# Novel Method for Face Recognition using Laplacian of Gaussian Mask with Local Contour Pattern

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## Abstract

We propose a face recognition method that utilizes the LCP face descriptor. The proposed method applies a LoG mask to extract a face contour response, and employs the LCP algorithm to produce a binary pattern representation that ensures high recognition performance even under the changes in illumination, noise, and aging. The proposed LCP algorithm produces excellent noise reduction and efficiency in removing unnecessary information from the face by extracting a face contour response using the LoG mask, whose behavior is similar to the human eye. Majority of reported algorithms search for face contour response information. On the other hand, our proposed LCP algorithm produces results expressing major facial information by applying the threshold to the search area with only 8 bits. However, the LCP algorithm produces results that express major facial information with only 8-bits by applying a threshold value to the search area. Therefore, compared to previous approaches, the LCP algorithm maintains a consistent accuracy under varying circumstances, and produces a high face recognition rate with a relatively small feature vector. The test results indicate that the LCP algorithm produces a higher facial recognition rate than the rate of human visual's recognition capability, and outperforms the existing methods.

***Keywords:*** Pattern Recognition, Face Recognition, Computer Vision Systems, Local Contour Pattern (LCP), Nearest Neighbor Classifier

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## 1. Introduction

Recently, the importance of security with regard to personal information has increased. The applicability of biometric technologies for personal information security and in the field of machine vision is expanding. Among such biometric technologies, face recognition has attracted considerable attention. Face recognition technology is widely used in the biometric field because the data are biological signals that characterize individuals [1]. In the process of capturing a visual image, the human face produces various images influenced by factors such as illumination, noise, and aging, rather than existing in a single state [2-3]. Therefore, for a commercial face recognition system, a robust recognition technology that is highly accurate under changes in illumination, noise, and aging is necessary [4-7]. The process of face recognition generally occurs in the following sequence: detection, alignment, feature extraction, and classification. First, face detection is the process of detecting the facial section within an image; Haar-like features [8] are typically used for this process. Second, face alignment is the process of normalizing the extracted facial image by aligning the rotation and specific size of the image. Elastic Bunch Graph Matching (EBGM) [9] which uses facial feature graphs, is often used for this process. Third, feature extraction is the process of applying a representation technique to the standardized facial image to extract a single feature vector. The Local Binary Pattern (LBP) [10] technique is a simple feature extraction algorithm that performs this task well. Fourth, face classification is the process of recognizing whether a given face should be classified as a face registrant, and tools such as the K-Nearest Neighbor Classifier (K-NN) [11] and Support Vector Machines (SVMs) [12] are typically used in this stage. In the face recognition process, the facial expression is an important factor in generating the feature vector of the face, and various techniques have been studied to enhance the facial recognition rate, decrease the number of dimensions in the feature vector, and reduce the algorithmic complexity [13], [39-40].

