Color Facial Image Representation with New Quaternion Gradients

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Abstract

- This paper proposes a new color image representation and multiple feature fusion based method for improving color face recognition performance. under different lighting conditions.
- We propose a novel feature representation/Quaternion Gradient-based LBP tool for color face recognition.
- We present the color facial recognition system based on the local quaternion gradient based LBP image representation, and a new color-to-gray new mapping.
- The presented concept can be used for surveillance, security systems, computer animation, face tagging, biometric identification, behavioral analysis, content-based image and video indexing applications.

Diagram of Facial Image Representation

The main parts of representation of the grayscale facial image $f_{n,m}$ of size $N \times M$ are shown in the block-diagram of Figure 1.

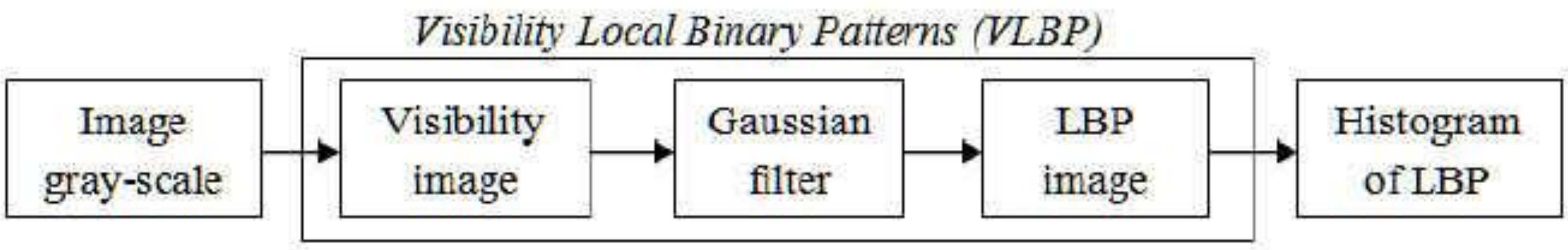


Figure 1. *(a) The block-diagram of the facial image representation*.

The algorithm of facial image processing:

Stage 1. The visibility image is calculated,

$$f_{n,m} \to V(f)_{n,m}, \qquad n = 0:(N-1), m = 0:(M-1).$$

The image $V(f)$ can also be the image obtained by applying one of the gradient operators.

Stage 2. The 2-D Gaussian function is circular convoluted with the visibility image.

$$V(f)_{n,m} \to \mathrm{V}(f)_{n,m} \otimes h_{n,m},$$

where the 2-D Gaussian function

$$h_{n,m} = \frac{1}{K}\exp\left(-\frac{n^2+m^2}{2\pi\sigma^2}\right)$$

is considered with the mean (0,0) and variance $\sigma^2 = 1/4$ and

$$K = \sum_{n=-L_1}^{L_1}\sum_{m=-L_2}^{L_2} h_{n,m} = \sum_{n=-L_1}^{L_1}\sum_{m=-L_2}^{L_2} \exp\left(-\frac{n^2+m^2}{2\pi\sigma^2}\right);$$

$(2L_1+1)\times(2L_2+1)$ is the size of the Gaussian function.

Stage 3. A complex gradient image composition:

$$A_1 = \begin{bmatrix} -1 & 0 & 0 \\ 0 & \underline{1} & 0 \\ 0 & 0 & 0 \end{bmatrix}, A_2 = \begin{bmatrix} 0 & -1 & 0 \\ 0 & \underline{1} & 0 \\ 0 & 0 & 0 \end{bmatrix}, A_3 = \begin{bmatrix} 0 & 0 & -1 \\ 0 & \underline{1} & 0 \\ 0 & 0 & 0 \end{bmatrix},$$

$$A_4 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & \underline{1} & -1 \\ 0 & 0 & 0 \end{bmatrix}, A_5 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & \underline{1} & 0 \\ 0 & 0 & -1 \end{bmatrix}, A_6 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & \underline{1} & 0 \\ 0 & -1 & 0 \end{bmatrix},$$

$$A_7 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & \underline{1} & 0 \\ -1 & 0 & 0 \end{bmatrix}, A_8 = \begin{bmatrix} 0 & 0 & 0 \\ -1 & \underline{1} & 0 \\ 0 & 0 & 0 \end{bmatrix}.$$

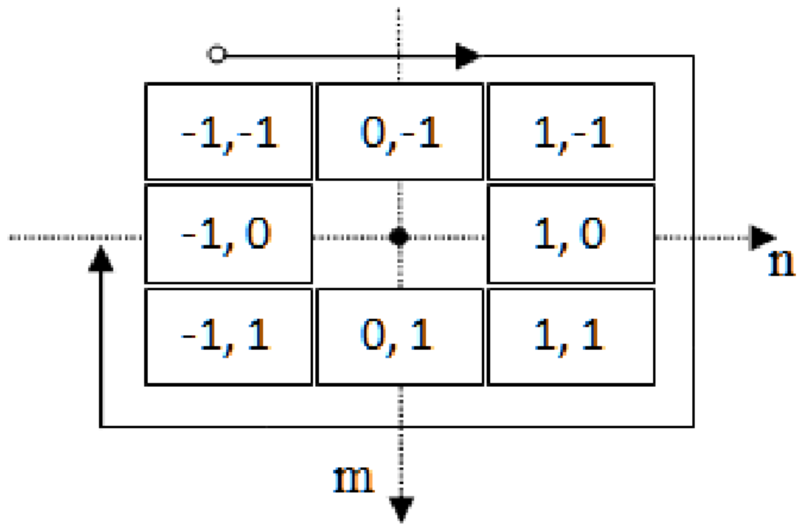


Figure 2. *The coordinates and the order of 8 neighbor sampling points.*

These eight neighbor points are called the sampling points (SP),

$$[(-1,-1),(0,-1),(1,-1),(1,0),(1,1),(0,1),(-1,1),(-1,0)].$$

The gradient operators are applied on the facial image $f_{n,m}$ and eight binary images are calculated by

$$B_{\mathrm{k}}(f)_{n,m} = \mathrm{u}\left[A_k(f)_{n,m}\right], \qquad k = 1{:}\,8.$$

Here, $u[t]$ is the Heaviside function that is defined as $u[t] = 1$, if $t \geq 0$, and $u[t] = 0$, otherwise. The new image, which is called the local binary pattern (LBP) image, is calculated by

$$b_{n,m} = B_1(f)_{n,m} + 2^1 B_2(f)_{n,m} + 2^2 B_3(f)_{n,m} + \cdots + 2^7 B_8(f)_{n,m}$$

or

$$b_{n,m} = \sum_{k=1}^{8} 2^{k-1}\left[f_{n,m} - f_{n+s(k),m+p(k)}\right].$$

Here, $(s(k), p(k))$ are the sampling points, which are ordered as shown in the sampling points SP. The LBP image has the range of 256 integer levels s, from 0 to 255. The histogram of this image, $H(s)$ is considered to be the feature of the facial image $f_{n,m}$, which can be used in face classification.

