ISSN 2707-1898 (print)
Український журнал інформаційних технологій
Ukrainian Journal of Information Technology
http://science.lpnu.ua/uk/ujit
https://doi.org/10.23939/ujit2020.02.008
Article received 27.07.2020 р.
Article accepted 25.10.2020 р.
UDK 004.93'14

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PERFORMANCE EVALUATION OF SELF-QUOTIENT IMAGE METHODS

Lighting Normalization is an especially important issue in the image recognitions systems since different illumination conditions can significantly change the recognition results, and the lighting normalization allows minimizing negative effects of various illumination conditions. In this paper, we are evaluating the recognition performance of several lighting normalization methods based on the Self-Quotient Image(SQI) method introduced by Haitao Wang, Stan Z. Li, Yangsheng Wang, and Jianjun Zhang. For evaluation, we chose the original implementation and the most perspective latest modifications of the original SQI method, including the Gabor Quotient Image(GQI) method introduced by Sanun Srisuk and Amnart Petpon in 2008, and the Fast Self-Quotient Image(FSQI) method and its modifications proposed by authors in previous works. We are proposing an evaluation framework which uses the Cropped Extended Yale Face Database B, which allows showing the difference of the recognition results for different illumination conditions. Also, we are testing all results using two classifiers: Nearest Neighbor Classifier and Linear Support Vector Classifier. This approach allows us not only to calculate recognition accuracy for each method and select the best method but also show the importance of the proper choice of the classification method, which can have a significant influence on recognition results. We were able to show the significant decreasing of recognition accuracy for un-processed (RAW) images with increasing the angle between the lighting source and the normal to the object. From the other side, our experiments had shown the almost uniform distribution of the recognition accuracy for images processed by lighting normalization methods based on the SQI method. Another showed but expected result represented in this paper is the increasing of the recognition accuracy with the increasing of the filter kernel size. However, the large filter kernel sizes are much more computationally expensive and can produce negative effects on output images. Also, we were shown in our experiments, that the second modification of the FSQI method, called FSQI3, is better almost in all cases for all filter kernel sizes, especially, if we use Linear Support Vector Classifier for classification.

Keywords: lighting normalization, illumination normalization, self-quotient image, SQI, Gaussian filter, Gabor filter, Gabor quotient image, GQI, fast self-quotient image, FSQI, illumination invariant face recognition.

1. Introduction

Lighting Normalization is an efficient, powerful, and usually a simple approach for improving recognition results for the object and facial recognition. Since the most recognition systems work with single images to provide the smallest latency for users, illumination variations can produce significant changes in recognition results. The reason for it is that image variation due to lighting changes is more significant than that due to the difference of information on it, what was shown by Y. Adini, Y. Moses and S. Ullman [1]. From another side, creating the recognition system which can be stable for illumination variances is a complex and expensive task, since natural, as well as artificial illuminations, can produce an extremely large number of lighting scenarios. As a result, the Lighting Normalization is one of the fastest and most efficient ways to minimize effects of illumination variances in the recognition systems, since it not requires any changes in the recognition system itself and works as a per-processing step for each input image.

The object of the study is illumination conditions on the image and their effect on the accuracy of the recognition systems.

The subject of the study is a lighting normalization and methods for the lighting normalization, which allow minimizing effects of different illumination conditions and improving recognition accuracy.

The purpose of the study. Lighting Normalization methods investigated for more than fifteen years, but new methods introduced almost every year. Previous research showed a lot of results of comparisons and surveys of previously created methods [13], [18], [34], but since new methods appear very frequently, and previous research usually use different criteria for evaluation, research in this area still actual and important.

The practical significance of the obtained results:

1. The obtained results provide the latest results of the evaluation and comparison of the most popular lighting normalization methods based on the Self-Quotient Image approach.
2. The obtained results allow analyzing the recognition accuracy of evaluated methods depending on the illumination conditions and filter kernel size.
3. The obtained results allow choosing the optimal lighting normalization method for practical usage.

Analysis of recent research and publications. Lighting Normalization methods usually divided into several types based on approaches which they use for lighting normalization:

- ***Simple methods or image enhancement methods***, which act directly on the dynamic range of the image and are regardless of the image content. The most well-known method of this kind of methods is Histogram Equalization [9]. Other methods of this method types are Gain/offset Correction, Adaptive Histogram Equalization [24], like Contrast Limited Adaptive Histogram Equalization (CLAHE) [24], [25], Homomorphic Filtering and Non-linear Transforms, like as a Log Transform and Gamma Intensity Correction (GIC) [9], [13], [14], [34].