## 2. Related Work

There have been considerable developments in facial recognition by means of feature extraction using the gray-level value of an image, and various techniques regarding this method are currently being researched. Moreover, it requires higher accuracy than the recognition rate of human's vision [14]. However, distortion that reduces the performance of facial recognition, such as reflection, changes in illumination, and noise, are also included in the gray-level value data [15]. Therefore, identifying an effective descriptor for representing the facial features prior to extraction is an important issue in the field of face recognition. An efficient descriptor should have a simple method of calculation and adequately identify the resemblance in various images collected from a single individual one. Furthermore, the descriptor must extract a consistent facial pattern, even under changes in illumination, noise, and time lapse. For this reason, much research has been conducted on pattern encoding methods for each pixel using the face descriptor. Representative pattern encoding methods are as follows. Ahonen et al. [16] proposed a method for applying an LBP by comparing gray-level values of the surrounding pixels with the center pixel to convert the facial area into a histogram and extract a single feature vector. However, this method uses a simple difference in magnitude; thus, it is highly influenced by changes in illumination and random noise. Zhang et al. [17] proposed the Local Gabor Binary Pattern Histogram Sequence (LGBPHS), which accumulates each corresponding histogram by combining the Gabor filter and LBP, and dividing the sub-regions according to the m x m size. LGBPHS is suitable for solving the LBP noise problem, but has a large computational load and cannot express facial details. Tan et al. [18] proposed the Local Ternary Pattern (LTP), which separates the upper pattern, with bright gray-levels, from the lower pattern, with dark gray-levels, to extract features. However, the LTP method requires a pretreatment process to extract strong patterns in relation to changes in illumination. Zhang et al. [19] proposed the Local Derivative Pattern (LDP), which sets LBP as the feature code extraction method for the first-order derivation and obtains second-, third-, and fourth-order derivations to extract feature codes from the 0°, 45°, 90°, and 135° directions. The LDP technique exhibits a high recognition level when combined with Gabor images. However, 8 bit binary codes are extracted for each direction, resulting in a total of 32-bits of binary code. Therefore, the dimension of the feature vector increases, and the algorithm becomes complex. Ramirez Rivera et al. [20] proposed the Local Directional Number (LDN) Pattern, which codes the top directionality of the positive and negative directions using a compass mask with eight directions. Compared to the LBP method, LDN is relatively unaffected by illumination or noise, because it knows the brightest and darkest locations, even when a bit changes because of noise. However, the technique cannot express the various fine patterns of facial images, and has disadvantages regarding the large computational load caused by the use of an eight-directional compass mask from the center pixel in order to generate the edge response. Other feature extraction techniques include CS-LBP [21], which shortens the code length, and MB-LBP [22], which calculates the average gray-level value of the block after dividing a random size area into an m x m block. As such, various face feature extraction techniques [16-22] have been studied to overcome problems with variations in expression, illumination, and noise. However, maintaining consistency in the code when the calculations become complex remains a challenge, and problems related to varying expressions, illumination, and noise persist. As verified through LDP [19] and LDN [20] studies that use derivatives and Gaussian techniques for facial recognition present higher recognition rates. The Local Contour Pattern (LCP) technique described in this paper minimizes the effects of noise and is robust to illumination variations. LCP, Similar to human visual system, extracts the face contour response value using the Laplacian of Gaussian (LoG) technique [23] and applies a threshold value by moving five pixels in the horizontal, vertical, and diagonal directions. Therefore, LCP can express important facial features precisely based on the center pixel. For example, the bit number of LBP [16] increases when pixels are extracted over a wider range. When pixels are extracted over a wide range, only a single pixel is considered, Information in neighboring pixels is not used although this information may be important.

The remainder of this paper is organized as follows: Section III introduces the details of the proposed method, before Section IV presents the facial classification method for facial recognition. Section V evaluates the recognition rates and reliability of the proposed method, and Section VI presents our conclusions.

## 3. Local Contour Pattern

LCP expresses facial information as an 8-bit binary code assigned to each image pixel. The facial elements in an image have various edge components. The features of a face composed of edge data have the advantage that information regarding facial features, such as the shape, size, and face type, does not change dramatically under the influence of illumination and noise, whereas information for facial features composed of texture data is subject to change under illumination and noise variations. The proposed method uses LoG to detect edges to determine the face contour response. This is a second-derivative value that has a value of zero in areas with a constant brightness variation (i.e., flat facial areas) or where brightness increases gradually; therefore, it has the advantage of not emphasizing flat facial areas (i.e., forehead, cheeks, and lips), which are easily affected by changes in feature data caused by the influence of illumination and noise variations. Furthermore, LoG has the advantage of being isotropic, so that it responds similarly to a change in brightness from all directions, and resembles the characteristics of the human vision system. The LCP proposed in this paper uses LoG to obtain codes for generating the face contour response values of the facial image. To represent the face contour response value generated from the face as an 8-bit binary code, the face contour response is explored in eight directions from the center pixel; each pixel is represented with an 8-bit binary code.

### 3.1 Comparison with Previous Studies

LBP [16] compares the gray-level value of the center pixel and the neighboring pixels, and encodes the data by converting the pixel value to 0 when the center pixel has a higher value, and to 1 when the center pixel value is lower or the same. Methods that simply use the gray-level value are not accurate, because they discard most of the neighboring data, and respond in a highly sensitive manner to noise. These limitations become more apparent when LBP is extended to extract codes through a large range of neighboring patterns [24]. For example, when the LBP neighboring range is expanded from 8 to 16 patterns, much more feature information is obtained as a 16-bit code, but this cannot be characterized as an accurate representation because most of the information from neighboring areas is discarded. To avoid this problem, various methods [19-20], [25-28], [37-38] for obtaining a large amount of data from the neighboring areas have been developed. The use of a large amount of data (i.e., various data from a wider area) may stabilize the recognition performance, but has the disadvantage of increasing the length of the code. For example, LDP [19] extracts a feature code in the 0°, 45°, 90°, and 135° directions. The 8-bit binary code is extracted for each direction, resulting in an increase of the feature vector dimension by a total binary pattern of 32 bits. This has the disadvantage of producing a complex algorithm. In contrast, LDN [20] uses the eight-directional compass mask to utilize the location of the brightest value and the darkest value to express the image in 6-bit code. Although LDN [20] has the benefit of a shorter code length, it also has the disadvantage of discarding much of the surrounding information and only using the greatest positive and negative values. Therefore, it does not produce good results when applied to facial recognition.