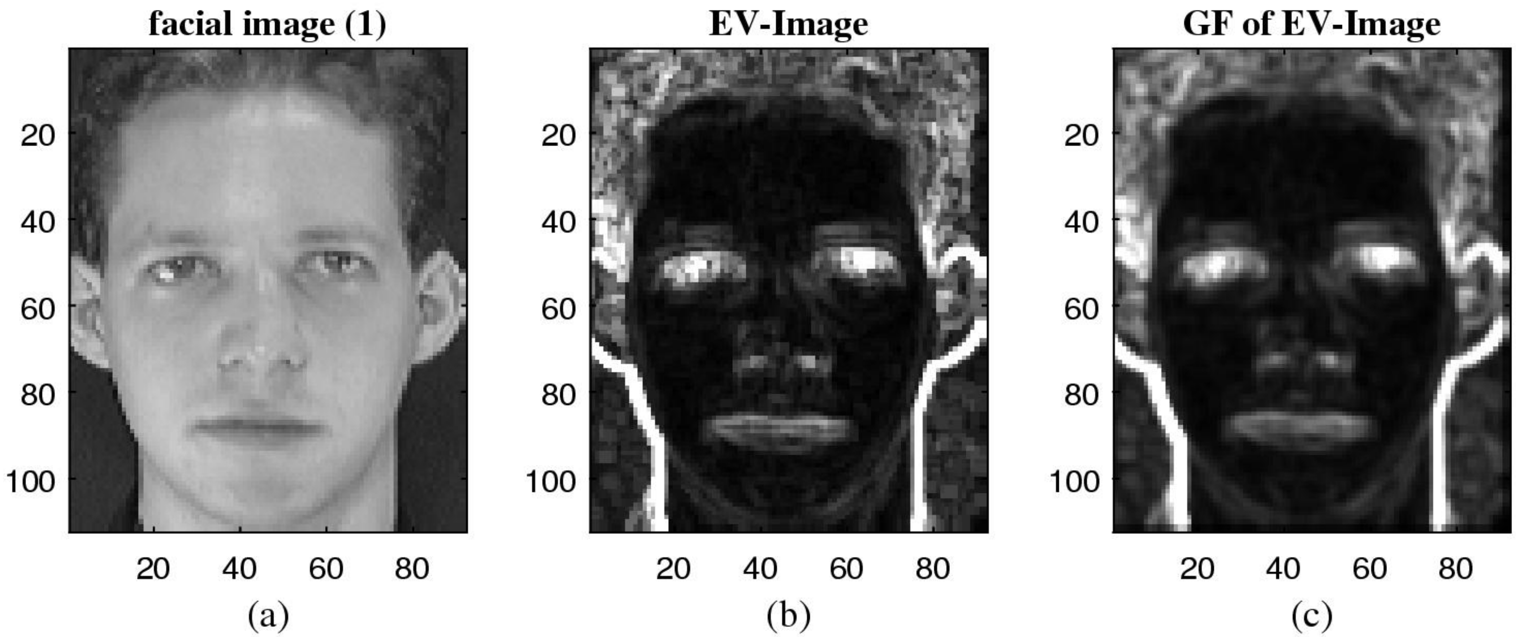


Figure 3. *(a) The 114×94 image and (b) the EME visibility image. (c) The EME visibility image filtered by the 2-D Gaussian function*.

Figure 4 shows the LBP image $b_{n,m}$ and its histogram.

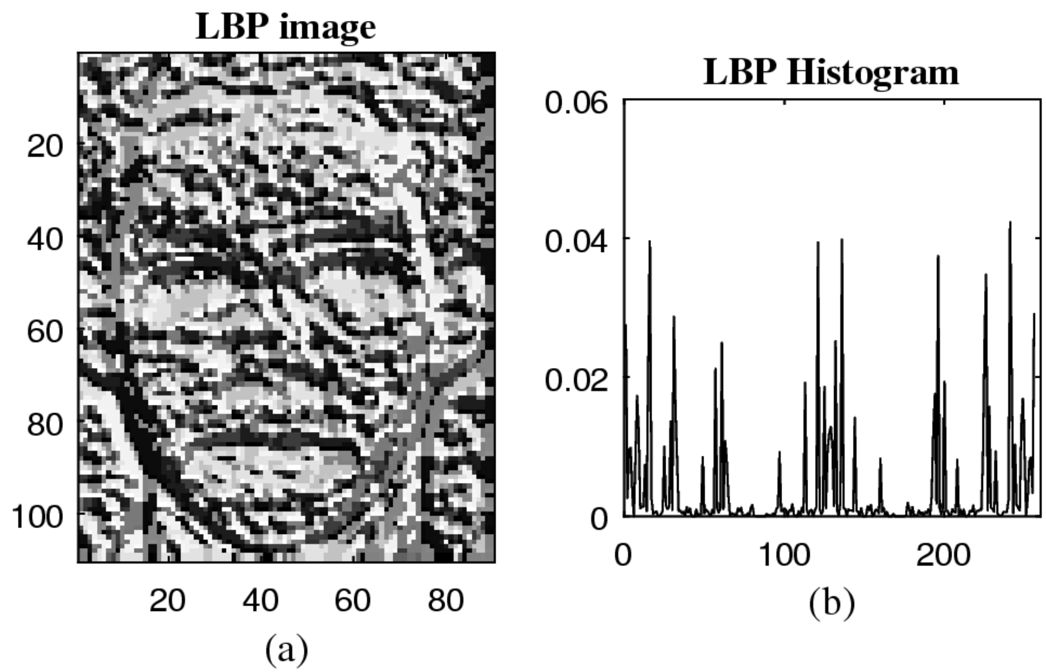


Figure 4. *(a) The LBP image and (b) the histogram of the image*.

The histogram of the image has 256 binary patterns and to reduce the number of binary patterns, the LBP image can be modified, by using the uniform LBP look up table (T) shown below.

$$
T = \begin{bmatrix}
0 & 1 & 2 & 3 & 4 & \bullet & 5 & 6 & 7 & \bullet & \bullet & \bullet & 8 & \bullet & 9 & 10 \\
11 & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & 12 & \bullet & \bullet & \bullet & 13 & \bullet & 14 & 15 \\
16 & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\
17 & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & 18 & \bullet & \bullet & \bullet & 19 & \bullet & 20 & 21 \\
22 & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\
\bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\
23 & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\
24 & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & 25 & \bullet & \bullet & \bullet & 26 & \bullet & 27 & 28 \\
29 & 30 & \bullet & 31 & \bullet & \bullet & \bullet & 32 & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & 33 \\
\bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & 34 \\
\bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\
\bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & 35 \\
36 & 37 & \bullet & 38 & \bullet & \bullet & \bullet & 39 & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & 40 \\
\bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & 41 \\
42 & 43 & \bullet & 44 & \bullet & \bullet & \bullet & 45 & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet & 46 \\
47 & 48 & \bullet & 49 & \bullet & \bullet & \bullet & 50 & 51 & 52 & \bullet & 53 & 54 & 55 & 56 & 57
\end{bmatrix}
$$

The total number of uniform patterns is 58 and they are labeled from 0 to 57. The label 58 is assigned for all other, non-uniform patterns. By using this table after each gradient image calculation, the new image is calculated as follows:

$$
\begin{aligned}
(g_1)_{n,m} &= T\left[(g_1)_{n,m}\right], \\
(g_k)_{n,m} &= T\left[(g_{k-1})_{n,m} + B_k(f)_{n,m}\right], \qquad k = 2:8.
\end{aligned}
$$

The last image $(g_8)_{n,m}$ has the range of 59 integer levels s, from 0 to 58. The histogram of this image is considered to be the feature of the facial image $f_{n,m}$, which is used in face classification. Thus, 256 integer levels in the original LBP image are reduced to 59 levels in the uniform LBP (ULBP) image.