- ***Methods based on Retinex theory*** use the lighting model defined in the Retinex theory proposed by Edwin H. Land and John J. McCann [16]. The Retinex theory describes the representation model of the colour and lighting of a natural scene for the human visual system. The Retinex theory uses two major assumptions:

1. The human visual system computes each colour channel independently;
2. The intensity signal of each channel is proportional to the product of the illumination and the surface reflectance:

$$I(x,y) = R(x,y)L(x,y), \tag{1}$$

where I – image channel, R – reflectance and L – illumination.

3. The two most popular methods based on Retinex theory are Multiscale Retinex [15] and Anisotropic Retinex Method [10].

- ***Model-based methods*** use the Lambertian model or its variations for describing the image as the product of the surface normals of the object n^T, its albedo (or surface texture) ρ and the point light source s (Fig. 1):

$$I(x,y) = \rho(x,y) \cdot n^T(x,y) \cdot s\ . \tag{2}$$

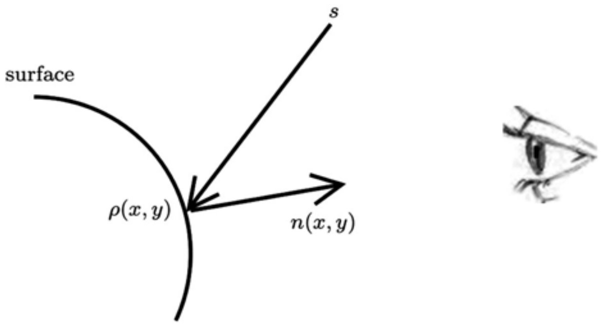

Figure 1. Lambertian lighting model [13]

Lighting Normalization methods based on the Lambertian model are represented by the large set of methods [2], [12], [22], [23], [26], [28], [30], [32], [33]. These methods can be divided into two types: 1) methods, which require training of the model and 2) methods, which not require training of the model [8], [11], [20], [27], [31]. The most popular model-based method, which requires training of the model, is the Quotient Image Method introduced by A. Shashua and T. Riklin-Raviv [26], [27]. The most popular model-based methods, which not require training of the model, are Self-Quotient Image Method [30], [31], [32] and its various modifications [4], [19], [21], [22], [23], [28], [33].

- ***Diffusion-based methods*** use partial differential equations to derive a blurred version of the original image, which considered as an approximation of luminance field $L(x, y)$ of the original image [13].

Since there is a large scope of various lighting normalization methods, complete evaluation of their performance requires creating a flexible and high-quality framework, which should be suitable for different types of methods. As the first step of the creation and testing such a framework, in this work we focused on a creation evaluation framework for various Self-Quotient ImagE(SQI) methods based on the Extended Yale Face Database B [7]. Self-Quotient Image methods chosen for evaluation for several reasons:

1. SQI methods are extremely simple and not require any preprocessing, alignment, or training.
2. SQI methods actively develop in the last years and a lot of new methods and their modifications introduced.
3. The authors worked with these methods last two years and proposed own modifications of the Self-Quotient Image method [22], [23].

The paper is organized in the following way. Section 2 contains a brief overview of the original Self-Quotient Image method and its stacked version [30], [31], [32]. Section 3 provides a description of the Gabor Quotient ImagE(GQI) introduced by Sanun Srisuk and Amnart Petpon in 2008 [28]. In section 4, we describe the Fast Self-Quotient ImagE(FSQI) [23] and its modifications [22]. Section 5 contains the description of the evaluation framework and provides results of performance evaluation of considered methods.

2. Overview of Self-Quotient Image Method

The Self-Quotient ImagE(SQI) Method is an original approach for robust face recognition under varying lighting conditions based on the Quotient Image method [26], [27] and introduced by Haitao Wang, Stan Z. Li, Yangsheng Wang, and Jianjun Zhang [32].

