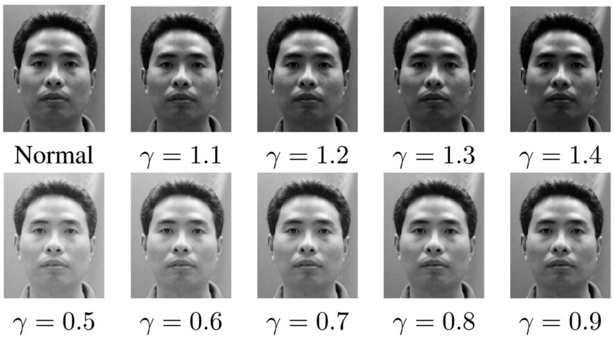

Fig. 3 *Brightness changes, where the face image intensity values are mapped to new values in the output image (images from CASPL [14])*

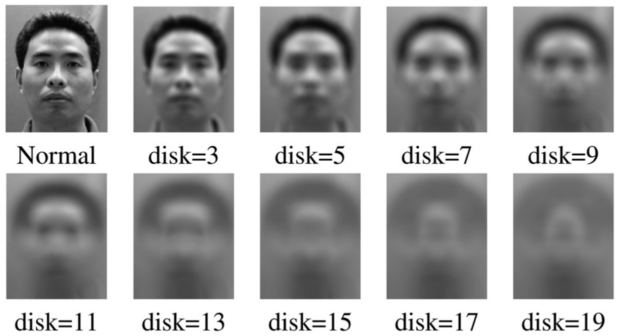

Fig. 4 *Blurring of the input face images using a circular averaging filter (denoted as 'disk') with various diameters (images from CASPL [14])*

the same performance $\left(\mathrm{corr}_{B_1} = 0.974,\ \mathrm{corr}_{B_2} = 0.993\right)$. However, the computation of B_2 is very time consuming, about 22 times compared to that required by B_1. Hence, the brightness measure is B_1.

Focus and sharpness: Each image, under study, was blurred using a circular averaging filter over a region of diameter equals to 3–19 pixels, in increments of 2 pixels (see Table 4 and Fig. 4). Empirical evaluation suggested that: (i) the two measures of the face image focus factor achieve almost the same performance ($\mathrm{corr}_{F_{L1}} = 0.752$, $\mathrm{corr}_{F_{\mathrm{EL}}} = 0.608$) and they require almost the same computational time. Hence, we decide to use an average of the two measures $F = F_{L_1} + F_{\mathrm{EL}}/2$ and (ii) similarly, in terms of sharpness, we use an average of the first two sharpness measures, that is, $S = S_1 + S_2/2$.

Illumination: Seven sets from the Yale [15] database, each captured under different illumination conditions were used, as shown in Table 5. From the empirical evaluation performed, we show that the two image illumination measures I_1 and I_2, achieve almost the same performance $\left(\mathrm{corr}_{I_1} = 0.938,\ \mathrm{corr}_{I_2} = 0.881\right)$. However, I_2 does not need a reference image, and requires less processing time to be computed. Hence, the illumination measure is I_2.

6 Proposed FQI

Each of the aforementioned IQMs can only provide an estimate of a single image quality factor. However, several biometric applications would require to have a general quality index used to indicate the overall quality of input data (e.g. face images, iris images etc.). The general quality can be used to: (i) reduce the number of poor quality face images acquired during enrollment thereby improving matching performance; and (ii) add weights in case of integrating the matching scores of several probes. Integrating these quality measures into a FQI ensures the collection of good quality images during enrollment. In this paper, we examine several criteria to calculate our proposed FQI and, via a set of experiments, illustrate that this FQI can complement the usage of conventional IQMs.

