Impact of Out-of-focus Blur on Face Recognition Performance Based on Modular Transfer Function

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Abstract

It is well recognized that face recognition performance is impacted by the image quality. As face recognition is increasingly used in semi-cooperative or unconstrained applications, quantifying the impact of degraded image quality can provide the basis for improving recognition performance. This study uses a range of real out-of-focus blur obtained by controlled changes of the focal plane across face video sequences during acquisition from the Q-FIRE dataset. The modulation transfer function (MTF) method for measuring sharpness is presented and compared with other sharpness measurements with a reference of the co-located optical chart. Face recognition performance is then examined at eleven sharpness levels based on the MTF quality metrics. Experimental results show the MTF quality metrics better quantify a range of blur compared to the optical chart and offer a useful range of interest for face recognition performance. This paper demonstrates the applicability of an image blur quality metric as auxiliary information to supplement face recognition systems through the analysis of a unique database.

1. Introduction

The quality of biometric data is operationally important since it can directly impact recognition performance [1]. It is desirable to analyze factors which are independent of an algorithm and to quantify their effect on recognition systems. Face recognition technique is the key component for unconstrained or semi-cooperative biometrics system at a distance. Although recent face recognition systems perform well under relatively controlled environments, a major research area is the study of face recognition over a wide range of quality factors, such as occlusion, aging, outdoor illumination, blur, etc. Out-of-focus blur is one crucial factor of image quality degradation that has a significant impact on face recognition performance.

Several efforts have been taken to explore out-of-focus blur. In early 90's [2], the Optical Transfer Function (OTF) was used to estimate blur parameters. Wu et al. proposed a method to determine the exact location of blurred edges using Line Spread Function (LSF) [3]. Recently, Moghaddam introduced a genetic algorithm to estimate blur [4]. Rooms et al. presented a wavelet transform to estimate out of focus blur [5]. At the same time, Vivirito et al. employed edge information detected by extended DCT approach of Bayer pattern to determine out-of-focus blur [6]. Saad et al. proposed a DCT statistic model based method to measure image quality [7]. Additionally, Beveridge el al demonstrated interactions of face recognition performance on focus by statistical modeling [8]. Most quality measurements are examined on the artificial blur and a few studies are conducted on incidental blur without ground truth or consistency of degradations. Hence, a study that measures image quality based on real out-of-focus blurry images from an appropriate database with controlled conditions at acquisition is needed.

Thus, the focus of this paper is an analysis of the impact of out-of-focus blur on face recognition systems, utilizing real blurred face images over a controlled continuous range generated by changing camera focus in the Q-FIRE database [9]. A co-located optical chart is used as a reference for the amount of blur in the image. We study a set of face blur measurements and their relationships with the impact on face recognition system based on the quantified blur levels.

The rest of this paper is organized as follows. Section 2 briefly describes four conventional approaches of image quality assessments for measuring face blur, as well as the proposed Modular Transfer Function (MTF) on face region and the standard optical chart co-located with the face. Section 3 performs our experimental analysis. Finally, a conclusion is summarized in Section 4.

2. Face blur quality measurements

2.1. Related measurements

One conventional method to examine the image quality is the Discrete Cosine Transform (DCT). DCT has been widely used in image compression systems due to its uniform response from low frequency to high frequency and the reduced sensitivity of higher frequency in human perceptive abilities. The out-of-focus blur typically leads to the loss of high-frequency information in images. Thus, these features show the strength of the DCT based method of sharpness measurement for out-of-focus face blur measurements. Differences between DCT and IDCT are utilized to measure the sharpness of image in [6] while a natural statistic DCT model is implemented to generate the probabilistic prediction of visual quality in [7]. The 2D DCT to an M-by-N matrix image is defined as:

$$C_{DCT}(x,y) = \alpha_x \alpha_y \sum_{m=1}^{M}\sum_{n=1}^{N} I_{mn} cos\frac{\pi(2m+1)x}{2M} cos\frac{\pi(2n+1)y}{2N} \quad (1)$$

where

$$\alpha_x = \begin{cases} \frac{1}{\sqrt{M}}, & x=0 \\ \sqrt{\frac{2}{M}}, & 1 \le x \le M-1 \end{cases}, \alpha_y = \begin{cases} \frac{1}{\sqrt{N}}, & y=0 \\ \sqrt{\frac{2}{N}}, & 1 \le y \le N-1 \end{cases}$$

The $C_{DCT}(x,y)$ are the DCT coefficients of the image. Horizontal frequencies increase as *x* increase, and vertical frequencies increase as *y* increase. Most information of an image is focused in lower index of *x* and *y*, showing high energy gathered in upper-left region of a 2-D coefficient image. The radial spatial frequencies in the 2-D coefficient matrix are representative of image sharpness.