In comparison with the Quotient Image method, the Self-Quotient ImagE(SQI) method has three advantages:

1. The SQI method uses only one face image for lighting normalization. It allows using the SQL method in real-time face recognition systems, which cannot provide the image series or video output. It also minimizes delays between image registration and getting processing result.
2. Since the SQI method uses only one image, it means that alignment is not needed and the method does not need any face detection to minimize the face movement on images. As a result, the SQI method is simpler and faster, than Quotient Image method, which needs at least a few images for training [26], [27].
3. The method works in three types of regions: 1) regions without shadows and with small surface normal variation, 2) regions without shadows but with the large surface normal variation, and 3) shadow regions.

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

$$Q = \frac{I}{\hat{I}} = \frac{I}{F \cdot I}, \tag{3}$$

where $\hat{I}$ is the smoothed version of I, F is the weighted Gaussian filter kernel, and the division is point-wise as in the original quotient image [30], [31], [32].

The most important processing step in the SQI is smoothing filtering. The SQI uses the weighted Gaussian filter designed for anisotropic smoothing and defined as

$$F = \frac{1}{N}WG, \tag{4}$$

where W is the weight, G is the Gaussian kernel, and N is the normalization parameter.

The weighted Gaussian filter must match the following property

$$\frac{1}{N}\sum_{\Omega} WG = 1, \tag{5}$$

where Ω is the convolution kernel size.

The weight matrix W defined as

$$W(i,j) = \begin{cases} 0, \text{ if } I(i,j) \in M_2; \\ 1, \text{ if } I(i,j) \in M_1, \end{cases} \tag{6}$$

where M_1 and M_2 are two sub-regions of the convolution region divided by a threshold τ:

$$\tau = Mean(I_{\Omega})\ . \tag{7}$$

Stacked SQI method [30] is implemented as the sum of several self-quotient images computed using the SQI method with different sizes of the weighted Gaussian filter. Additionally, to operations of the original SQI method, the stacked SQI method uses nonlinear transformation for reducing noise in Q and weighted summarizing function. The general flow of the stacked SQI method contains the following operations:

1. Select several smoothing kernels G_1, G_2, …, G_n with different size;
2. For each smoothing kernel, calculate corresponding weights W_1, W_2, …, W_n according to the image I;
3. Smooth I with each Weighed Anisotropic filter $F_i = Wg_i$:

$$\hat{I}_k = I \cdot \frac{1}{N} WG_k, k = \overline{1,n} ; \tag{8}$$

4. Calculate Self-Quotient Image between each input image I and its smoothing version;

$$Q_k = \frac{I}{\hat{I}_k}, k = \overline{1,n} ; \tag{9}$$

5. Transfer Self-Quotient Image with a nonlinear transform function T;

$$D_k = T\left(Q_k\right), k = \overline{1,n} ; \tag{10}$$

6. Summarize results of the transformation;

$$Q = \sum_{k=1}^{n} m_k D_k , \tag{11}$$

where m_1, m_2, …, m_n are the weights for each scale of the filter. In [30], all weights are equal to 1.

3. Gabor Quotient ImagE(GQI) Method

Gabor Quotient ImagE(GQI) method [28] defined in the same way as Self-Quotient Image method, however, instead of the weighted Gaussian filter kernel, the GQI method uses the even Gabor filter kernel G_{even} defined as

$$G_{even}\left(x, y\right) = \cos\left(\frac{2\pi}{\lambda} x_r\right) Exp\left(-\frac{1}{2}\left(\frac{x_r^2}{\sigma_x^2} + \frac{y_r^2}{\sigma_y^2}\right)\right). \tag{12}$$

In this case, the equation (1) for GQI method ca be rewritten as [28]

$$Q = \frac{I}{\hat{I}} = \frac{I}{F \cdot I} = \frac{I}{G_{even} \cdot I} . \tag{13}$$

Additionally, the GQI method uses linear transformation function to normalize the quotient image in a range of [0, 1] and exponential normalization to increase contrast of the image [28]:

$$Q'\left(x, y\right) = \frac{Q\left(x, y\right) - Q_{min}}{Q_{max} - Q_{min}} , \tag{14}$$

$$Q_{norm}\left(x, y\right) = 1 - Exp\left(-\frac{Q'\left(x, y\right)}{E\left(Q'\left(x, y\right)\right)}\right), \tag{15}$$

where Q_{max} and Q_{min} are maximum and minimum values of Q respectively, and $E(.)$ is a mean value.

