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Fast Self-Quotient Image Method for Lighting Normalization based on modified Gaussian Filter Kernel

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The Self-Quotient Image (SQI) Method [Wang H, Li SZ, Wang Y, et al. Self quotient image for face recognition. International Conference on Image Processing (ICIP'04); 2004; Vol. 2. p. 1397 – 1400; Wang H, Li SZ, Wang Y. Generalized quotient image. IEEE CVPR; 2004; Vol. 2. p. 498 – 505] is a simple method for lighting normalization based on the Quotient Image method [Shashua A, Riklin-Raviv T. The quotient image: class-based re-rendering and recognition with varying illuminations. T Pattern Anal Mach Intel. 2001;23(2):129 – 139; Riklin-Raviv T, Shashua A. The quotient image: class based recognition and synthesis under varying illumination. Proceedings of the 1999 Conference on Computer Vision and Pattern Recognition; 1999; Fort Collins (CO). p. 566 – 571]. The main advantage of the SQI is the use of only one image for lighting normalization. Nevertheless, the SQI still has few disadvantages which make hard to use it in some face recognition systems. In this paper, we introduce the modified version of the SQI method based on globally modified Gaussian filter kernel. In this modification, we tried to solve the disadvantages of the original SQI method, simplify the computational process, and increase the quality of illumination normalization. We have investigated two modification of the original SQI method and shown how they normalize different shadow regions.

Keywords: self-quotient image, sqi, quotient image, gaussian filter, face recognition, lighting normalization, illumination normalization

Introduction

The Self-Quotient Image (SQI) Method is a good approach for robust face recognition under varying lighting conditions, which was introduced by Haitao Wang, Stan Z. Li, Yangsheng Wang, Jianjun Zhang [1].

This method was well accepted by the scientific community and found extensive applications in recent researches, for example [2-5]. Nevertheless, most of them used the SQI only for small illumination changes. In 2013, Ognjen Arandjelovic [6] explored the possibility of using the method for large variations of illumination and showed that it is more effective than previously thought. Along with this, a lot of modifications of the method presented. In 2007, the authors of the original SQI method presented Morphological Quotient Image (MQI) and its dynamic version (DMQI) [7]. However,

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they used morphological operations, instead of the weighted Gaussian filter. More close modifications to the original SQI method presented by others researchers, for example, Total Variation Quotient Image (TVQI) based on the total variation (TV) model by Terrence Chen et al. [8], Gabor Quotient Image (GQI) based on the Gabor filter by Sanun Srisuk and Amnart Petpon [9], Classified Appearance-based Quotient Images (CAQI) with the modified weighted function by Masashi Nishiyama, Tatsuo Kozakaya and Osamu Yamaguchi [10], Exaggerate Self Quotient Image (ESQI) with the multiscale version of the Gaussian filter by S. Muruganantham and T. Jebarajan [11]. However, they solve different issues than we tried to solve in this paper.

The Self-Quotient Image (SQI) Method is based on the Quotient Image method [12,13], but has three advantages:

(1) The SQI method uses only one face image for lighting normalization.

It is very useful in a lot of real-time face recognition systems, which cannot provide the image series or video output or need to minimize delays between image registration and getting processing result.

(2) Since there is only one image, it means that alignment is not needed.

It is also a very important factor, which means that the SQI method didn't need any face detection to minimize the face movement on images. The fact that the method doesn't need face detection makes the SQI method simpler and faster, than other similar methods which need few images [12,13].

(3) The method works in shadow regions.

In [1,14] was shown that SQI works in three types of regions:

- regions without shadows and with small surface normal variation;
- regions without shadows but with large surface normal variation;
- shadow regions.

In the other side, the usage of only one face image means that lighting information can be got only from one source and for better result needs more complex processing than when the method processes few images. Also, availability to use few face images allows creating the 3D face and lighting models to increase the quality of lighting normalization. As result, the SQI method has few disadvantages:

(1) It needs the complex computational process which computes a weighted Gaussian filter kernel for each convolutional region.

(2) The SQI method decreases contrast and textural information of the face image, which are usually very important for face recognition methods.

To solve this issue, Haitao Wang, Stan Z Li, and Yangsheng Wang introduced Stacked Self-Quotient Image Method [15], which calculates few self-quotient images with different Gaussian filter kernels and summarize them into result's image. This approach allows to save textural information and improves the contrast of result's image. Nevertheless, this approach needs to compute several self-quotient images, each of them uses own weighted Gaussian filter kernels. It makes the stacked SQI method a

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very slow and unusable for real-time face recognition even if these self-quotient images are computing in parallel threads.