6.1 Quality measures fusion schemes

Grother and Tabassi [31] combined 'normalised' quality measures, that is, in the range [0, 1], where '0' corresponds

Table 5 Illumination measures evaluation using real sets from yale database obtained with different illumination effects, and time in milliseconds

Yale	I_1	I_2
set1	0.9442	0.8886
set2	0.9295	0.9636
set3	0.8579	0.5650
set4	0.7947	0.8162
set5	0.6704	0.5766
set6	0.5439	0.5744
set7	0.2069	0.2124
corr	0.938	0.881
time, ms	20.8	2.3

Table 4 Focus and the sharpness measures, where smoothing of the input face images was introduced by using a circular averaging filter (denoted as 'd') with various diameters, and time in milliseconds

CASPL	Focus		Sharpness			
	F_1	F_2	S_1	S_2	S_3	S_4
normal	0.0374	0.2879	0.7161	0.6819	0.4748	0.4354
$D = 3$	0.0125	0.0259	0.4573	0.4363	0.0296	0.0014
$D = 5$	0.0072	0.0074	0.3641	0.3460	0.0071	0.0002
$D = 7$	0.0049	0.0032	0.3035	0.2876	0.0024	4×10^{-5}
$D = 9$	0.0036	0.0016	0.2566	0.2427	0.0010	1×10^{-5}
$D = 11$	0.0028	0.0009	0.2174	0.2057	0.0004	7×10^{-6}
$D = 13$	0.0022	0.0006	0.1859	0.1761	0.0002	4×10^{-6}
$D = 15$	0.0019	0.0004	0.1610	0.1527	0.0001	3×10^{-6}
$D = 17$	0.0016	0.0003	0.1413	0.1341	7×10^{-5}	2×10^{-6}
$D = 19$	0.0015	0.0003	0.1250	0.1187	4×10^{-5}	1×10^{-6}
corr	0.752	0.608	0.918	0.917	0.592	0.560
time, ms	10.2	7.1	4.2	4.3	6.6	3.8

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to bad quality and ‘1’ corresponds to good quality, for two compared fingerprints using several methods [32]:

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

Kalka *et al.* [33] used Dempster-Shafer theory approach as a combination scheme for ‘normalised’ quality measures. Given the belief that quality is bad (value = A), and the belief that quality is good (value = B), Kalka *et al.* [33] adopt Murphy’s combination rule to integrate beliefs. The following equation is a generalised expression for combining beliefs from ($k = 5$) quality factors m_1 to m_k:

$$\widehat{m_i(A)} = \frac{(\widehat{m_{i-1}(A)} \cdot \widehat{m_i(A)})^n}{(\widehat{m_{i-1}(A)} \cdot \widehat{m_i(A)})^n + (\widehat{m_{i-1}(B)} \cdot \widehat{m_i(B)})^n} \tag{13}$$

where $\widehat{m_i(B)} = 1 - \widehat{m_i(A)}$ since these propositions are complements of each other, and with equal probabilities, ($n = 0.5$) for all evidence.

As each individual quality measure (e.g. the one estimating the contrast factor) yields a raw number in the range $[-\infty, \infty]$. This raw number needs to be mapped to a specific score range [0, 1] that conveys meaningful interpretations from poor to good quality [4]. As it will be seen in Section 8, linear normalisation schemes are shown to be inefficient for combining quality measures. This is because, in practical scenarios, there are ranges corresponding to good and bad quality.

To find a better normalisation scheme, we studied the distributions of the quality measures. We used a subset from the ‘good’ set (as will be discussed in Section 8). Based on these distributions, we found the Gaussian models $f(Q_m) = G(Q_m)$ to be a closer approximation for non-linear normalisation. This non-linear normalisation method was shown to be more efficient than the linear normalisation one.