4. Fast Self-Quotient ImagE(FSQI) Method and its modifications

Fast Self-Quotient ImagE(FSQI) Method based on the equation (1) of the original SQI method, but the FSQI method, as well as the GQI method, uses another representation of the smoothing filtering kernel F. In the case of the FSQI method, the smoothing filtering kernel F is equal to the circularly shifted Gaussian filter kernel G^S and the general equation of the FSQI method can be rewritten as [23]

$$Q = \frac{I}{\hat{I}} = \frac{I}{F \cdot I} = \frac{I}{G^S \cdot I} . \tag{16}$$

The circularly shifted Gaussian kernel was created by shifting the filter kernel on the selected number of cells vertically and horizontally [23]. For our experiments, we used the one-cell shifting for each filter kernel size, since it is applicable as for smalL(for example, 3×3 pixels) as for large kernels. However, the proposed approach can be used with any number of cells less than the size of the filter kernel.

Also, [23] propose alternative implementation of the stacked SQI method based on FSQI method called the Stacked FSQI method. However, this implementation is still computation complex and slow as the original stacked SQI method.

Since the FSQI method uses the same approach for normalization of the quotient image as the original SQI method, the [22] proposes two modifications of the FSQI method based on the different normalization functions. Normalization of the FSQI method uses nonlinear transformation represented as Logarithm function, which was recommended as the optimal normalization function since it has similar characteristics of the human visual ability [15]. However, authors of the original SQI method shown that Arctangent and Sigmoid functions can have similar or superior results [30].

The first modification of the FSQI method proposed in [22] uses the Histogram Truncation to truncate the lowest and highest values of the quotient image histogram and normalize the image. Histogram Truncation can reduce the contrast of the quotient image, but allows reinforcing medium values of the colour histogram, which contains the maximum of textural information. In our experiments, this modification called FSQI2.

The second modification proposed in [22] uses the normalization proposed by Sanun Srisuk and Amnart Petpon for the GQI method [28] and based on linear normalization function (14) and exponential normalization function (15). In our experiments, this modification called FSQI3.

5. Experiments

For the evaluation framework of recognition results, we used the cropped version [17] of the Extended Yale Face Database B [7]. The Cropped Extended Yale Face Database B [17] contains 38 subjects each seen under 65 viewing conditions (1 pose × (64 illumination conditions + ambient)), which equal 2470 images in total. Since 18 images corrupted, we manually fixed them using original images from the Extended Yale Face Database B [7]. As a result, the testing database contains 2470 images, which divided into 5 sets according to the angle of the light source directions. Each set contains the next number of images:

- Set 1 ([-12°, +12°]) – 14 face images under different illumination conditions for each identity, 532 images in total for all identities.
- Set 2 ([-25°, -13°], [+13°, +25°]) – 10 face images under different illumination conditions for each identity, 380 images in total for all identities.
- Set 3 ([-50°, -26°], [+26°, +50°]) – 12 face images under different illumination conditions for each identity, 456 images in total for all identities.
- Set 4 ([-77°, -51°], [+51°, +77°]) – 10 face images under different illumination conditions for each identity, 380 images in total for all identities.

- Set 5 ([<-78˚], [>+78˚]) – 19 face images under different illumination conditions for each identity, 722 images in total for all identities.

The idea of this configuration bases on the proposed experiment in [28], but we changed the distribution of images between test sets. Also, we skipped manual rotation, resizing and cropping to 100×100 pixels, since all images of the Cropped Extended Yale Face Database B are already rotated and cropped to 168x192 pixels [17].

The evaluation process consists of three steps:

1. All images are processed using the following methods:
   - Histogram Equalization (HE) [9];
   - Contrast Limited Adaptive Histogram Equalization (CLAHE) [24], [25];
   - Self-Quotient Image Method (SQI) [30], [31], [32];
   - Gaussian Self-Quotient Image Method (GSQI) [23];
   - Gabor Quotient Image Method (GQI) [28];
   - Fast Self-Quotient Image Method (FSQI) [23];
   - Fast Self-Quotient Image Method (FSQI2) with Histogram Truncation [22];
   - Fast Self-Quotient Image Method (FSQI3) with Exponential Normalization [22].
2. All processed images transformed into the principal component analysis (PCA) [29] with 1000 principal components.
3. All principal components representations classify using two classifiers:
   - Nearest Neighbor Classifier (NNC) based on L^2 distance between the representation of the training image x and the test image y

$$D_{L^2} = \sqrt{\sum (x-y)^2}\ ; \qquad (17)$$

   - Linear Support Vector Classifier (LSVC) uses the implementation of the C-Support Vector Classification [3], [5] provided in the liblinear library [6].