In our work, we wanted to solve these issues or at least minimize them and improve the SQI method for fully shadowed images (e.g. Figure 1).

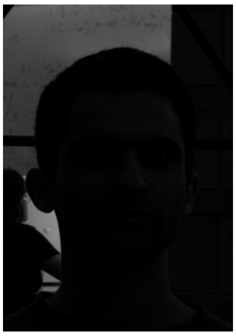

Figure 1. Example from Extended Yale Face Database B [16].

To simplify the computational process, we decided to move away from weighted Gaussian filter kernel and create special globally modified Gaussian filter kernel. It done in two steps. At first, we investigated work of the SQI method based on the original Gaussian filter kernel. At second, we circularly shifted the original Gaussian filter kernel to get modified Gaussian filter kernel, which still saves smoothing characteristics of the Gaussian filter but also has anisotropic characteristics.

The paper consists of several sections. Sections 2 and 3 overview the original SQI and stacked SQI approaches. Sections 4 and 5 describe the proposed method in terms of the SQI and stacked SQI methods and show how they work on face images from Extended Yale Face Database B [16]. In section 6, we compare our proposed method with the original method for different images. In the last section, we do the conclusion.

Original SQI Approach [1,14,15]

The Self-Quotient image Q of the image I is defined by:

$$Q = \frac{I}{\hat{I}} = \frac{I}{F * I} \tag{1}$$

where $\hat{I}$ is the smoothed version of I, F is the smoothing kernel, and the division is point-wise as in the original quotient image [1,14,15].

The most important processing step in the SQI is the smoothing filtering. Weighted Gaussian filter introduced for the SQI designed for anisotropic smoothing, where W is the weight and G is the Gaussian kernel, and N is the normalization parameter which defined as

$$\frac{1}{N} \sum_{\Omega} \mathrm{WG} = 1 \tag{2}$$

where Ω is the convolution kernel size. The convolution region is divided into two sub-regions M_1 and M_2 with respect to a threshold τ. Assuming that there are more pixels in M_1 than in M_2, τ is calculated by

$$\tau = \mathrm{Mean}\left(I_{\Omega}\right) \tag{3}$$

For the two sub-regions, W has the corresponding value.

$$W(i,j) = \begin{cases} 0 & I(i,j) \in M_2 \\ 1 & I(i,j) \in M_1 \end{cases} \tag{4}$$

As result, F calculated as

$$F = \frac{1}{N}\mathrm{WG} \tag{5}$$

Stacked SQI Implementation Model [15]

Stacked SQI implementation based on the computation of several self-quotient images using the SQI method and summarizing them into one image. For this, in [15] was additionally added two operations: nonlinear transformation for reducing noise in Q and weighted summarizing function.

In terms of the SQI, stacked SQI approach can be described as:

(1) Select several smoothing kernels $G_1, G_2, \ldots, G_n$.

(2) For each smoothing kernel, calculate corresponding weights $W_1, W_2, \ldots, W_n$ according to the image I.

(3) Smooth I with each weighed anisotropic filter $F_i = WG_i$:

$$\hat{I}_k = I \oplus \frac{1}{N}\mathrm{WG}_k, \quad k = 1,2,\ldots,n \tag{6}$$

(4) Calculate self-quotient image between each input image I and its smoothing version

$$Q_k = \frac{I}{\hat{I}_k}, \quad k = 1,2,\ldots,n \tag{7}$$

(5) Transfer self-quotient image with nonlinear function

$$D_k = T\left(Q_k\right), \quad k = 1,2,\ldots,n \tag{8}$$

where T is a nonlinear transformation.

(6) Summarize nonlinear results

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$$Q = \sum_{k=1}^{n} m_k D_k \tag{9}$$

The m_1, m_2, …, m_n are the weights for each scale of the filter. In [15], weights set to 1 for all experiments, for our experiments we also used these weights.

Modified SQI based on shifted Gaussian kernel

As described before, two modifications were investigated. In both modifications, we used the original model of the SQI:

$$Q = \frac{I}{\hat{I}} = \frac{I}{F * I} \tag{10}$$

But the representation of F was changed. In the first case, we simply replaced F by classical Gaussian filter kernel G:

$$Q = \frac{I}{\hat{I}} = \frac{I}{G * I} \tag{11}$$

In the second case, we used circularly shifted Gaussian filter kernel G^S:

$$Q = \frac{I}{\hat{I}} = \frac{I}{G^S * I} \tag{12}$$

We called it the Fast SQI method since it doesn't require calculation of weighted Gaussian filter kernel for each convolution region.