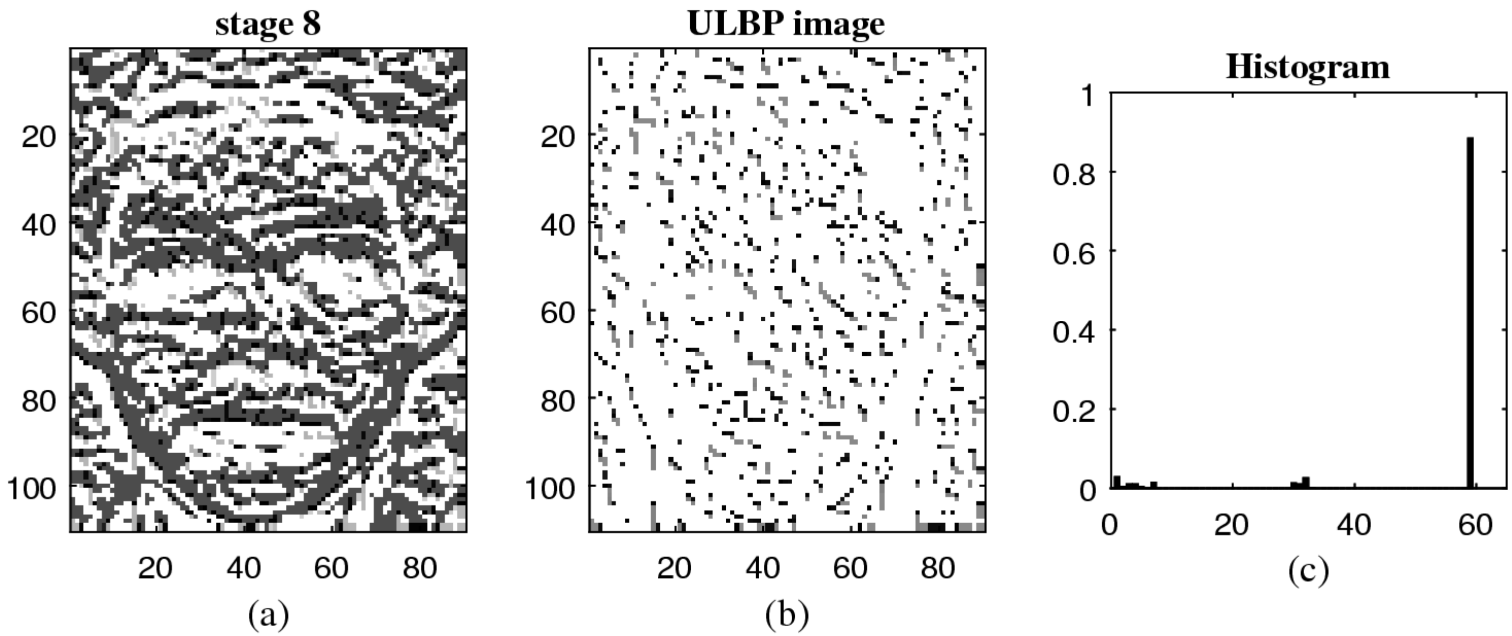


Figure 5. *(a) The image $(g_8)_{n,m}$ before the mapping, (b) the uniform LBP image, and (c) the histogram of the image*.

Color Visibility Images

We consider the visibility images that are related to the enhancement measure EME, which calculates the average range of intensity of the image in the logarithm scale and the enhancement of the image $f_{n,m}$ is the estimated in small not overlapping blocks or windows $W_{k,l}$ of small size. This quantitative measure of the enhanced image, $f_{n,m} \rightarrow g_{n,m}$, is defined by

$$EME(g) = \frac{1}{k_1 k_2} \sum_{k=1}^{k_1} \sum_{l=1}^{k_2} 20\ln\left[\frac{\max_{W_{k,l}}(g_{n,m})}{\min_{W_{k,l}}(g_{n,m})}\right]. \qquad (6)$$

Here, $k_1 k_2$ is the numbers of windows dividing the image, and $\max_{k,l}(g)$ and $\max_{k,l}(g)$ respectively are the maximum and minimum of $g_{n,m}$ inside the window $W_{k,l}$. $EME(g)$ is called a measure of enhancement of the image f. The value of $EME(f)$ is called the enhancement measure of the original image f.

The EME related visibility image at the pixel (n, m) is defined as

$$E(f)_{n,m} = \ln\left[\frac{\max_W\left(f_{n,m}\right)}{\min_W\left(f_{n,m}\right)}\right]\left(f_{n,m}\right)^{\beta}, \tag{7}$$

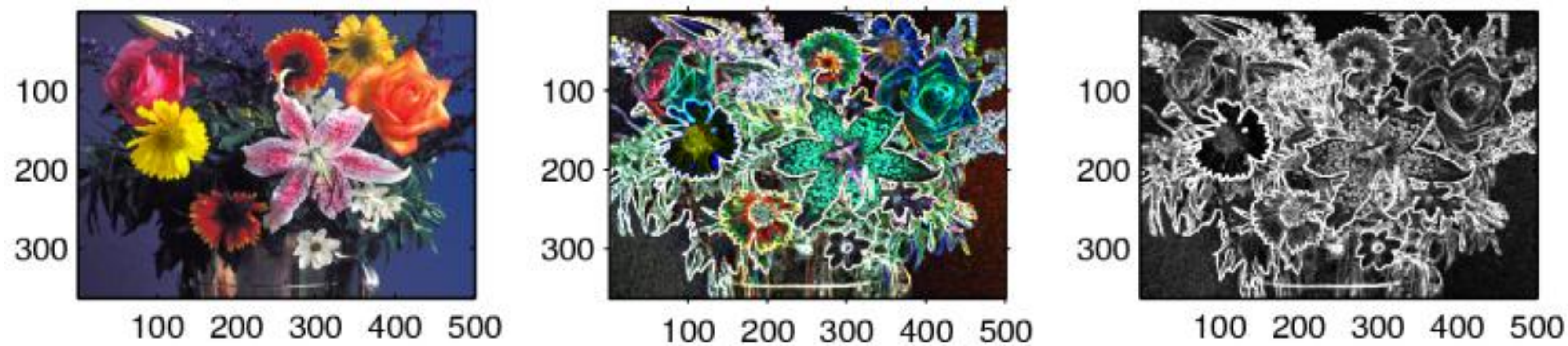
where β is a parameter.

The EME measure can be used for the color image in the RGB model, when image is composed by red, green, and blue components, $f_{n,m} = (r_{n,m}, g_{n,m}, b_{n,m})$. The EME visibility color image (EVCI) is defined by the operator

$$f_{n,m} \rightarrow \mathrm{E}\left(f_{n,m}\right) = \left[E\left(r_{n,m}\right), E\left(g_{n,m}\right), E\left(b_{n,m}\right)\right], \tag{8}$$

where the color components of this image are calculated by Eq. 7.