The geometric mean was found to be the best fusing rule to integrate the above mentioned quality measures [34]. Thus, the Gaussian-based face quality index is defined as follows

$$\mathrm{FQI} = \sqrt[5]{G_c(C) * G_b(B) * G_f(F) * G_s(S) * G_i(I)} \tag{14}$$

6.2 Neural network (NN)

In this paper, we proposed to use NN scheme to integrate the quality measures. One of the main advantages of NNs is the

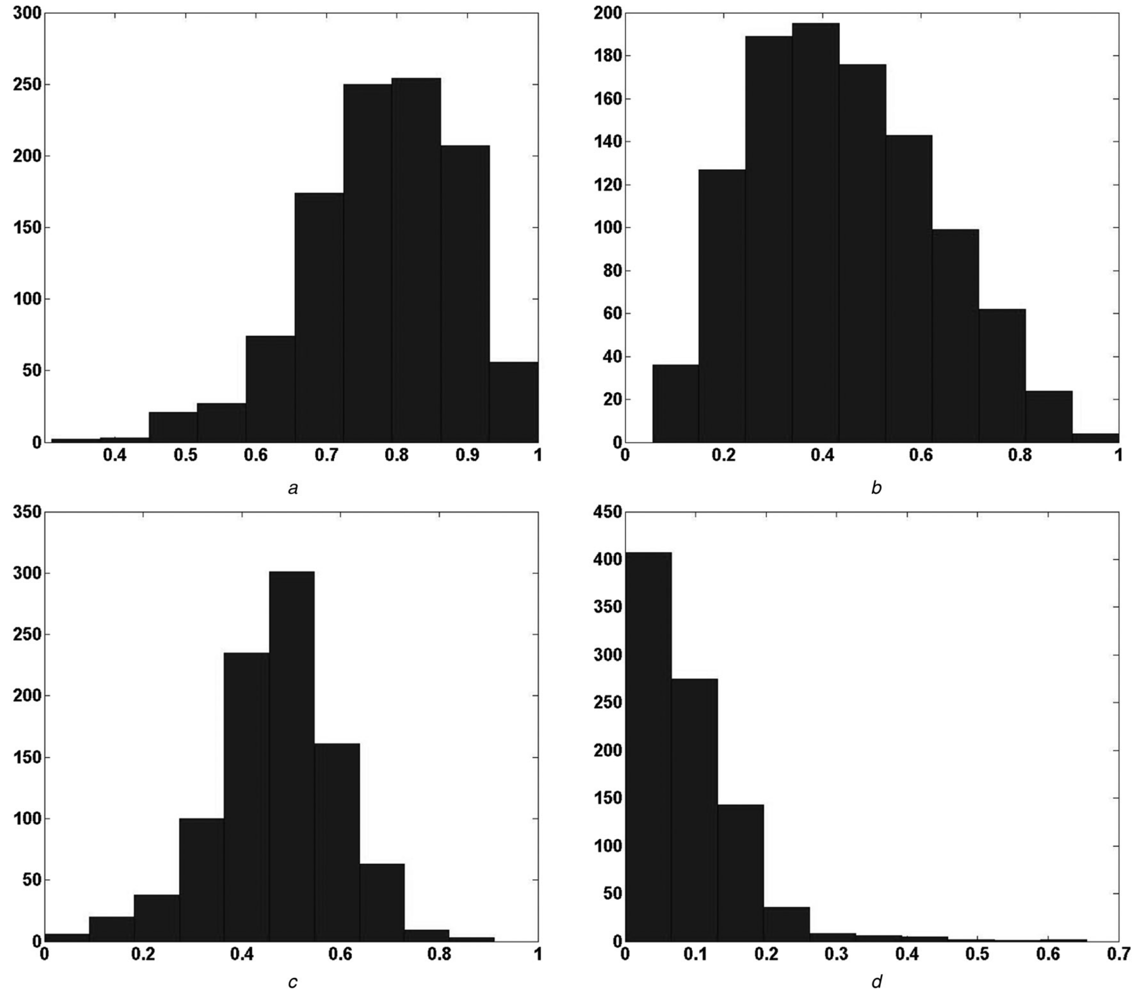

Fig. 5 *Distribution of face image scores using*

a LBP for good set
b Commercial Software (PittPatt) for good set
c LBP for ugly set
d PittPatt for ugly set

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ability to use raw quality measures; in other words they do not need the normalisation step. We designed several NNs to classify the input images as either 'good' or 'ugly', and hence the expected matching performance using these images. Results from the FRVT 2006, showed the performance rates for the verification rate at false accept rate = 0.001 are [18]: GOOD = 0.98, and UGLY = 0.15.