The second blur assessment metric is the Squared Gradient (SG) method. The magnitude of the gradient can be computed as the edge magnitude which measures the sharpness of the image. Using SG to evaluate blur levels of an M-by-N matrix image is defined as:

$$G(x,y) = \sum_{x=1}^{M}\sum_{y=1}^{N} \sqrt{|I(x,y+k)-I(x,y)|^2 + |I(x+k,y)-I(x,y)|^2} \quad (2)$$

Where $I(x,y)$ represents the intensity of an M-by-N image, and *k* is the differencing step.

Frank Weber from Cognitec proposed a method to measure sharpness in a NIST biometric workshop[10], which utilized the similar concept to Edge Density (ED) assessments of images quality by applying a 3×3 mean filter to the image and calculating the distance between original image and filtered image. This method is called the Edge Density (ED) :

$$D(x,y) = \sum_{x=1}^{M}\sum_{y=1}^{N} |I(x,y) - I_m(x,y)| \quad (3)$$

where $I_m(x,y) = I(x,y) \times f_m(x,y)$, $f_m(x,y)$ is a 3×3 mean filter. The mean filter could also be replaced by Sobel filter or low pass filter in other ED methods [11].

The fourth quality measurement is the Laplacian of Gaussian (LoG) method. It has been introduced to iris image quality assessment by Wan et al. [12] when applying the 2-D Laplacian of Gaussian (LoG) operator for the overall edge measurements. It combines the Laplacian measure with the Gaussian filter for efficient evaluation of iris images in high frequency. The 2-D function centered on zero and with Gaussian standard deviation σ is defined as:

$$LoG(x,y) = -\frac{1}{\pi\sigma^4}\left[1-\frac{x^2+y^2}{2\sigma^2}\right]e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (4)$$

The sharpness level is higher if the convolution result is larger. Given that face images contain less high frequency information, a 10×10 operator and the standard deviation σ = 1.0 are applied in our study for the LoG method.

2.2. Modulation Transfer Function (MTF)

The Modulation Transfer Function (MTF) is widely used as a standard way to evaluate the performance of optical imaging system because it can provide an objective and quantitative expression of imaging quality, as well as the capability of calculation from the lens design data. MTF is defined as the magnitude of Optical Transfer Function (OPT) which is the Fourier transform of the incoherent Point Spread Function (PSF) [13]. Using discrete Fourier transform to numerically approximate the Fourier transform, the MTF could be calculated as:

$$MTF = DFT[PSF] = \sum_{n=0}^{N-1} y_n e^{-ikn\frac{2\pi}{N}} \quad (5)$$

where $k \in [0, N-1]$, and y_n is the position of the n^{th} pixel. Thus, MTF allows for the simplified description of the spatial resolution capabilities in imaging system.

When considering the performance based on an optical chart, the MTF also defined as the contrast between a given special frequency and low frequencies [14], which usually measures the intensity of black and white lines, as shown in Equation 6 and Figure 1. I_{max} and I_{min} are the maximal and minimal intensity from the optical chart:

$$MTF = \frac{I_{max} - I_{min}}{I_{max} + I_{min}} \quad (6)$$

For this study, face images from the special subset of Q-FIRE dataset have a reference optical chart beside the face region. Equation 5 is only applied to face region while the Equation 6 is only applied to the optical chart as a gold standard chart reference.

3. Experimental analysis

Our experiments conducted here aim to examine the impact of out-of-focus blur on face recognition performance with a standard optical chart. The quality measurements of blur are implemented through the methods described in Section 2 and then compared to the standard chart reference. We perform experiments on three different face recognition techniques (LBP, LPQ and FaceIt commercial SDK) on real blurred face images based on a quantified group of different out-of-focus blur levels.