### 3.2 Face Contour Response

LCP uses LoG to obtain the face contour response of the facial image. LoG is an edge detection method that combines Laplacian and Gaussian features. The Gaussian feature is defined in (1), and the standard deviation ($\sigma$) acts as the parameter. A bigger standard deviation in the Gaussian induces a greater effect for noise reduction, but can result in the image being blurred.

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\pi\sigma^2}} \tag{1}$$

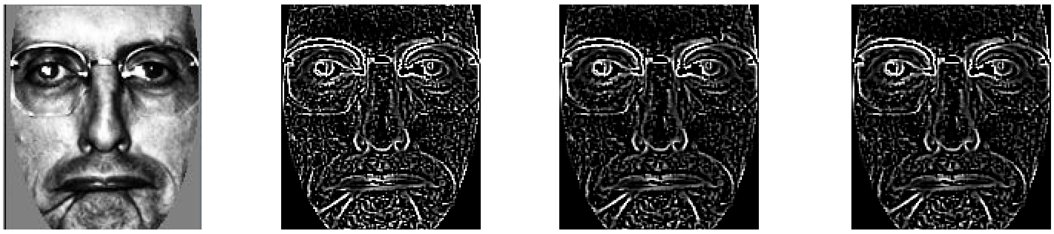
The Laplacian based on the second-derivative is defined as:

$$\nabla^2 f(x,y) = \frac{\partial^2 f(x,y)}{\partial x^2} + \frac{\partial^2 f(x,y)}{\partial y^2} \tag{2}$$

The Laplacian emphasizes the edge in all directions, and the values that correspond to high-frequency components appear more clearly, whereas the low-frequency components are eliminated. In this way, the Laplacian can emphasize edges in all directions, but has the disadvantage of being sensitive to noise. Therefore, LoG is used to generate the face contour response value. LoG has the characteristic of being isotropic (rotation invariant), so it responds the same way to changes in brightness from all directions, resembling the human vision system. Furthermore, the need for multiple masks to calculate the maximum response of a certain area on the image is eliminated. This paper applies LoG to a facial image to extract a face contour response that is similar to the human vision system [29-30]. The Laplacian mask is applied after the Gaussian mask for the process of implementing the LoG method. LoG is defined as shown in (3) with the combination of (1) and (2):

$$LoG(x,y) = -\frac{1}{\pi\sigma^4}\left[1 - \frac{(x^2+y^2)}{2\sigma^2}\right] e^{\frac{-(x^2+y^2)}{2\sigma^2}} \tag{3}$$

The mask size and σ value function as parameters in the detection of the face contour response value using the LoG mask. The value of the face contour response is represented on a scale of 0–255, with 0 being the darkest value and 255 being the brightest. **Figs. 1** and **2** show the mapping of the face contour response by the LoG mask in the images. **Fig. 1** indicates the image variations caused by an increase in σ. As shown in **Fig. 1**, Noise on the facial image is reduced when σ value is increased. As shown in Fig. 1. (b), noise increases while face contour response is highly detected when sigma value is low as 0.1. Therefore, choice of optimal value needed in order to both remove noise and detect exact face contour response. With large illumination variations shown in **Fig. 2(a)**, mask with a low σ value cannot detect the face contour response due to the illumination manifested by **Fig. 2(b)** Therefore, large masks of 9 × 9 and 11 × 11 are applied to images greatly affected by illumination, whereas small masks of 3 × 3 and 5 × 5 are used to detect the detailed face contour response on images with minor illumination variations.