We used the following scheme to combine the quality vectors of the probe and gallery by taking the minimum of each quality measure

$$\begin{aligned} Q(P, G) &= \min(\boldsymbol{Q}(\boldsymbol{P}), \boldsymbol{Q}(\boldsymbol{G})) \\ &= [\min(C_p, C_g), \min(B_p, B_g) \\ &\quad \min(F_p, F_g), \min(S_p, S_g), \min(I_p, I_g)] \end{aligned} \tag{15}$$

Q5 where $\boldsymbol{Q}(\boldsymbol{P})$, and $\boldsymbol{Q}(\boldsymbol{G})$ are the quality vectors $\boldsymbol{Q}(\boldsymbol{P}) = [C_p, B_p, F_p, S_p, I_p]$, and $\boldsymbol{Q}(\boldsymbol{G}) = [C_g, B_g, F_g, S_g, I_g]$ for probe and gallery face images, respectively.

To classify the input, we applied the following hypothesis of good and ugly. To mark a face image as good, or low-quality, we define the following hypothesis: 'high-quality face image persists yielding high-matching score regardless of the used matching technique or the matching image (i.e. various good probes of the same person), and vice versa'.

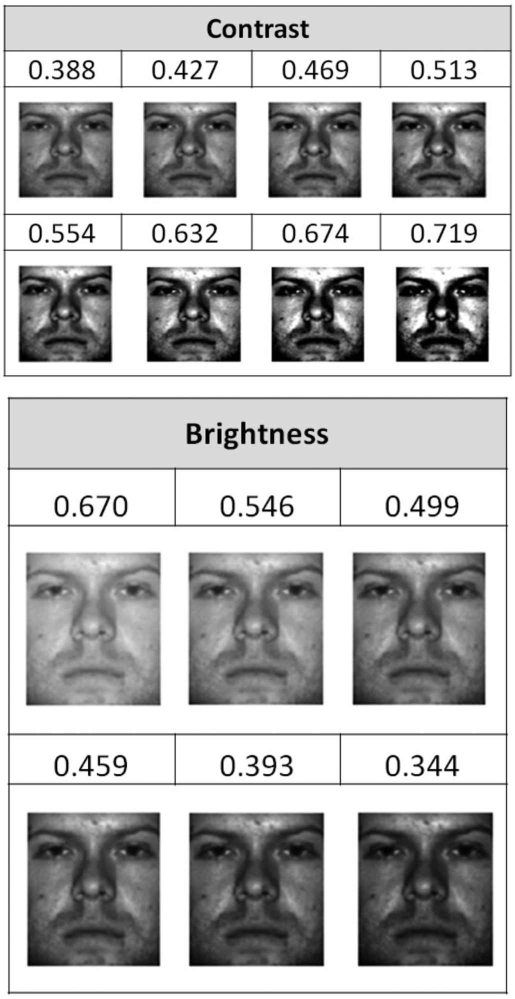

Fig. 6 *Example of deviations in: (upper) contrast intensity; (lower) brightness intensity (images from YALE [15])*

The NN output can be defined as

$$y^n = [C_I, B_I, F_I, S_I, I_I] \tag{16}$$

where $[C, B, F, S, I]$ are the quality measures, and the output is either good '1', or bad '0'.

Figs. 5*a* and *b* show the performance of two face recognition techniques [a research technique namely local binary pattern (LBP) and a commercial software (PittPatt)], using the 'good subset' from the FOCS database. We kept the higher 50% for LBP and PittPatt, respectively, then we switched the gallery images for the same probe and apply the same rule

$$\min(M^t(P_i, G_{i,1}), M^t(P_i, G_{i,2})) > \text{Threshold}^t \tag{17}$$

where M is the matching score, P_i, G_i are the probe and gallery images for sample i, using recognition technique t.