3.1. Database

To assess the performance of the proposed approaches in face recognition, we considered real out-of-focus blurred face images from Q-FIRE database [9] which provides a range of quality (high, medium, low) for both face and iris videos for factors of illumination, angles, blur, resolution, and occlusion for 188 subjects. This dataset is available by request to the researchers through the CITeR website [15]. Real out-of-focus blur images in Q-FIRE database are generated by turning the camera ring from out-of-focus to sharp to out-of-focus over 6 seconds at 24 frames per second.

For each subject, one sharp image is extracted from the 'High Illumination' video sequence under a controlled condition from the first visit, and around 200 images with a range of real out-of-focus blur degraded by adjusting the camera focus lens under the same illumination condition are extracted from the 'Focus' video sequence from the second visit. Two visits are separated by a minimum of 2 weeks. Face videos captured at 5ft, 15ft and 25ft are used for this study. In total, 1062 video sequences with more than 35600 images of 177 subjects from the Q-FIRE dataset are selected.

The Q-FIRE database also provides a good reference for measuring the real out-of-focus blur by a standard optical chart (from the standard ISO 12233 test charts [17]) co-located with the face during acquisition (see Figure 1). This enables the comparison of the sharpness metrics computed from the face region to the standard optical chart.

We notice that increasing numbers on the optical chart represent increase of spatial frequencies corresponding to different camera resolution performances. Thus, we chose number 2 region on the standard optical chart according to its robust performance on degraded sharpness (shown in Figure 2). In order to guarantee the consistency of the spatial performance from the optical standard chart, all segmented number 2 region are aligned to maintain a vertical central line. The MTF for number 2 region of the chart, implemented by Equation 6, is computed and used as the standard chart reference for studying face recognition performance as a function of out-of-focus blur. Additionally, we apply the MTF method (Equation 5) to the face region segmented by the Viola-Jones [16] face detection with the alignment of eye-centre coordinates, as well as other blur quality metrics described in Section 2.

To analyse the impact of face recognition, we consider three different face recognition methods including LBP [18] as one of the state-of-art methods, LPQ [19] as a baseline for blur-invariant descriptors for face recognition, FaceIt SDK (a commercial software from L-1 Identity Solutions) as a general performance of face recognition. The FaceIt recognition module is based on Local Feature Analysis (LFA) [20] combined with skin features.

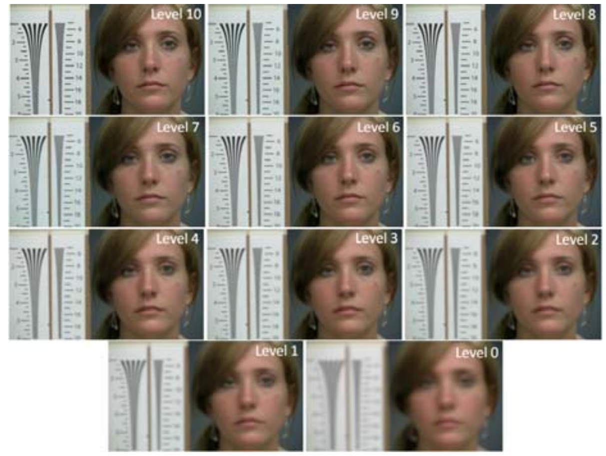


Figure 1: Example frames of real out-of-focus blur from Q-FIRE dataset with standard optical chart on the side of face at 5ft

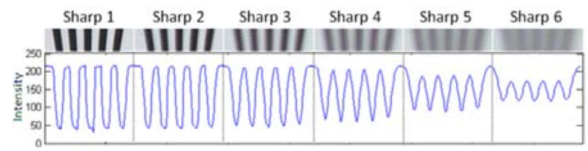


Figure 2: Example of intensities of number 2 region from the standard optical chart showing 6 different sharpness levels (from sharpest to blurry) within one video sequence

3.2. Results

We first implement five different approaches for out-of-focus blur measurement in each video sequence for all 177 subjects compared with MTF response on the optical chart. Figure 3 shows an example for one subject comparing the MTF response on optical chart (MTF-R) as the ground truth to four other methods plus the quality metric from FaceIt SDK, as well as the MTF measurement of out-of-focus blur on the face region. Points are closer to a line with 45° to x and y axis if the method is more correlated to the MTF-R. The MTF on face region shows the highest correlation to the MTF-R. DCT, SQ, and LoG responses show higher correlation while the correlation of ED and FaceIt quality metric are lower in Table 1.