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

**Fig. 1.** Images of variations in LoG σ value: (a) original image; (b) σ: 0.1; (c) σ: 0.5; (d) σ: 1.

Therefore, the LCP method proposed in this paper applies the LoG σ value and mask size as experimental parameters to measure the recognition rate of facial images. σ values of 1.8 and 0.3 were applied to the small mask and large mask, respectively, as experimental parameters to detect the value of the face contour response in each image.

(a) (b) (c) (d) (e)

**Fig. 2.** Images of variations in LoG mask size: (a) original image; (b) 3 × 3 mask; (c) 5 × 5 mask; (d) 7 × 7 mask; (e) 9 × 9 mask.

### 3.3 Local Contour Pattern

The face contour response must be extracted before LCP can extract patterns. As shown in **Fig. 3**, a random image block is defined, and then pixels in each direction are searched in order to express the values of the face contour response as a binary pattern. In **Fig. 3**, the center pixel is identified as $g_c$, and the subscript 0 in $g_0^R$ indicates the pattern search direction. Therefore, eight directions (from 0–7) are indicated. The superscript R in $g_0^R$ i indicates the pixel radius; thus, R + 1 and R + 2 signify the distance from the center pixel. The most stable results when moving and applying the pixels in the R – R+10 range were obtained for the range R – R+4. Therefore, LCP used the information of five pixels in each direction based on the center pixel. By applying a threshold value to the navigation value, the limitation of the LBP, i.e., most of the surrounding information is discarded, and the limitation of gathering excessive information [19-20], [27-28], which leads to an increase in code length, can be overcome.

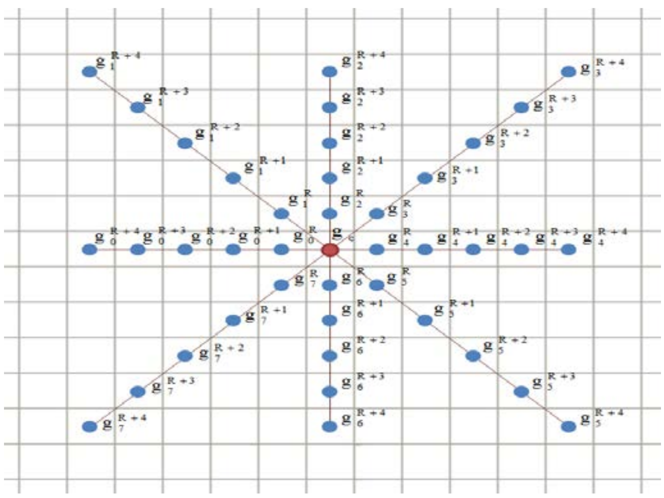


**Fig. 3.** Moving the neighboring pixels around the center pixel (moving the vertical, horizontal, and diagonal pixels around the center pixel. $\mathbf{g_c}$ is the center pixel; 0 in $\mathbf{g_0^R}$ represents the eight navigation directions from 0-7; R is the radius; and R+1 and R+2 are the distances from the center pixel).

The binary pattern calculation of LCP first searches the face contour response values in the n-th direction, and then compares the center pixel with the n-way pixels. When the pixel values in the n-th direction are less than or equal to that of the center pixel, the search results are accumulated as:

$$LCP_n = \sum_{i=0}^{4} s(g_{c} - g_n^{R+i}), \quad s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \tag{4}$$

where $g_c$ is the center pixel, and $g_n^{R+i}$ indicates the neighboring pixels in the n-th direction at a distance of R + i. In (4), n can take values of 0–7, as confirmed on the left-hand image of the code computation process in **Fig. 4** A larger $LCP_n$ value in this left-hand image indicates that the area is darker than the center pixel, and a smaller value indicates that the area is lighter than the center pixel. Second, the function f(x) applies the threshold value to the $LCP_n$ value to express the $LCP_n$ value of each direction as a binary value, as shown in the center image of the code computation in **Fig. 4** $LCP_n$ is defined as:

$$LCP_{R_0,t,R_{max}}^{\sigma}(x_c, y_c) = \sum_{n=0}^{7} c(LCP_n)\, 2^n, \quad c(x) = \begin{cases} 1, & x > t \\ 0, & x \leq t \end{cases} \tag{5}$$

where $R_0$ indicates the starting point of the center pixel, and $R_{max}$ indicates the end point. In addition, t indicates the threshold value, σ is the LoG σ value, $(x_c, y_c)$ is the center pixel, and n is the search direction. The face contour response value of the feature changes in relation to the small or large mask; therefore, different parameters are applied according to the experimental values. Here, $R_0 = 1$ and $R_{max} = 5$ and σ = 0.3 and t = 3 or $R_0$=1 and $R_{max} = 5$ and σ = 1.8 and t = 2 were applied for the small and large masks, respectively. On the other hand, Small mask parameters are robust to noise and have excellent contour line extraction feature; On the other hand, large mask parameters have an excellent illumination variation feature.