For our experiments, we selected a small Gaussian filter kernel with a 3×3 size. The circularly shifted Gaussian kernel was created by shifting on one cell vertically and horizontally.

Results of our experiments for different face images from Extended Yale Face Database B [16] represented in Figure 2. Additionally, we compared normalized images processed using the original Gaussian filter kernel (Figure 3) and the modified Gaussian filter kernel (Figure 4) with different kernel size.

Stacked SQI method using shifted Gaussian kernel

For our stacked SQI implementation we used the original stacked SQI approach, but we replaced the weighted Gaussian filter kernel by classical Gaussian filter kernel and our modified Gaussian filter kernel. For stacked Fast SQI method, we also skipped nonlinear transformation, since our experiments shown that the method works better without it and noise reduction is very low. Results of experiments shown in Figure 5, organized in the same way as in Figure 2.

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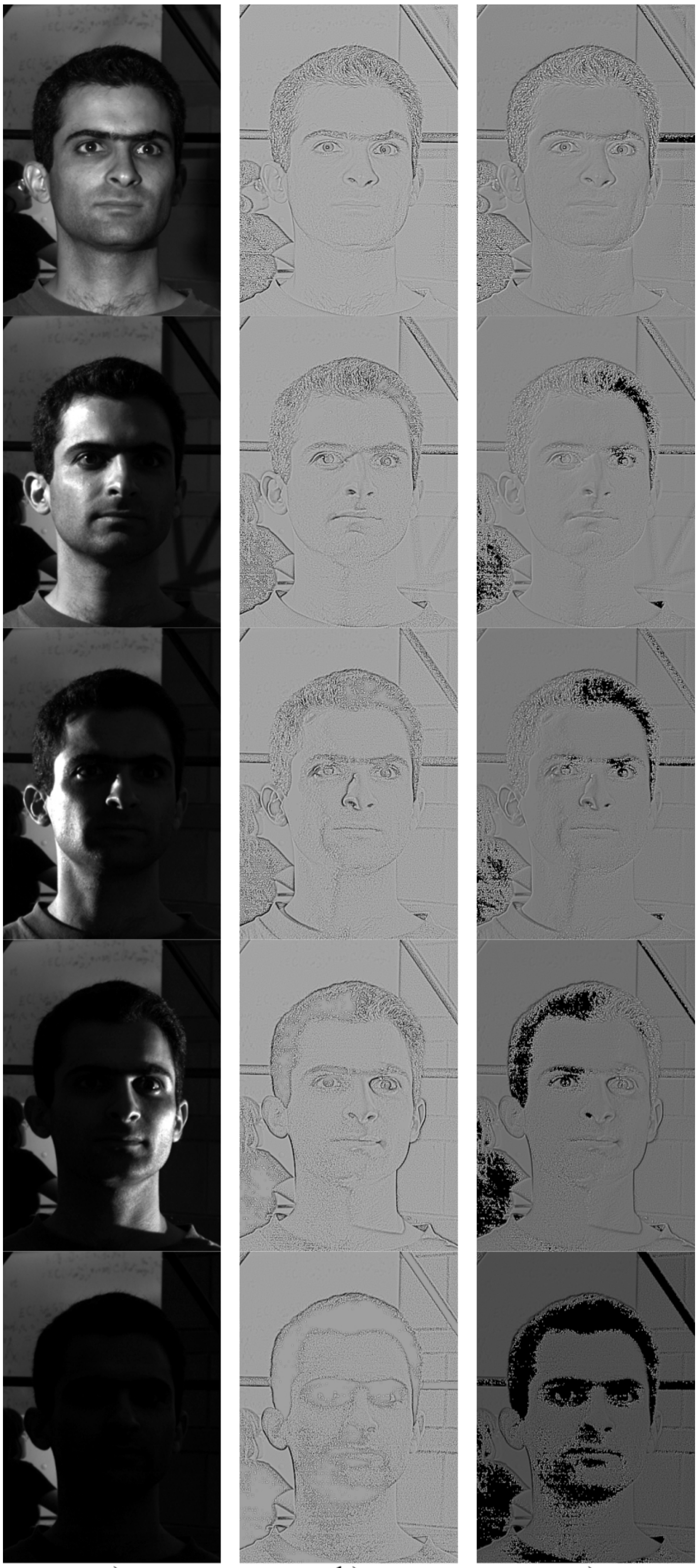

a) b) c)

Figure 2. a) Original images from Extended Yale Face Database B [16]; b) Normalized images using SQI based on Gaussian filter kernel; c) Normalized images using SQI based on shifted Gaussian filter kernel.