Three face recognition methods including LBP, LPQ and FaceIt commercial software are applied to generate the distribution of match scores based on eleven sharpness levels grouped in terms of the MTF metrics on face region. Figure 4 shows distributions of three face recognition techniques based on different sharpness levels. All three recognition techniques show a shift of the match score distributions when blur increases. The LBP algorithm shows a less consistency of shifting, in Figure 4a, comparing to other results. LPQ algorithm is well known as its blur-invariant features, showing (in Figure 4b) a good resistant performance for first 7 sharpness levels (from level 10 to level 4) and a big jump of shifting distribution between level 3 and level 4. This analysis shows that LPQ is robust to small blur but suffers for a larger amount of blur. Meanwhile, the FaceIt commercial software shows a smooth shifting along with the increasing blur. Overall, a good separation between genuine match scores of level 4-10 and imposter scores are shown in Figure 4.

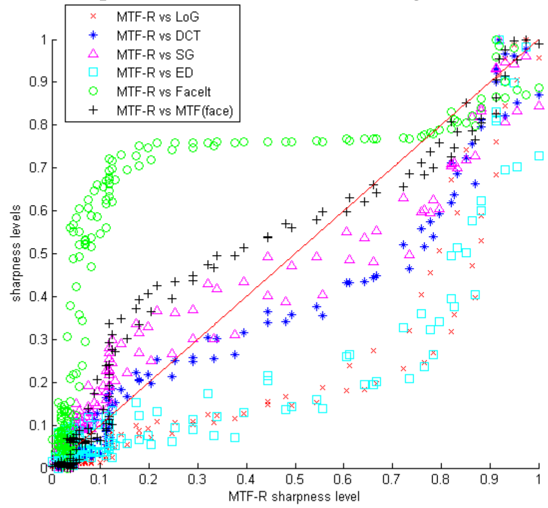


Figure 3: Example comparisons of normalized blur measurements for one subject: MTF-R versus LoG, DCT, SG, ED, FaceIt and MTF of the face region. 0 presents the lowest sharpness level and 1 presents the sharpest (no blur) level.

Table 1, Average correlation coefficients for all subjects between five blur measurements and the MTF on the optical chart.

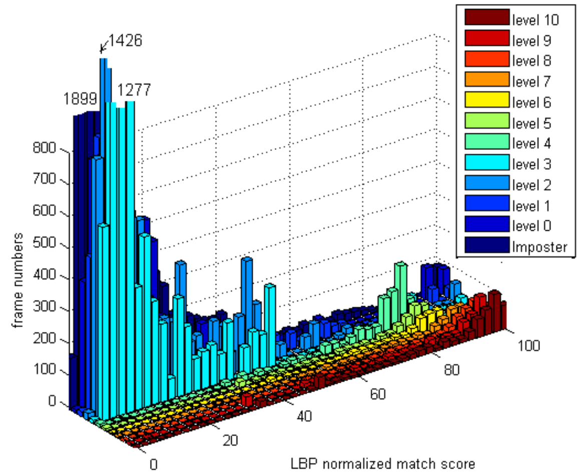
	LoG	DCT	SG	ED	FaceIt	MTF(face)
MTF-R	0.950	0.973	0.963	0.899	0.828	0.985

We also notice that the number of images in lower level of sharpness (such as level 0, level 1 and level 2) are larger than other levels because of the data capture procedure from Q-FIRE dataset, i.e. more time is spent at the lower levels as the camera is adjusted to cover the entire range of focus during six seconds. This phenomenon can also be seen in Figure 3.

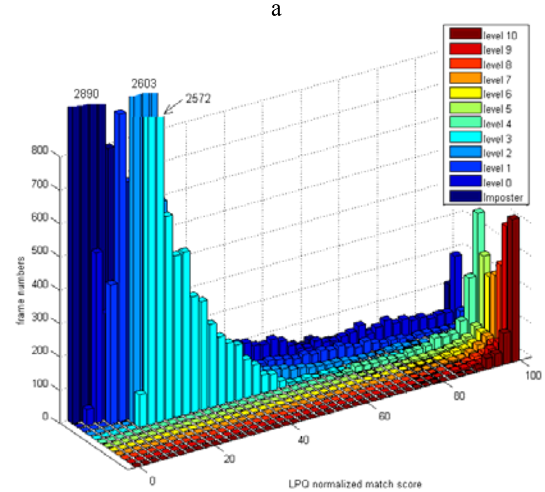
EER and verification rates at 1% FAR of different quality measures for 11 blur levels are examined and shown in Table 2, 3 and 4. All three tables show a tendency that the EER increases and the verification rate decreases when the sharpness level decreases. Table 1 shows less robust matching performances from LBP methods than other two methods when blur increases. Results in Table 2 demonstrate better verification rates from LPQ comparing to LBP on most sharpness levels. Meanwhile, results from FaceIt commercial software in Table 3 show that the verification rate drops until level 2 from 96.5% to 64.5%.