Finally, for the LCP algorithm, a new LCP value is applied to the center pixel after changing the image into a binary code in a certain direction, as shown in the right-hand image of the code computation **Fig. 4**. The LCP image is the result of applying the LCP code to every pixel in the image. The upper section of **Fig. 4** shows the face contour response detected by the LoG mask convolution.

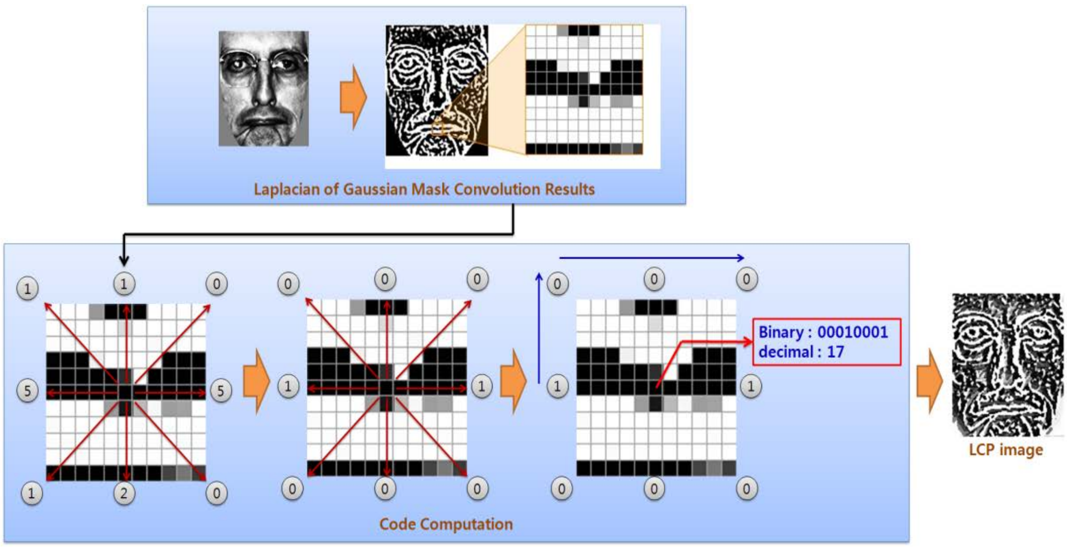



**Fig. 4.** LCP code computation (upper section shows the result of detecting the face contour response in the LoG mask convolution results, where σ= 1.8, and small masks are applied. The code computation shown on the left is the $LCP_n$ value that moved five pixels in the 0–7 directions. The result of applying a threshold value of 2 to the $LCP_n$ is shown in the center. The result of converting to a binary pattern in a certain direction is shown on the right.).

### 3.3 Face Classification For Face Recognition

The result of applying the LCP algorithm to all pixels in order to assign a new LCP code to the center pixel is shown in **Fig. 5(a)** As shown in **Fig. 5(b)**, the facial image is divided into a constant grid, and all grids must consist of a histogram to effectively express the facial image. A single histogram contains information on the facial feature of the area, and the vector that connects all histograms in series is used as the final vector of the facial image [16].

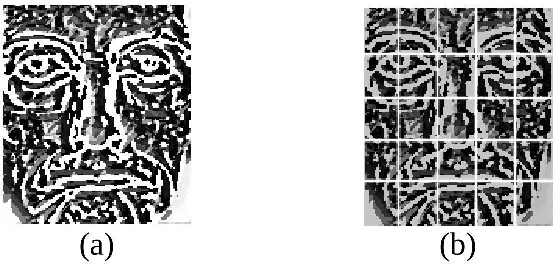


**Fig. 5.** LCP image and image divided into 25 areas: (a) image represented through LCP; (b) image divided into 25 areas.