Figs. 5*c* and *d* show the performance of the two face recognition techniques using the 'ugly subset' from the FOCS database. We kept the lower 50% for LBP and PittPatt, respectively, then we switched the gallery images for the same probe and apply the same rule

$$\min(M^t(P_i, G_{i,1}), M^t(P_i, G_{i,2})) < \text{Threshold}^t \tag{18}$$

7 Experimental results

In this section, first, we evaluate several face recognition algorithms. Second, we present a set of experiments to evaluate the performance of independent quality measures against the proposed FQI index when using both simulated (image quality was synthetically changed) as well as real data. Finally, we present a case study on the beneficial usage of the proposed face quality index.

7.1 *Evaluation of face recognition algorithms*

For face detection we used a commercial software developed by the Pittsburgh Pattern Recognition (PittPatt) [http://www. Q6 pittpatt.com/]. For the selected FTMC (as well as the good–ugly, and the QFIRE data sets), PittPatt was used to segment the face region and locate eyes-centres. Each image was initially normalised by fixing the inter-pupilary pixel distance to 75 pixels. Then the face image is rotated to set the line between the eyes horizontally. Finally, the face image, 250 × 200 pixels, [35] is segmented such that the eye-level is at 115 pixel-level, left eye is at 62.5 pixel-level.

Various face recognition algorithms that can be classified as, intensity-based like principal component analysis (PCA), and independent component analysis (ICA) [36]; distribution-based like LBP [37], and local ternary patterns

Table 6 Face recognition performance using various techniques; Rank1 score represents the performance of identification experiments

FTMC set	Rank 1, %
PCA	87.8
ICA	85.8
LBP	91.3
LTP	90.7
PittPatt	99.4

(LTP) [38] were used in an evaluation experiment. We conduct this comparison experiment (as shown in Table 6) using the FTMC data set. The commercial software (PittPatt) achieved the best performance followed by the LBP technique. We used LBP (a texture-based technique) in addition to the commercial face recognition system since we do not have control of the pre-processing step of the commercial system.

In this experiment, we used FTMC data set, which carries one training face image. We could not apply face recognition techniques which requires multiple training samples per subject [39–42].

7.2 Performance of various quality measures

In a first set of experiments to evaluate the performance of various quality measures, we used the Yale data set (real database that has various illumination setups), the QFIRE (real database that has various focus and illumination setups) and the FTMC data set by adding synthesised changes.

To evaluate how the contrast measure reflects the image contrast factor, artificial contrast variation of the input face images are induced. For example, '0.05–0.95' maps the intensity values in face image I to new values in the output image such that 10% of data is saturated at low and high intensities of I. This increases the contrast of the output image. Table 7 shows that: (i) face recognition performance degrades while contrast increases, (ii) LBP performance degraded dramatically with contrast and (iii) the proposed contrast measure is highly correlated with the image contrast change. Fig. 6*a* illustrates proper response to contrast changes.

To evaluate how the brightness measure reflects deviations of the brightness intensity factor, brightness is artificially adjusted via the γ parameter. This parameter specifies the shape of the curve describing the relationship between the values of the input and output images, after the brightness level is manually adjusted. In case γ is less than 1, the mapping is weighted towards higher (brighter) output values, and vice versa. Table 7 shows that: (i) face recognition slightly changes for the various brightness levels, and (ii) the proposed brightness measure picks the change in the image brightness. Fig. 6*b* illustrates proper response to brightness changes.