Example with the “flowers” image, with β=1: The color image composed by EME visibility images of 3 color components $c_{n,m}$, is shown in (b) and the grayscale component of this image in (c).



(a) (b) (c)

Figure 5. *(a) The color “flowers” image, (b) the MEVCI, and (c) grayscale image of the MEVCI*.

Visibility images can be calculated by gradient operators as

$$E(\mathrm{c}_{n,m}) = \mathrm{kln}\left|\frac{c_{n,m} - \mathrm{mean}_W(c_{n,m})}{c_{n,m} + c_0}\right|. \qquad (10)$$

The Michelson visibility images for each component $c_{n,m}$ are calculated by using the ratios of difference of the local maximums

$$E(c)_{n,m} = k\frac{\max_{\mathrm{W}}(c_{n,m}) - \min_{\mathrm{W}}(c_{n,m})}{\max_{\mathrm{W}}(c_{n,m}) + \min_{\mathrm{W}}(c_{n,m})}, \quad k = \text{const.} \quad (11)$$

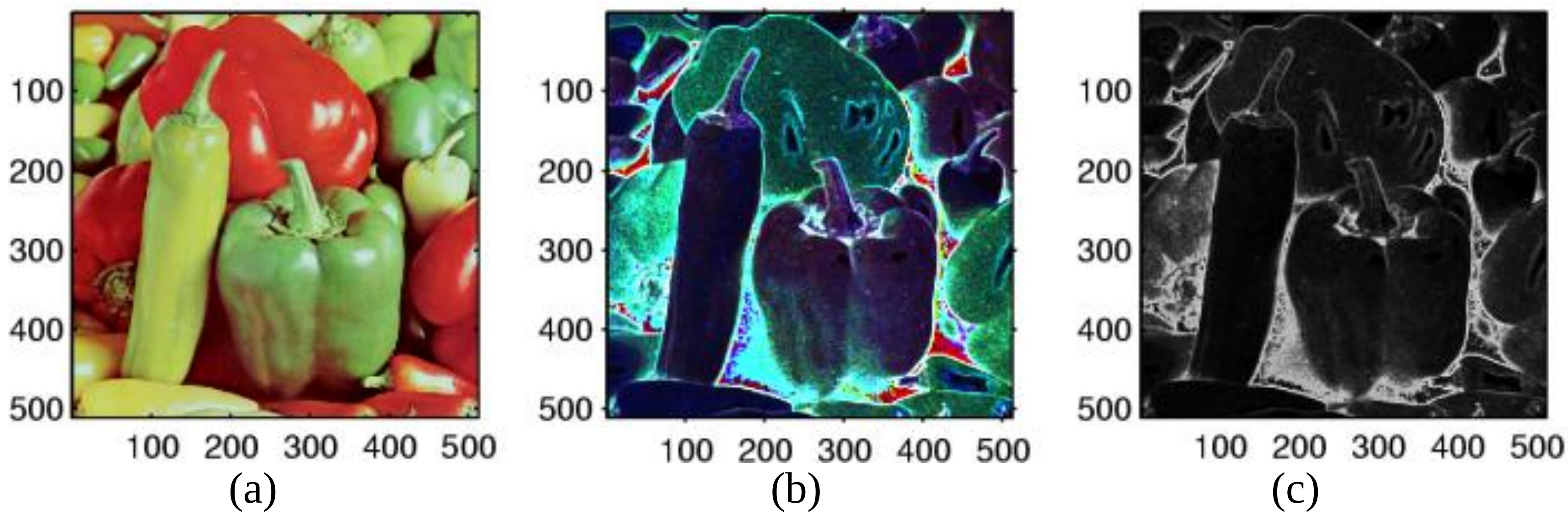


***Figure 6**. (a) The color "pepper" image, (b) the MVCI, and (c) grayscale image of the MVCI.*

Quaternion Image Gradients (in RGB model)

The $N \times M$ color image $f_{n,m} = (r_{n,m}, g_{n,m}, b_{n,m})$ can be represented in the quaternion space as

$$q_{n,m} = a_{n,m} + \left(ir_{n,m} + jg_{n,m} + kb_{n,m}\right). \tag{12}$$

Here, i, j, and k are pure quaternion units, and the real part is

$$a_{n,m} = (r_{n,m} + g_{n,m} + b_{n,m})/3, \qquad (\text{or } a_{n,m} = 0).$$

The windowed convolution of this image with a quaternion mask

$$H_{n,m} = (H_e)_{n,m} + (i(H_i)_{n,m} + j(H_j)_{n,m} + k(H_k)_{n,m}),$$

with the right-side multiplication as

$$y_{n,m} = \sum_{n_1=L_1}^{L_1} \sum_{l=L_2}^{L_2} q_{n-n_1,m-m_1} H_{n_1,m_1}$$

where $(2L_1 + 1) \times (2L_2 + 1)$ are size of the mask.

The $H_i, H_j, H_k = 0$ case corresponds to the traditional component-wise color image processing by the real mask by the same real mask H_e. Let the convolution mask is the quaternion gradient

$$H_{n,m} = (1 + (i + j + k)](H_e)_{n,m}, \tag{13}$$

and real mask H_e is defined as for the gradient operator G_x or G_y in the X and Y directions, respectively. Thus, we consider gradients

$$H_x = (1 + (i + j + k)]G_x$$

and

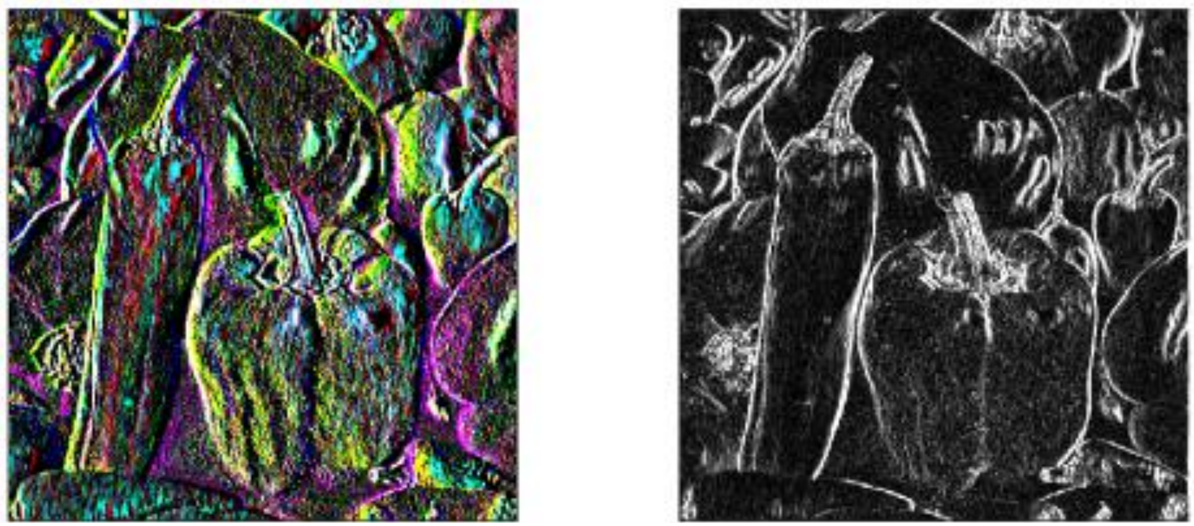
$$H_y = (1 + (i + j + k)]G_y.$$

Example with the 3×3 Sobel gradients with masks

$$G_x = \frac{1}{4}\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}, \quad G_y = \frac{1}{4}\begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}.$$

The quaternion operators defined with such masks are called the quaternion Sobel gradients.