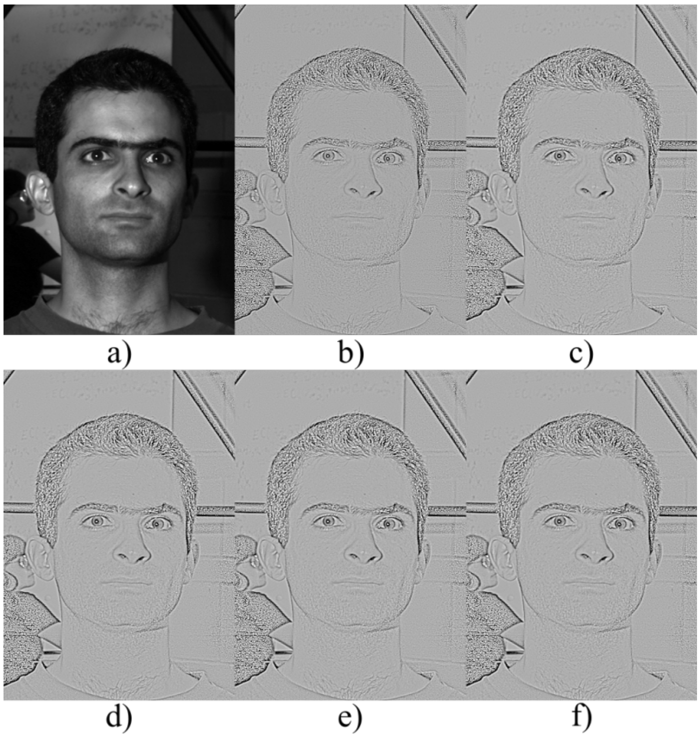

Figure 3. Normalized images using SQI based on Gaussian filter kernel with different kernel size: a) original image; b) 3×3; c) 5×5; d) 7×7; e) 9×9; f) 11×11.

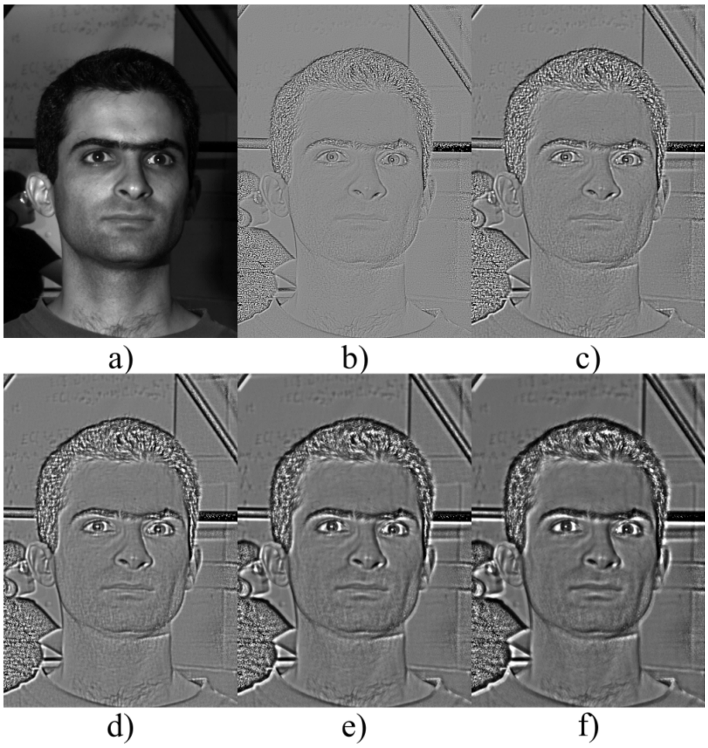

Figure 4. Normalized images using SQI based on shifted Gaussian filter kernel with different kernel size: a) original image; b) 3×3; c) 5×5; d) 7×7; e) 9×9; f) 11×11.