Figure 6 provides the comparison of verification rate at 1% FAR of three face recognition techniques. It supports the conclusion above for Table 1, 2 and 3.

Figure 5 shows ROC curves for LBP and FaceIt. LBP



a



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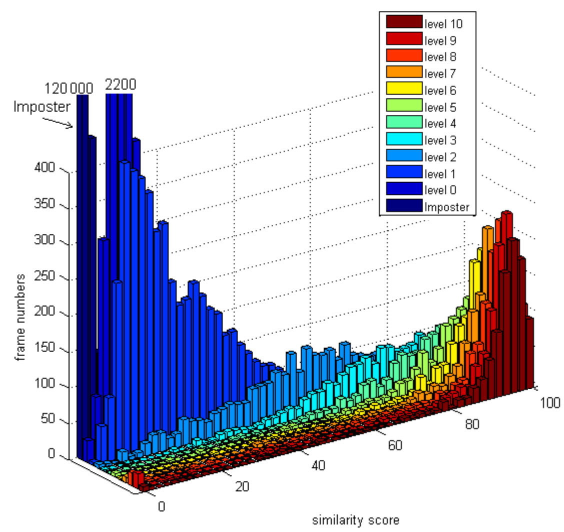


c

Figure 4, Results of distribution of face genuine and imposter match scores on eleven different sharpness levels based on MTF metric of face region. Match scores are generated by (a) LBP. (b) LPQ (c) FaceIt

Table 2. EER and Verification rate at 1% FAR at different sharpness levels by implementing LBP method on face images

Sharpness Level	Norm MTF %	EER %	Verification rate at 1% FAR, %
10	95-100	4.1	78.9
9	85-95	5.0	76.0
8	75-85	5.4	70.3
7	65-75	5.6	71.1
6	55-65	6.2	65.0
5	45-55	7.9	61.8
4	35-45	8.2	16.7
3	25-35	42.0	3.1
2	15-25	46.0	2.5
1	5-15	48.1	1.5
0	0-5	48.5	1.0

Table 3. EER and Verification rate at 1% FAR at different sharpness levels by implementing LPQ method on face images

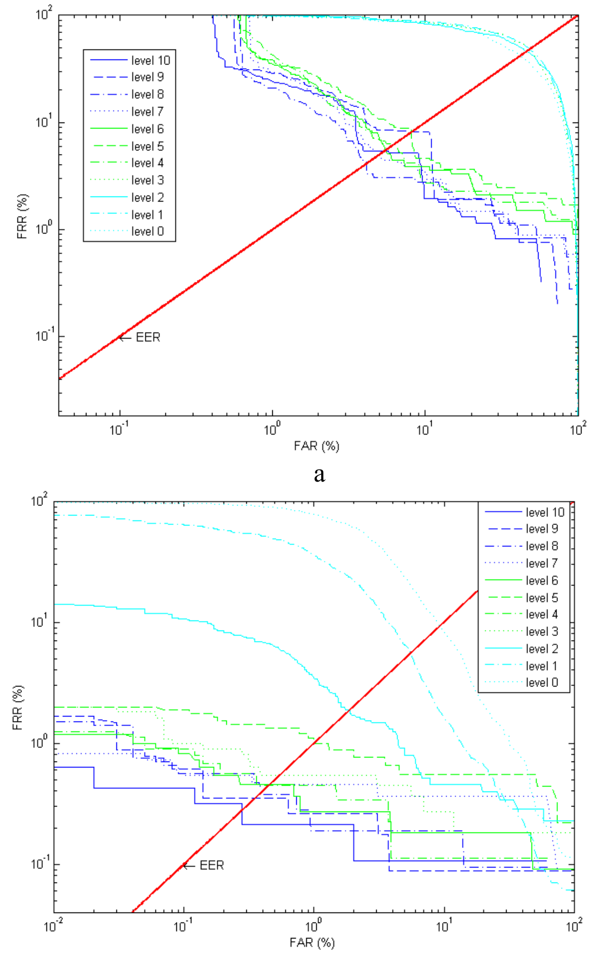
Sharpness Level	Norm MTF %	EER %	Verification rate at 1% FAR, %
10	95-100	1.4	92.2
9	85-95	1.6	89.7
8	75-85	1.7	86.7
7	65-75	1.8	84.4
6	55-65	1.8	68.1
5	45-55	1.9	66.4
4	35-45	3.0	33.8
3	25-35	3.4	5.4
2	15-25	31.3	4.1
1	5-15	34.5	0.9
0	0-5	35.0	0.1