Figure 7 shows the imaginary part of the quaternion H_x-Sobel gradient as a color image is shown in part (a) and the real part of the gradient in part (b).



(a) (b)

Figure 7. *(a) The imaginary part and (b) the real part of the quaternion H_x-Sobel gradient image.*

Figure 8 shows the imaginary part of the quaternion H_y-Sobel gradient as a color image is shown in part (a) and the real part of the gradient in part (b).

(a) (b) (c)

***Figure 8**. (a) The imaginary part and (b) the real part of the quaternion H_y-Sobel gradient image. (c) The magnitude of the real part of the quaternion Sobel gradient image which is calculated by*

$$|[H(q)]_e| = |]H_x(q)]_e\big|+|[H_y(q)]_e\big|.$$

The main parts of processing the color facial image $f_{n,m}$ of size $N \times M$ are shown in the block-diagram of Fig. 9. The color image is considered in the RGB model.

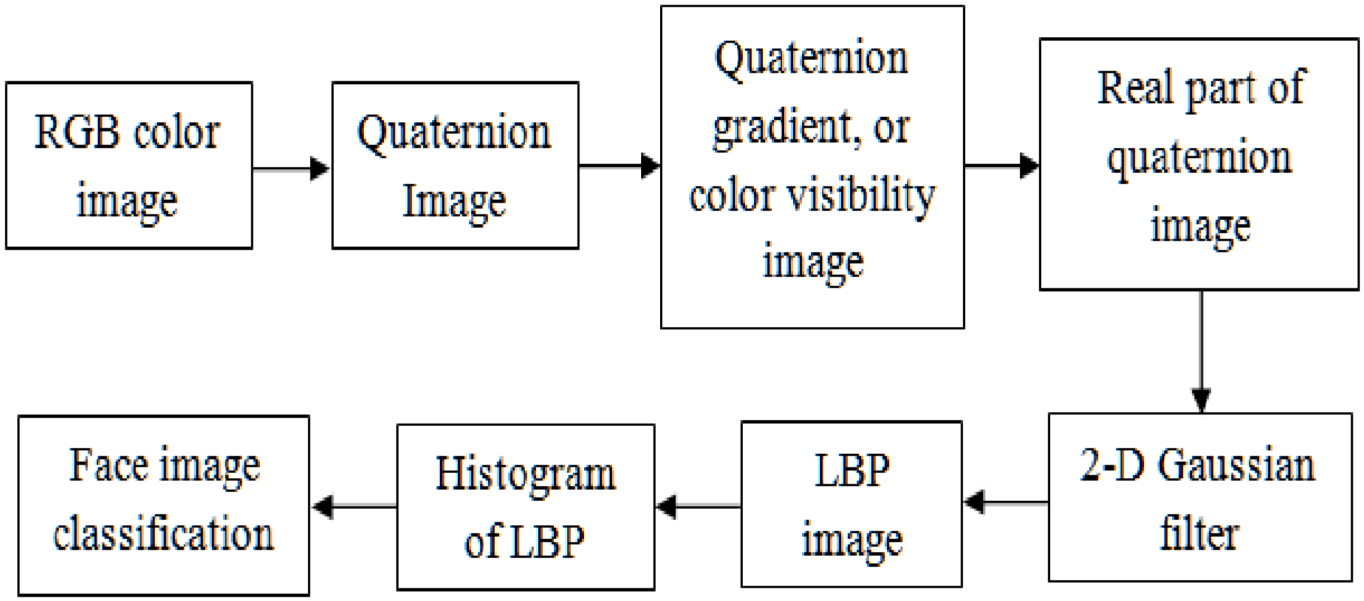


Figure 9. *The block-diagram of color facial image processing.*

The processing of color images in the XYZ, CMY, CMYK, and other color models is described similar to the RGB model case.

Example: Fig. 10 shows the color facial image of size 230×266 in part (a). The quaternion gradient image $H(q)_{n,m}$ calculated by using the quaternion gradient in Eq. 13 is shown in part (b), and after filtering by the 2-D Gaussian function with the standard deviation of 0.5 in part (c).

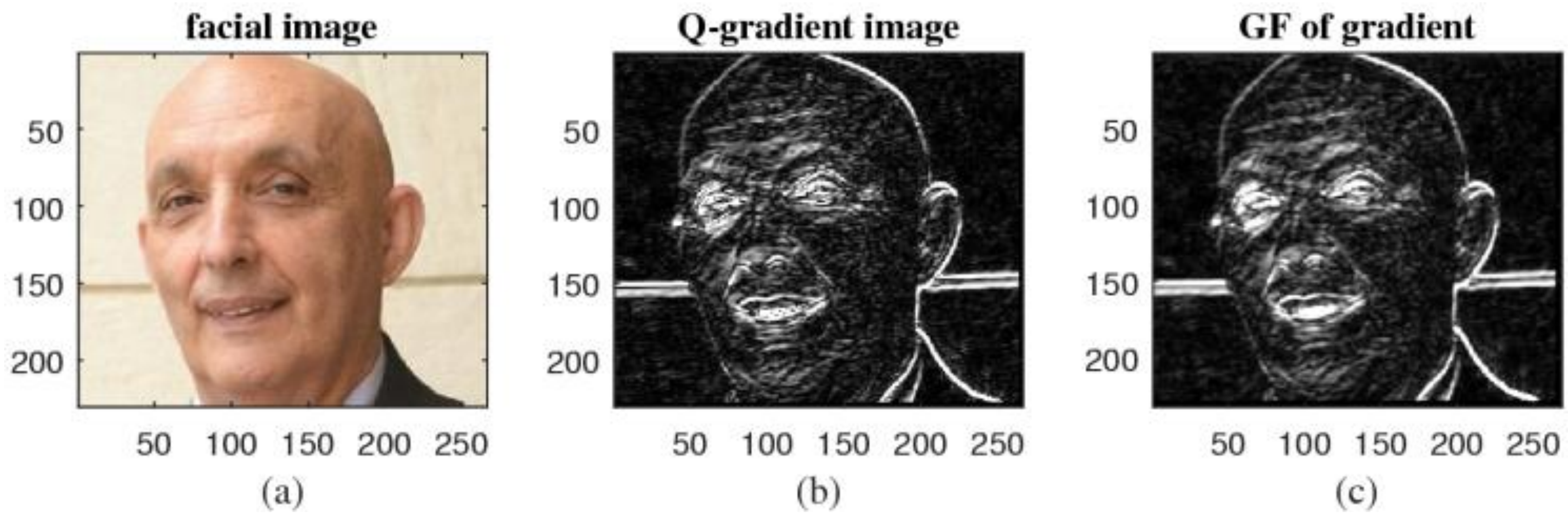


Figure 10. *(a) The* original image and the quaternion gradient image (b) before and (c) after filtering by the 2-D Gaussian function.

Figure 11 shows the LBP image in part (a) together with its histogram in part (b).