Since, evaluation database divided into 5 sets, we made 5 experiments, and each of them uses the one set as the training set and others as test sets. Then for each method, we calculated average accuracy. Additionally, we provided similar experiments for four different sizes of the filter kerneL(3×3, 5×5, 7×7, and 9×9). Filter kernel size is one of the most important parameters of Self-Quotient Image methods since large filter kernel extracts more details from the image and provides a better estimation of lighting conditions on the image. However, a large filter kernel is more computationally expensive and can increase side effects, like halo effects near step-edge regions. Therefore, selecting the optimal size of the filter kernel is an especially important issue of the practical usage of Self-Quotient Image methods.

Results for each filter kernel size generalized in 4 tables, each of them contains results for one filter kernel size and all 5 experiments for each classifier (see Table I-IV). Such structure allows analyzing the recognition accuracy for each set of data and the lighting normalization method for the used filter kernel size. These tables also show how the lighting angle effects on recognition accuracy. The main goal of these tables is not only to show that the recognition accuracy increases after the lighting normalization. But they also show that the lighting normalization decreases dependency of the recognition accuracy from the lighting angle and the distribution of the recognition accuracy after the lighting normalization is more uniform than without the lighting normalization.

Table I. Recognition results for filter kernel size 3×3

Training set	RAW images	HE	CLAHE	SQI	GSQI	GQI	FSQI	FSQI2	FSQI3
Nearest Neighbor Classifier (NNC), %									
Set 1	23.82	44.30	35.19	26.60	85.38	65.91	62.35	80.89	68.85
Set 2	27.35	50.07	36.01	18.28	77.51	63.03	58.76	67.38	65.05
Set 3	20.61	51.33	30.38	9.67	76.98	26.27	49.64	72.62	34.14
Set 4	22.33	56.60	37.73	4.39	73.23	16.19	47.74	65.50	22.34
Set 5	7.54	35.75	18.15	6.35	45.20	15.45	22.74	39.75	17.28
Average Accuracy	20.33	47.61	31.49	13.06	71.66	37.37	48.25	65.23	41.53
Linear Support Vector Classifier (LSVC), %									
Set 1	62.05	90.93	65.42	87.05	97.02	97.80	98.16	97.90	98.34
Set 2	61.75	89.09	67.54	53.81	94.89	96.36	93.77	94.40	97.25
Set 3	83.57	98.79	81.21	86.80	95.02	95.49	95.41	94.48	96.20
Set 4	87.12	98.03	91.39	81.16	92.98	93.16	94.44	93.11	94.20
Set 5	30.39	88.72	42.28	69.94	90.47	90.69	93.30	92.01	92.61
Average Accuracy	64.98	93.11	69.57	75.75	94.08	94.70	95.02	94.38	95.72

Table II. Recognition results for filter kernel size 5×5

Training set	RAW images	HE	CLAHE	SQI	GSQI	GQI	FSQI	FSQI2	FSQI3
Nearest Neighbor Classifier (NNC), %									
Set 1	23.82	44.30	35.19	29.50	89.06	81.59	77.60	87.06	87.67
Set 2	27.35	50.07	36.01	22.64	82.43	77.26	77.71	77.12	82.55
Set 3	20.61	51.33	30.38	24.31	81.98	61.25	75.13	84.10	74.72
Set 4	22.33	56.60	37.73	20.51	78.29	59.38	77.06	81.90	69.22
Set 5	7.54	35.75	18.15	9.47	58.42	37.15	49.65	67.05	54.17
Average Accuracy	20.33	47.61	31.49	21.29	78.04	63.33	71.43	79.45	73.67
Linear Support Vector Classifier (LSVC), %									
Set 1	62.05	90.93	65.42	94.91	97.49	98.53	98.63	98.60	98.77
Set 2	61.75	89.09	67.54	86.01	95.57	97.28	95.53	96.46	97.96
Set 3	83.57	98.79	81.21	94.07	95.34	96.81	95.88	95.93	97.37
Set 4	87.12	98.03	91.39	90.63	93.91	95.72	95.77	95.38	96.81
Set 5	30.39	88.72	42.28	88.23	92.20	93.63	94.69	94.47	95.50
Average Accuracy	64.98	93.11	69.57	90.77	94.90	96.39	96.10	96.17	97.28