To evaluate how the focus and sharpness measures reflects deviations in the image blurriness. Focus and sharpness were changed by smoothing the input face images at various levels. The used smoothing factor is a circular averaging filter

Table 7 Face recognition performance (r1: rank1) using images where contrast and brightness intensities were changed

DATA	PittPatt	LB0050	
FTMC	R1, %	R1, %	(C)
normal	**99.42**	**91.30**	**0.388**
0.05–0.95	98.84	91.30	0.427
0.1–0.9	99.13	90.44	0.469
0.15–0.85	98.84	88.99	0.513
0.2–0.8	97.39	82.61	0.554
0.25–0.75	96.23	71.01	0.534
0.3–0.7	94.20	52.75	0.632
0.35–0.65	89.57	25.51	0.674
0.4–0.6	84.35	4.64	0.719
0.45–0.55	74.20	0.87	0.770
DATA	PittPatt	LBP	
FTMC	R1, %	R1, %	(B)
$\gamma = 0.5$	98.84	91.01	0.670
$\gamma = 0.6$	99.13	91.01	0.603
$\gamma = 0.7$	99.13	91.01	0.546
$\gamma = 0.8$	99.13	90.73	0.499
$\gamma = 0.9$	99.13	91.01	0.459
normal	**99.42**	**91.30**	**0.424**
$\gamma = 1.1$	99.42	91.30	0.393
$\gamma = 1.2$	98.26	91.30	0.367
$\gamma = 1.3$	99.42	91.01	0.344
$\gamma = 1.4$	99.42	90.44	0.324

Table 8 Face recognition performance using images where blurriness intensity was artificially changed

FTMC	PittPatt, %	LBP, %	(F)	(S)
normal	**99.42**	**91.30**	**0.194**	**0.223**
disk = 3	99.42	50.73	0.041	0.109
disk = 5	99.13	36.81	0.023	0.091
disk = 7	98.55	32.17	0.016	0.080
disk = 9	98.55	30.15	0.013	0.072
disk = 11	96.23	27.54	0.011	0.065
disk = 13	91.59	25.22	0.010	0.060
disk = 15	87.83	21.16	0.009	0.056
disk = 17	82.03	20.00	0.008	0.053
disk = 19	71.88	17.10	0.008	0.049

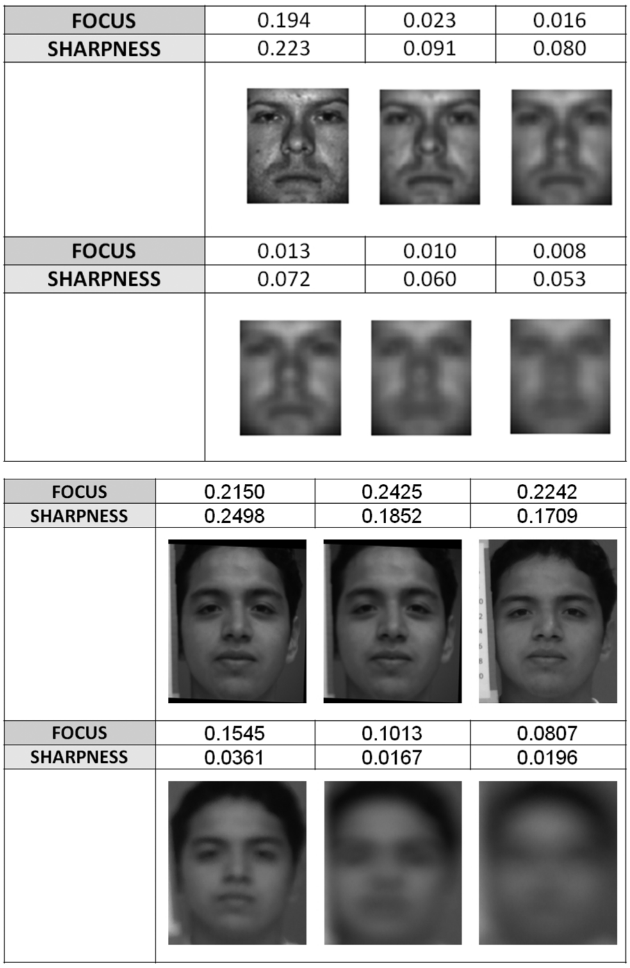

Fig. 7 *Examples for blurring face images: (upper) synthesised blurring using circular average filter (images from Yale [15]); (lower) real data from QFIRE database*