To generate the feature vector of the facial image, the LCP histogram of each grid is calculated after dividing the facial area into a uniform sized grid. Equation (6) indicates the method of accumulating the histogram of an M × N input image.

$$H(i) = \sum_{x=1}^{M}\sum_{y=1}^{N} f(LCP(x,y),i), f(a,b) = \begin{cases} 1, a = b \\ 0, a \neq b \end{cases} \quad (6)$$

where x and y indicate the pixel location and i is the pixel value calculated through LCP. The size of the histogram bin is determined from the direction number of the LCP code. Because the LCP used in this paper is eight-directional, the size of each histogram bin is 25,600. Each histogram on the grid is connected by a line and used as the final feature vector to describe the entire facial image.

As shown in **Fig. 6**, it is claimed that the code length is 256, but because histogram sequences are used and assumed that the final feature length is 25,600. As shown in **Fig. 6**, the image is divided into s – n areas, each defined as $R_0$, $R_1$, …, $R_{s-1}$, and histogram $H_s$ is calculated for each area. Finally, the histogram bins calculated by area to represent the feature vector of the entire face are connected to create a single histogram. The size of the final histogram is determined by multiplying the area number divided by s – n and the length of the LCP code.

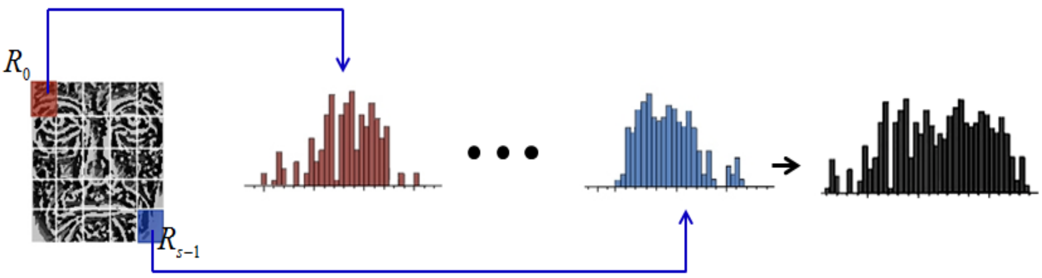



**Fig. 6.**Feature vector of facial image composed as the sum of histogram bins.

The classifier performance will affect the facial recognition rate. Therefore, it is important to select the optimal classifier [41]. For this reason, the Nearest Neighbor Classifier [11], which uses the existing techniques of LDP [19] and LDN [20] is used to objectively evaluate the recognition rate of the facial feature extraction method proposed in this paper. To apply the nearest neighbor classifier, the similarity and distance between the feature vectors extracted from the gallery image (G) and probe image (P) must be calculated. Methods such as Histogram Intersection [19] and the chi-squared statistic [20] can be used to calculate the distance or similarity. We use histogram intersection, which has been identified as the most efficient method for dividing features, to compare similarities. Histogram intersection is defined in (7), where s is the grid number, and p is the pattern number.

$$H(G,P) = \frac{\sum_{j=1}^{s}\left(\sum_{i=1}^{2^p} min(G_{i,j},P_{i,j})\right)}{min\left(\sum_{j=1}^{s}\left(\sum_{i=1}^{2^p}(G_{i,j},P_{i,j})\right)\right)} \tag{7}$$

## 4. Experiments

The facial recognition accuracy of the proposed method was evaluated using images from the FERET database [31] and the Extended Yale B database [32-33] and CAS-PEAL-R1 Database [36]. These three databases were used to conduct several experiments that objectively evaluate the performance of the proposed LCP method. Recognition rates under variations in illumination, expression, noise, and time lapse were examined using the three databases, and the results were compared with those from other methods. All facial images were aligned at a size of 130 × 150 pixels to maintain consistency. The results were compared with those reported by Ramirez Rivera et al. [20] to objectively evaluate the LCP algorithm proposed in this paper. LCP did not apply any pretreatment to ensure a fair comparison with the existing methods. All image grids in the experiment were divided into 10 × 10 regions, as in [20]. Moreover, the average time of code conduction is 13ms when an image size of 130x150 pixel was applied. We used an un-optimized C++ code, a Dual-Core CPU with 3.30GHz, 8GB RAM and Window7 OS.