Table III. Recognition results for filter kernel size 7×7

Training set	RAW images	HE	CLAHE	SQI	GSQI	GQI	FSQI	FSQI2	FSQI3
Nearest Neighbor Classifier (NNC), %									
Set 1	23.82	44.30	35.19	48.51	89.21	87.44	80.90	87.93	91.81
Set 2	27.35	50.07	36.01	37.69	82.63	82.79	78.43	79.26	89.22
Set 3	20.61	51.33	30.38	56.36	82.64	74.01	79.47	88.41	82.24
Set 4	22.33	56.60	37.73	52.45	78.78	73.85	80.76	90.01	82.98
Set 5	7.54	35.75	18.15	26.96	59.43	55.01	56.35	80.63	79.41
Average Accuracy	20.33	47.61	31.49	44.39	78.54	74.62	75.18	85.25	85.13
Linear Support Vector Classifier (LSVC), %									
Set 1	62.05	90.93	65.42	97.20	97.68	98.67	98.66	98.77	98.91
Set 2	61.75	89.09	67.54	91.42	95.72	97.73	96.40	96.77	98.28
Set 3	83.57	98.79	81.21	96.11	95.53	97.42	96.68	97.11	97.86
Set 4	87.12	98.03	91.39	94.48	94.08	96.84	96.73	96.78	98.22
Set 5	30.39	88.72	42.28	91.82	92.36	96.23	96.13	96.16	97.22
Average Accuracy	64.98	93.11	69.57	94.21	95.07	97.38	96.92	97.12	98.10

Table IV. Recognition results for filter kernel size 9×9

Training set	RAW images	HE	CLAHE	SQI	GSQI	GQI	FSQI	FSQI2	FSQI3
Nearest Neighbor Classifier (NNC), %									
Set 1	23.82	44.30	35.19	57.14	89.30	89.66	79.08	83.24	94.70
Set 2	27.35	50.07	36.01	52.97	82.66	84.97	73.50	76.55	91.88
Set 3	20.61	51.33	30.38	69.40	82.67	79.02	80.06	88.78	87.46
Set 4	22.33	56.60	37.73	62.97	78.92	78.39	83.01	91.67	86.96
Set 5	7.54	35.75	18.15	41.02	59.49	65.12	60.03	84.33	86.49
Average Accuracy	20.33	47.61	31.49	56.70	78.61	79.43	75.14	84.91	89.50
Linear Support Vector Classifier (LSVC), %									
Set 1	62.05	90.93	65.42	98.05	97.68	98.73	98.66	98.84	99.01
Set 2	61.75	89.09	67.54	94.56	98.76	97.94	96.97	97.09	98.34
Set 3	83.57	98.79	81.21	96.73	95.53	97.59	97.35	97.98	98.38
Set 4	87.12	98.03	91.39	95.58	94.11	97.34	97.91	98.02	98.41
Set 5	30.39	88.72	42.28	93.13	92.41	97.29	97.39	97.32	97.90
Average Accuracy	64.98	93.11	69.57	95.61	95.70	97.78	97.66	97.85	98.41

Table V. Average Recognition Accuracy for all methods

Method	NNC, %				LSVC, %			
	3×3	5×5	7×7	9×9	3×3	5×5	7×7	9×9
RAW images	20.33				64.98			
HE	47.61				93.11			
CLAHE	31.49				69.57			
SQI	13.06	21.29	44.39	56.70	75.75	90.77	94.21	95.61
GSQI	71.66	78.04	78.54	78.61	94.08	94.90	95.07	95.70
GQI	37.37	63.33	74.62	79.43	94.70	96.39	97.38	97.78
FSQI	48.25	71.43	75.18	75.14	95.02	96.10	96.92	97.66
FSQI2	65.23	79.45	85.25	84.91	94.38	96.17	97.12	97.85
FSQI3	41.53	73.67	85.13	89.50	95.72	97.28	98.10	98.41

Table V contains generalized results for all experiments and displays the average accuracy of face recognition for each method depending on the filter kernel size and used classifier. This table allows showing the dependency on the recognition accuracy from the filter kernel size and choosing the optimal configuration for each illumination normalization method.