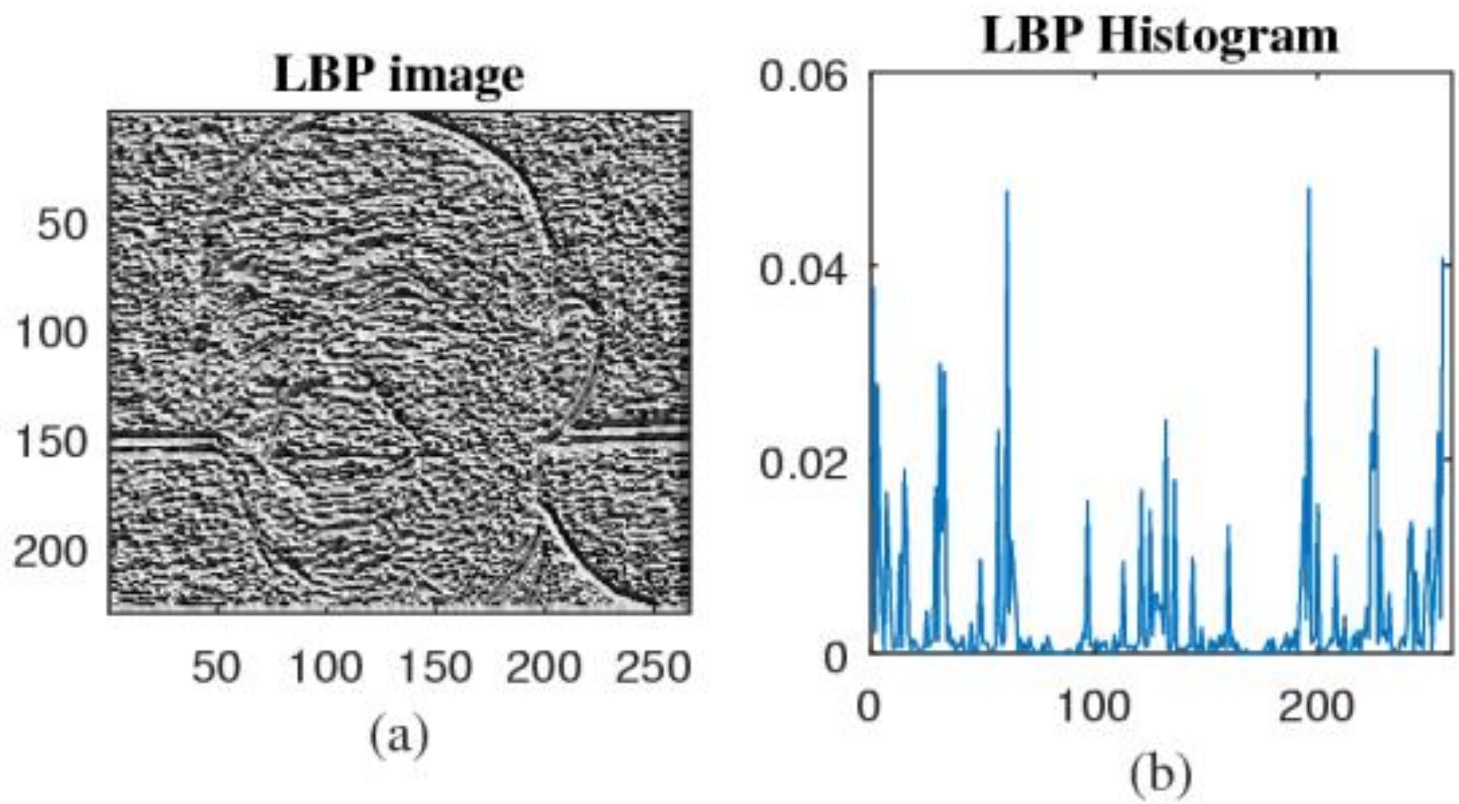


***Figure 11**. (a) The LBP* image and (b) the histogram of this image.

The results of further facial image processing are shown in Fig. 12. The binary image $(g_8)_{n,m}$ before and after using the mapping by the uniform LBP table is shown in (a) and (b), respectively. The normalized histogram of the uniform LBP image is given in (c).

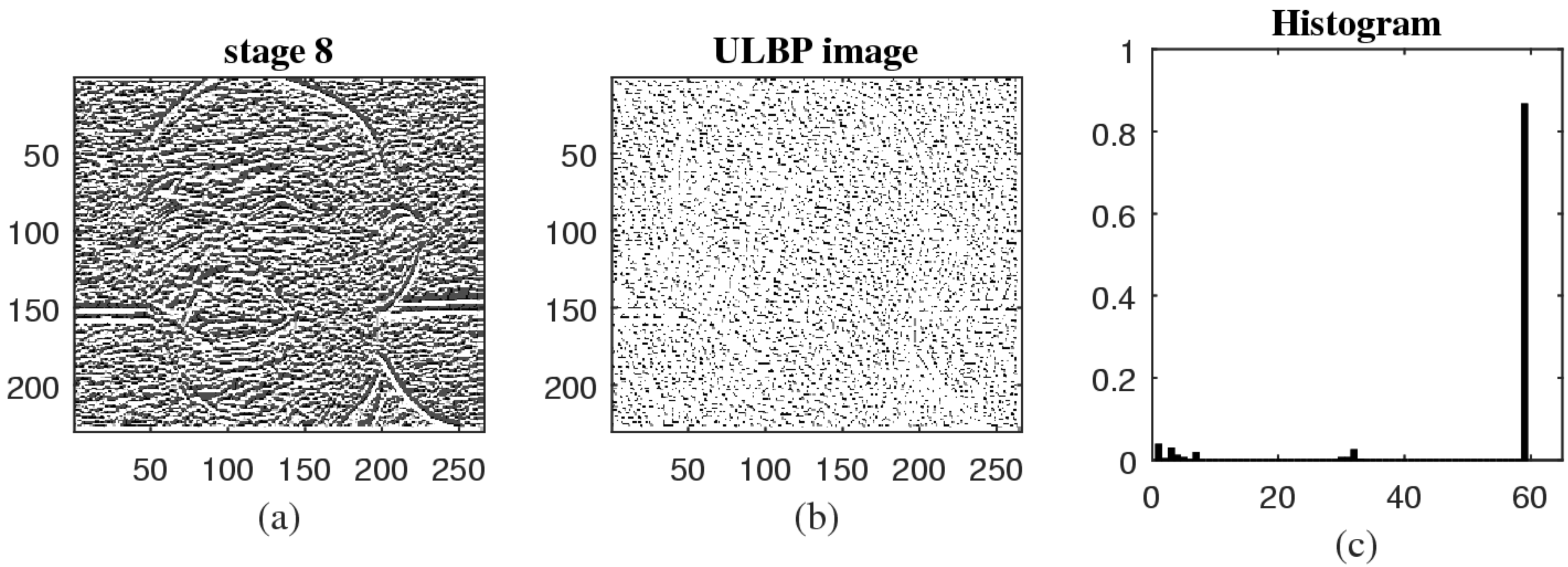


Figure 12. *(a) The last binary image $(g_8)_{n,m}$ before the mapping, (b) the uniform LBP image, and (c) the histogram of the image.*

Example: The image from the database of Dr. Libor Spacek by address: http://cswww.essex.ac.uk/mv/allfaces/faces94.html.