Table 4. EER and Verification rate at 1% FAR at different sharpness levels by implementing FaceIt SDK on face images

Sharpness Level	Norm MTF %	EER %	Verification rate at 1% FAR, %
10	95-100	0.3	99.9
9	85-95	0.3	99.8
8	75-85	0.4	99.7
7	65-75	0.5	99.5
6	55-65	0.5	99.4
5	45-55	1.0	99.0
4	35-45	0.5	98.6
3	25-35	0.5	98.5
2	15-25	1.9	96.5
1	5-15	5.6	64.5
0	0-5	9.3	22.1

performance curves at 0-3 sharpness levels on Figure 5a are clustered together at high EER and low verification rate while 4-10 sharpness levels are clustered together at lower EER and higher verification rate with a big interval. The performance curves for FaceIt shifts smoother and shows little clustering with the increase of blur.

In general, we find that LPQ method is more robust on blurry images than LBP and FaceIt commercial software. It could expected that LBP and LPQ methods could reach higher verification rate and lower EER with a carefully preprocessing steps and a better features selection scheme for these two methods.



a

b

Figure 5: Results of ROC curves with different MTF-based sharpness levels by implementing (a) LBP and (b) FaceIt.

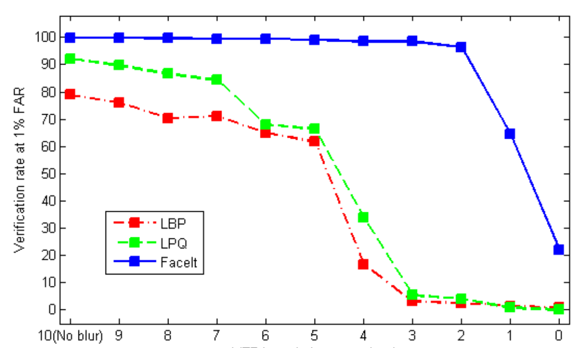


Figure 6: Verification rates at 1% FAR for three face recognition algorithms on Q-FIRE with MTF-based sharpness levels

4. Conclusion

Our experiments on real blurred face images with a continuous range of camera focus from the Q-FIRE database enables the study of the performance of face recognition as a function of image quality. We compare several measures of blur based on MTF response of the optical chart (MTF-R) and find that the best correlation is achieved with the MTF response of the face region. This measure of blur, thus, can practically serve as a proxy for MTF-R which is difficult to measure in most real world conditions. Additionally, most measures of blur tested in our work are highly correlated with response of the optical chart and give a useful range of interest for face matching performance. The Q-FIRE database can be useful for benchmarking measures of blur based on the face image using MTF of the optical chart as a reference. This database also could provide a baseline for evaluating the robust of different face recognition algorithms to real blur.

Analyses of our experimental results reveal the robustness of recognition performance to blur with an abrupt degradation in performance at larger amounts of blur. They also disclose a correlation between quality metrics and face recognition performance leading to the possible incorporation of quality measures in a face performance prediction scheme to reduce the negative effect of poor quality samples.

While in this study we concentrate on pure effect of blur on face recognition performance, the measures of blur suggested here are also expected to be sensitive to other factors such as illumination and resolution which we held constant. For our future work, it is of interest to exploit other factors of degraded image quality (e.g. resolution, illumination) represented by the Q-FIRE database in combination with blur to offer a means of improving face recognition performance by accurately characterizing the acquisition environment.

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