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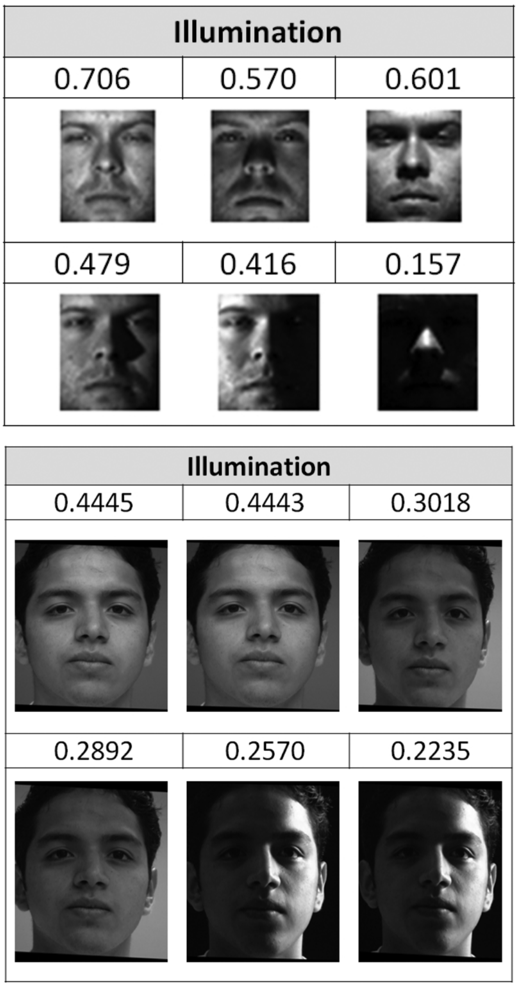

Fig. 8 *Examples deviations in illumination intensity from: (upper) Yale database; (lower) QFIRE database*

(denoted as 'disk') over a region of diameter equals to 3–19 pixels in an increment 2 pixels. Table 8 shows that: (i) PittPatt face recognition performance degrades when smoothing increases, and (ii) LBP, as a distribution-based, performance degraded dramatically with image blurring. Fig. 7 illustrates proper response to blurring variation using: (i) synthesised blurring by circular average filter with various diameters, and (ii) real data from QFIRE varying out-of-focus blur, where videos were captured at 5, 15 and 25 feet while adjusting the focal plane of the camcorder.

To evaluate the illumination measure deviations in the input illumination intensity, real data of various illumination changes from Yale set and QFIRE set were used. Fig. 8 illustrates proper response to illumination change using real data from: (i) YALE database, where the light source direction with respect to the camera axis, and (ii) QFIRE database, where three different levels of face contrast are achieved by three different illumination settings. Table 9 shows LBP performance was reasonable for minor illumination change, then degraded dramatically with major change.

Table 9 Face recognition performance using images where illumination intensity was changed

Yale	LBP, %	(*I*)
G = A + 000E + 00		0.694
P = A + 010E + 00	100	0.706
P = A + 000E–35	97.37	0.570
P = A + 000E + 45	92.11	0.601
P = A + 050E + 00	89.47	0.479
P = A + 070E + 00	26.32	0.416
P = A + 000E + 90	5.26	0.157

Table 10 Neural network

Layers	Nodes	Train perf, %	Test perf, %
2	20–5	94.78	73.15
2	15–5	87.39	76.85
2	10–5	94.35	70.37
2	9–5	88.26	78.24
2	9–3	86.52	78.70
2	7–3	90.00	75.93
1	7	88.70	80.09
1	**6**	**85.65**	**81.02**
1	5	84.78	78.24
1	4	83.91	77.78

(i) Simulate the matching score using minimum of probe and gallery qualities. (ii) Classify the image as good or ugly.

7.3 Performance of various quality measures

In a second set of experiments, we trained several NNs to differentiate between 'good' and 'ugly'. Table 10 shows 1-layer (six neurons) is yielding the best classification performance (81.02%).