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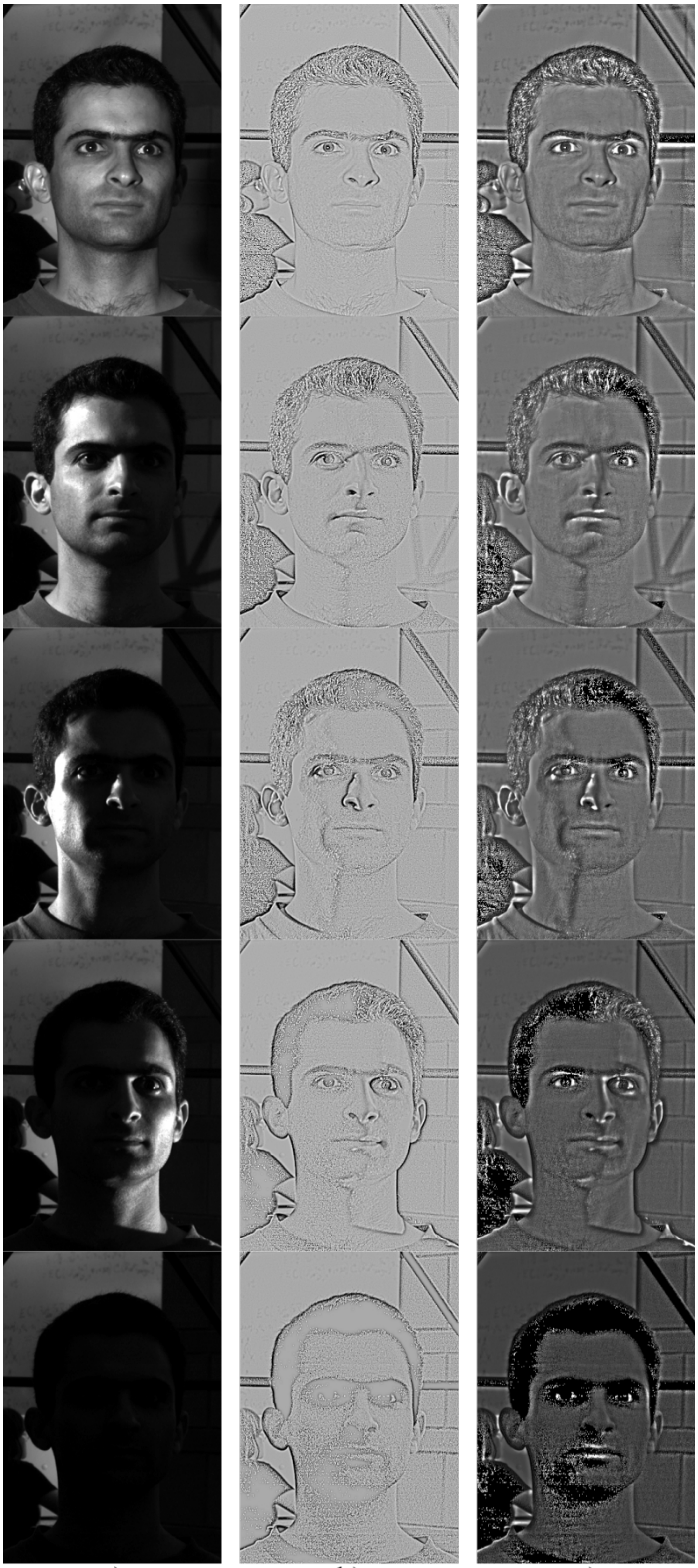

Figure 5. a) Original images from Extended Yale Face Database B [16]; b) Normalized images using stacked SQI based on Gaussian filter kernel; c) Normalized images using stacked SQI based on shifted Gaussian filter kernel.

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Experiments

To compare our Fast SQI method with original SQI method, we selected several images from Extended Yale Face Database B [16] with various identities and different lightning conditions. For both methods we checked base and stacked implementation, results presented in Figures 6 and 7.

a) b) c) d) a) b) c) d)

Figure 6. Comparison of different images: a) Original images from Extended Yale Face Database B [16]; b) images using the original SQI method; c) Normalized images using SQI based on Gaussian filter kernel; d) Normalized images using SQI based on shifted Gaussian filter kernel.

Conclusion

In the paper, we have shown modifications of the original SQI method and its stacked implementation. The main advantages of these modifications are 1) simplifying of the computational process since we use one Gaussian filter kernel for all image instead of the locally weighted Gaussian filter kernel, which was introduced in original works [1,14,15] and 2) improving the contrast and the lighting normalization even without using the stacked SQI implementation. Nevertheless, proposed modifications still not

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perfect and have disadvantages. For example, our SQI method using the original Gaussian filter kernel has a low sensitivity and cannot normalize lighting in very dark shadow regions. The Fast SQI method solves this issue, but cannot normalize the transition between shadow and lighted regions. Since, it can be very important in some face recognition systems, in the future works, we hope to solve these issues and improve results of the Fast SQI method. Another area of future research is a detailed comparison of the proposed methods not only with the original SQI method but with other methods designed for the lighting normalization of the image.

Figure 7. Comparison of different images: a) Original images from Extended Yale Face Database B [16]; b) images using the original SQI method; c) Normalized images using stacked SQI based on Gaussian filter kernel; d) Normalized images using stacked SQI based on shifted Gaussian filter kernel.

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