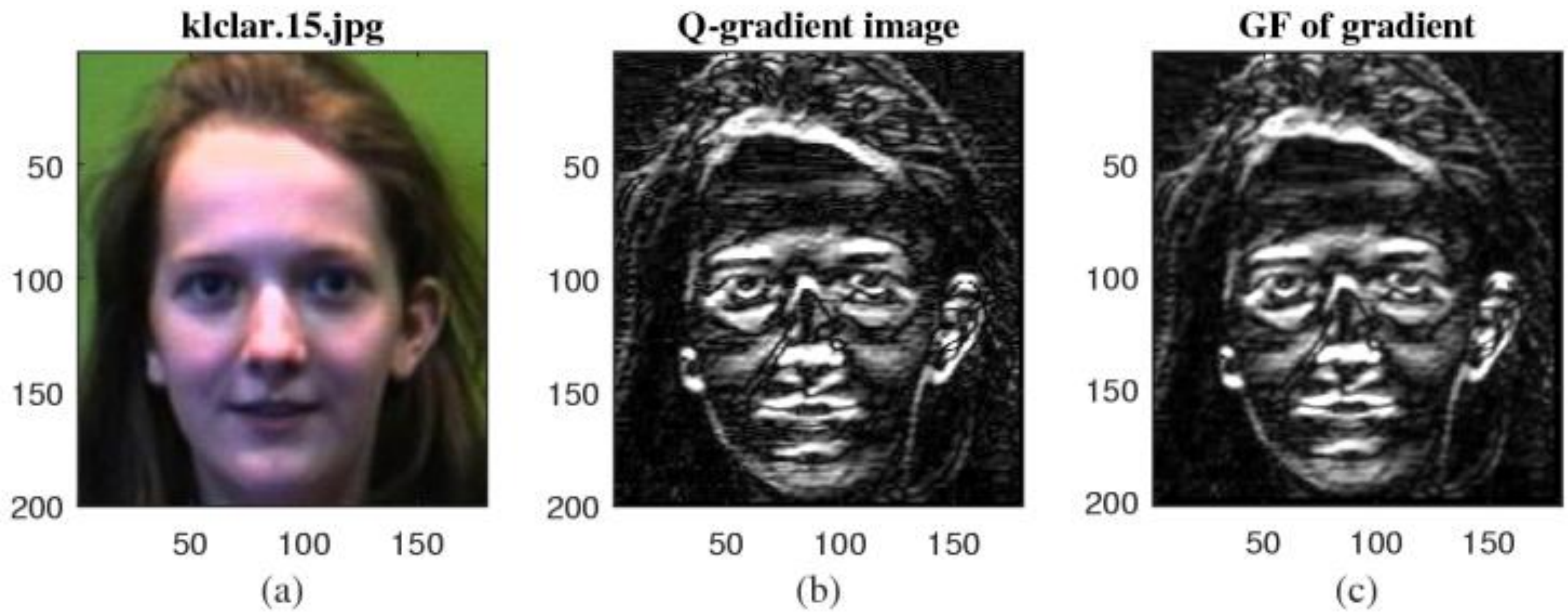


***Figure 13**. (a) The* image and the quaternion Sobel gradient image (b) before and (c) after filtering by the 2-D Gaussian function with the standard deviation of 0.5.

Figure 14 shows the results of further facial image processing. The image $(g_8)_{n,m}$ before and after using the mapping by the uniform LBP table is shown in part (a) and (b), respectively. The normalized histogram of the uniform LBP image is given in (c).

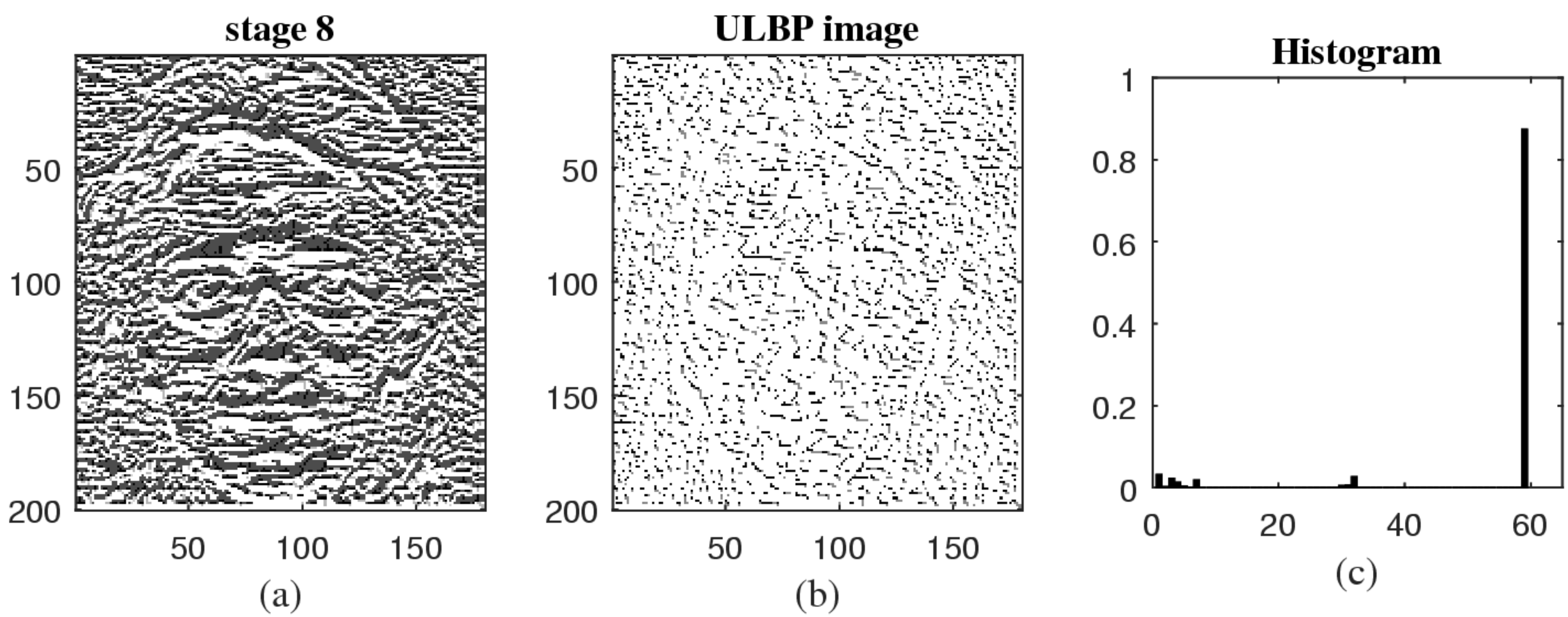


Figure 14. *(a) The last binary image* $(g_8)_{n,m}$ *before the mapping, (b) the uniform LBP image, and (c) the histogram of the image*.