6. Conclusion

The obtained results show the high accuracy of the face recognition, especially for the Fast Self-Quotient Image method and its modifications. These results again confirmed conclusions which we got during the investigation of modifications of the FSQI method [22]. The unexpectedly high result shown the Gaussian Self-Quotient Image method, which uses a Gaussian filter kernel without any modification. From another side, the obtained results show the importance of choosing proper classifier for such evaluation, since it can have a significant effect on not only recognition accuracy, but also on the choosing of the method with the highest recognition accuracy.

Despite the high recognition accuracy and the choosing of the optimal filter kernel size investigated in this paper, Self-Quotient Image methods still have other parameters required for the proper configuration of these methods. Most of them are related to the configuration of the filter kernel used by some method. The optimal selection of these parameters not completely investigated and can be a subject of future research. Also, in future research, we plan to investigate other classifiers and their effect on the recognition accuracy and, probably, investigate other approaches for retrieving the image representation instead of the PCA. From the other side, we are interested in the even more complex evaluation using larger databases, like the Extended Yale Face Database B [7], which also can be investigated in future research.

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ОЦІНКА ЕФЕКТИВНОСТІ МЕТОДІВ САМООЦІНЮВАННЯ ЗОБРАЖЕННЯ

Нормалізація освітлення є дуже важливою проблемою в системах розпізнавання зображень, оскільки різні умови освітлення можуть істотно змінити результати розпізнавання, а нормалізація освітлення дає змогу мінімізувати негативні наслідки різних умов освітлення. У цій роботі ми оцінюємо ефективність розпізнавання декількох методів нормалізації освітлення, заснованих на методі самооцінювання зображення SQI (англ. *Self-Quotient Image method*), запровадженому Haitao Wang, Stan Z. Li, Yangsheng Wang, та Jianjun Zhang. Для оцінки ми вибрали оригінальну реалізацію та найперспективніші модифікації оригінального методу SQI, в т.ч. й метод Gabor Quotient ImagE(GQI), запропонований Sanun Srisuk та Amnart Petpon у 2008 році, а також метод Fast Self-Quotient ImagE(FSQI) та його модифікації, запропоновані авторами статті в попередніх роботах. У цій роботі ми запропонували модель оцінки, яка використовує Cropped Extended Yale Face Database B, що дає змогу показати відмінність результатів розпізнавання для різних умов освітлення. Також ми перевіряємо всі результати за допомогою двох класифікаторів: класифікатора найближчих сусідів (англ. *Nearest Neighbor Classifier*) та лінійного класифікатора опорних векторів (англ. *Linear Support Vector Classifier*). Такий підхід дає змогу не тільки обчислити точність розпізнавання для кожного методу та вибрати найкращий метод, але й показати важливість правильного вибору методу класифікації, який може мати значний вплив на результати розпізнавання. Нам вдалося показати значне зменшення точності розпізнавання для необроблених (RAW) зображень із збільшенням кута між джерелом освітлення та нормаллю до об'єкта. З іншого боку, наші експерименти показали майже рівномірний розподіл точності розпізнавання для зображень, оброблених методами нормалізації освітлення на підставі методу SQI. Ще одним отриманим, проте очікуваним результатом, представленим у цій роботі, є підвищення точності розпізнавання із збільшенням розміру ядра фільтра. Однак великі розміри ядра фільтра є більш обчислювально-затратні і можуть спричинити негативні ефекти на вихідних зображеннях. Окрім цього, в наших експериментах було показано, що друга модифікація методу FSQI, яку ми скорочено позначаємо як FSQI3, краща майже в усіх випадках для всіх розмірів ядра фільтра, особливо якщо ми використовуємо лінійний класифікатор опорних векторів для класифікації.

Ключові слова: нормалізація освітлення, метод самооцінювання зображень, SQI, фільтр Гауса, фільтр Габора, метод Габора для самооцінювання зображень, GQI, метод швидкої самооцінювання зображень, FSQI.

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Цитування за ДСТУ: Парубочий В. О., Шувар Р. Я. Оцінка ефективності методів самооцінювання зображення. *Український журнал інформаційних технологій*. 2020, т. 2, № 1. С. 08–14.

Citation APA: Parubochyi, V. O., & Shuvar, R. Ya. (2020). Performance evaluation of Self-Quotient image methods. *Ukrainian Journal of Information Technology, 2*(1), 08–14. https://doi.org/10.23939/ujit2020.02.008