Using the same data set, we compare the performance of NN combination of quality measures to other methods which does not need normalisation step, like logistic-regression, and support-vector-regression [43]; as well as other methods which need normalisation step like minimum, maximum, mean, geometric mean and Dempster-Shafer [33]. Also we recorded the performance using linear normalisation and Gaussian-models (as shown in Table 11).

Table 11 Comparison of several quality measures fusion schemes, to classify the input image as 'good' or 'ugly'

Fusion Rule	Linear, % Normalisation, %	Gaussian, % Models, %
minimum	50.00	70.37
maximum	48.61	51.39
mean	48.15	72.69
geometric-mean	50.00	**75.46**
dempster-shafer	48.61	65.28
logistic-regression	71.30%	
support-vector-regression	76.39%	
neural-network	**81.02%**	

a *b* *c*

Fig. 9 *Examples*

a High quality (gallery)
b High quality (probe)
c Low-quality (probe) images (images from FOCS [18])

Table 12 Comparison of several identification performance (rank1)

	LBP, %	PittPatt, %
good–good	77.00	98.33
good–ugly	2.00	1.33
mean fusion	60.67	92.33
selective	69.00	94.67

(i) Good gallery–good probe ‘ideal situation’. (ii) Good gallery–ugly probe – ‘worst situation’. (iii) Fusion of scores of good and ugly probes – while keeping good galleries. (iv) Selective between good and ugly probes – while keeping good galleries.

The findings of these experiments are:

- The best configuration for a NN (six neurons on 1-layer), yields the best classification performance (‘good’ against ‘ugly’) of 81.02%.
- NN yields the best classification performance among other methods, which do not require normalisation steps, like logistic-regression, support-vector-regression and so on.
- For other fusion methods, which need normalisation steps, Gaussian models yield better performance compared with linear normalisation.

7.4 Case study

The performance of the proposed strategy was evaluated using a subset of the FOCS collection (the good, bad and ugly database). Images from the FOCS database are of frontal faces taken under uncontrolled illumination, both indoors and outdoors. The partitions of interest are referred to as ‘good’ and ‘ugly’, that have an average identification accuracy of 0.98 and 0.15, respectively [18]. Fig. 9 shows examples of high- and low-quality face images.

The used dataset composed of 300 subjects, three frontal instances of faces: two high-quality images (from the good dataset), and one low-quality image (from the ugly dataset). PittPatt [http://www.pittpatt.com/] software, and LBP were used for generating the face match scores. These results are generated from two different matching scenarios: both the gallery and probe are of high-quality, referred to as ‘good–good’ and the gallery is high-quality, but the probe is low-quality, referred to as ‘good–ugly’. Table 12 shows the following:

- Blind fusion (mean fusion), ugly probe and good probe, the identification rank 1 is 60.67% using LBP, and 92.33% using PittPatt.
- Selective fusion (basically to reject ‘ugly’) probes, using the propped face quality index, the system performance was enhanced to 69.00% using LBP, and 94.67%.

This case study shows that the proposed face quality index can be used to filter low-face quality image and hence to enhance the overall face recognition performance using PittPatt.

8 Conclusions and future works

In this paper, we first, evaluated a variety of face IQMs related to the following quality factors: contrast, sharpness, focus, brightness and illumination. We used both synthetic as well as real-world data. Then, we illustrated that the usage of supervised learning methods (e.g. NNs) is very important to understand the relationship between these measures and matching score prediction when used in practical face recognition scenarios. Our study resulted in the development of a more efficient FQI that manages to reflect the changes of input quality factors in correlation with face recognition performance. Experimental results indicate that certain image quality factors, namely contrast, sharpness and focus, highly affect the performance of texture-based face matching schemes such as LBP.

Our plan for future work includes: (i) studying other quality factors that affects face recognition performance (e.g. pose, image compression [44], reducing the spatial and grey-level resolution of the normalised images [45], or noisy night time images [46]); (ii) developing more sophisticated techniques that target to enhance the efficiency of the proposed face quality index; and (ii) investigating the image effect of various IQMs on other important biometric modalities, namely the human ear image.

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