Image processing with the quaternion 3×3 Prewitt gradients:

$$G_x = \frac{1}{5}\begin{bmatrix} 1 & 1 & -1 \\ 1 & -2 & -1 \\ 1 & 1 & -1 \end{bmatrix}, \quad G_y = \frac{1}{5}\begin{bmatrix} 1 & 1 & 1 \\ 1 & -2 & 1 \\ -1 & -1 & -1 \end{bmatrix}.$$

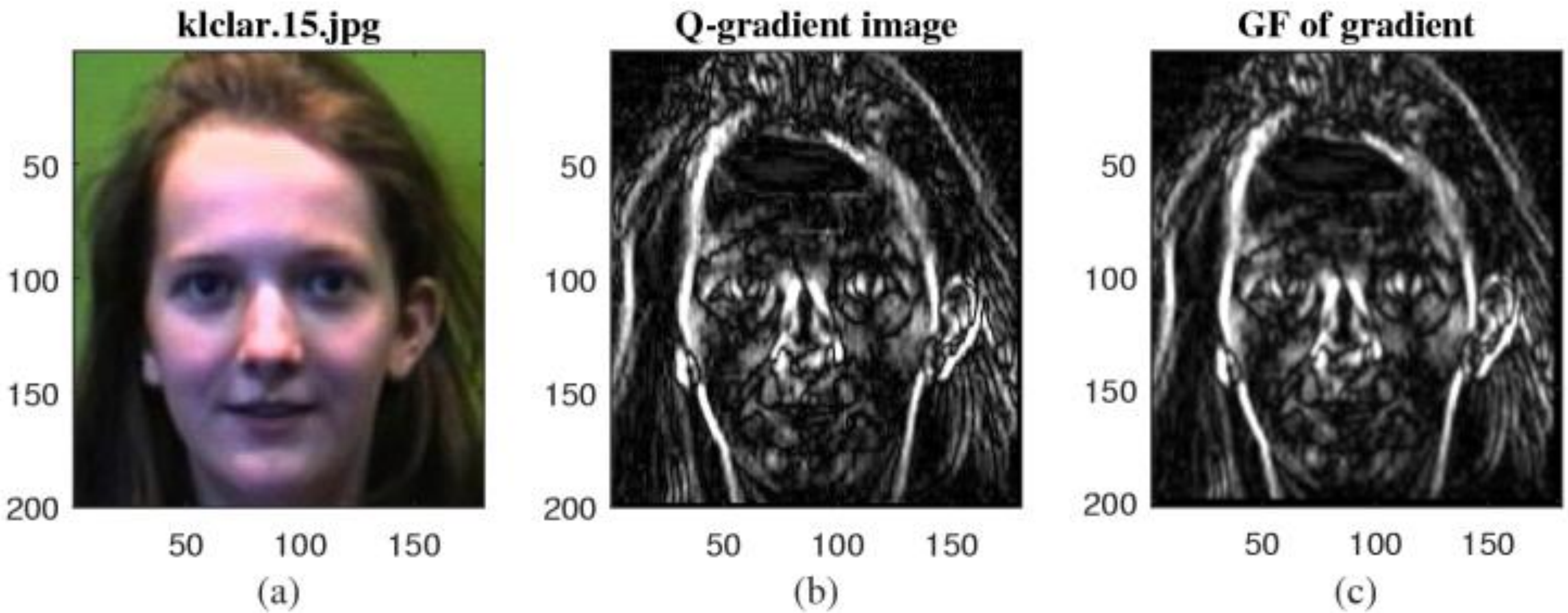


***Figure 15**. (a) The* image and the quaternion Prewitt gradient image (b) before and (c) after filtering by the 2-D Gaussian function.

The image $(g_8)_{n,m}$ before and after using the mapping by the uniform LBP table is shown in Fig. 16(a) and (b), respectively. The normalized histogram of the uniform LBP image is given in (c).

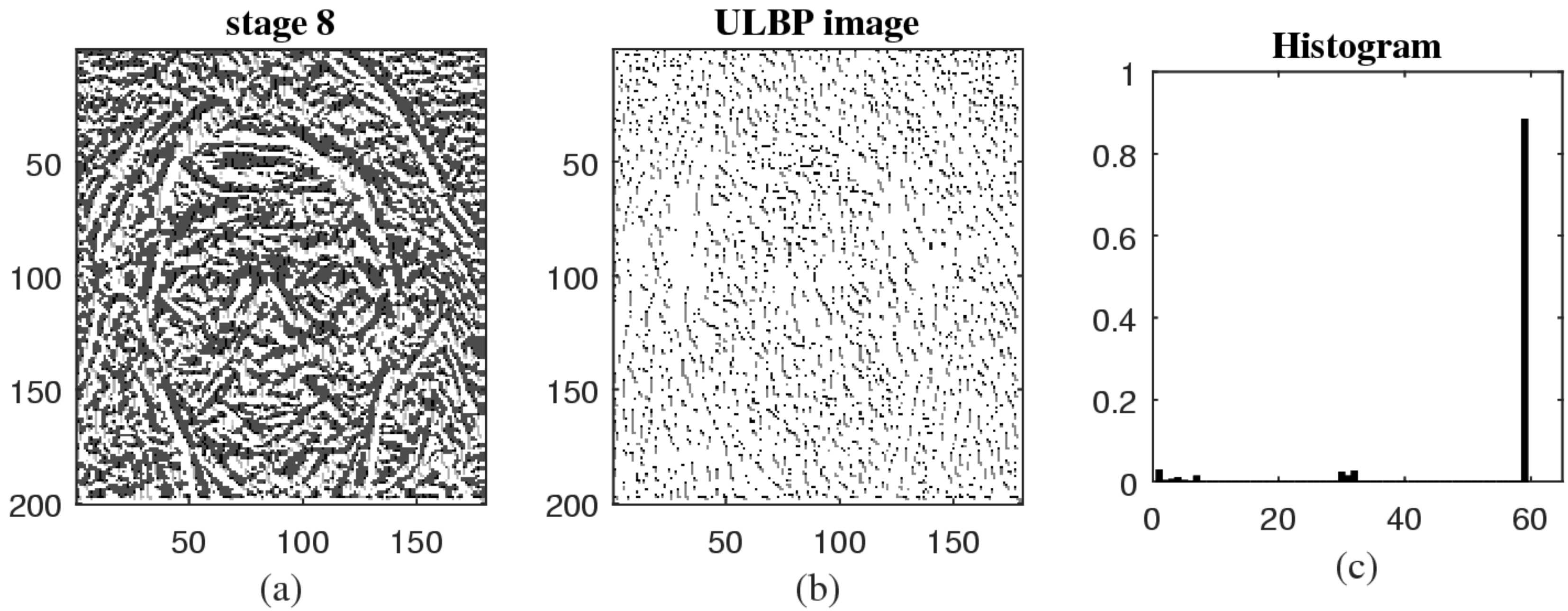


Figure 16. *(a) The last binary image* $(g_8)_{n,m}$ *before the mapping, (b) the uniform LBP image, and (c) the histogram of the image*.

Summary

A novel face recognition approach is proposed, by using multiple feature fusion across color, spatial and frequency domains. The proposed approach is useful and applicable not only for face recognition, but also for object recognition. We are planning to evaluate the presented face recognition concept, by using the color FERET database: http://www.face-rec.org/databases/.

References

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3. K.A. Panetta, C. Gao, S.S. Agaian, "No Reference Color Image Contrast and Quality Measures," *IEEE Transactions on Consumer Electronics*, vol. 59, no. 3, pp. 643–651, 2013.
4. ...