The LCP proposed in this paper was tested with various σ values on images from the FERET database to analyze the code performance under diverse algorithm parameters. The superscript 1.8 in $\mathrm{LCP}_{1,3,5}^{1.8}$ indicates the LoG σ value. The subscript 1 indicates the starting point, 5 is the end point, and 3 is the threshold value. As LCP relies on the LoG σ value, the changes in the recognition rate were measured with respect to the σ value. We thus found that the maximum recognition rate was achieved when σ = 1.8, as confirmed in **Fig. 7** Although accurate face contour responses cannot be detected as the σ value increases, the recognition rate increased with the σ value because the elevated σ value reduces noise in the image, which interrupts the extraction of facial features. For this reason, the parameters were set according to the characteristics of the LoG parameters in the LCP experiment. The parameters were set as follows: Small masks (excellent contour extraction) of 3 × 3 and 5 × 5 were applied to a σ value of 1.8 (excellent noise reduction), and large masks (excellent illumination variations) of 9 × 9 and 11 × 11 were applied to a σ value of 0.3 (excellent contour extraction).

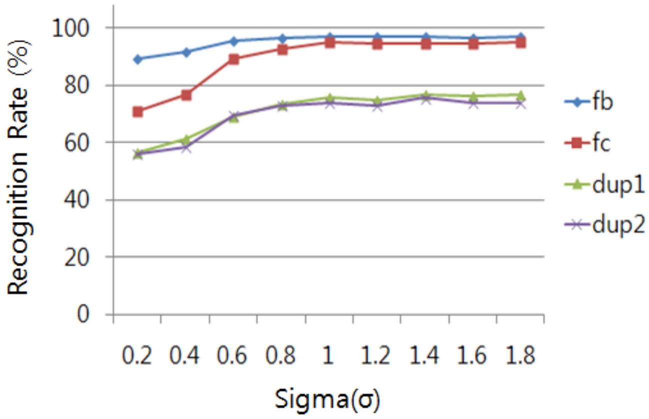



**Fig. 7.** FERET database recognition rate results of LCP algorithm according to changes in the σ value.

## 4.1 FERET Database Results

The images in the FERET database [31] were not obtained under uniform conditions in terms of the location of the person, target range, brightness, and background. Therefore, the images underwent a standardization process prior to the experiment. We used the gray-level images of the FERET database for the experiment, and the CSU Face Identification Evaluation System [34] was applied to the gray-level images to collect a standardized image for the objective evaluation of the facial feature extraction method. Five image subsets, i.e., fa, fb, fc, dup1, and dup2, were used as probe images in the LCP facial recognition experiment, where fa denotes frontal face images, fb denotes expression variations, fc denotes illumination variations, dup1 denotes images captured within three years of fa, and dup2 contains three sets of dup1, in which an image was captured 18–36 months after fa.

**Table 1** presents a comparison of the LCP algorithm proposed in this paper with the results under identical conditions from other algorithms, as reported by Ramirez Rivera et al. [20]

As indicated in **Table 1**, the $\mathrm{LCP}_{1,3,5}^{1.8}$ with the small mask ($3 \times 3$, $5 \times 5$) generally achieved a higher recognition rate than the algorithms proposed in other papers. The images in the FERET database were not greatly influenced by illumination variations; therefore, good results were obtained when detecting the face contour response using the small mask of $\mathrm{LCP}_{1,3,5}^{1.8}$. This is because a smaller LoG mask size detects an accurate face contour response, and a greater σ value has the effect of reducing noise in the LCP algorithm. When the large mask was applied to $\mathrm{LCP}_{1,2,5}^{0.3}$, a high recognition rate was achieved for all images with large variations of illumination. However, this did not produce better results than $\mathrm{LCP}_{1,3,5}^{1.8}$ when the face contour response was accurately detected under monotonous illumination changes in images, such as for set fc. However, misrecognitions in the form of identifying the individual as another person were observed with the dup1 and dup2 (time lapse variations) results because of additional distortions, such as beards, cosmetic surgery, and glasses, which caused many modifications to the feature vector. However, there are limitations to the ability to solve recognition problems related to the passage of time using only facial feature extraction. To solve variation problems in relation to the passage of time, as in the dup1 and dup2 images, a large amount of facial feature data must be collected in accordance with the facial changes of an individual, and further research in solving the additional distortions (i.e., beards, cosmetic surgery, and glasses) is required. The LDN technique uses the biggest positive and negative values from the edge response of the Kirsch compass mask to represent patterns. $LDN^K$ has a length of 56, and the code of $LDN^G$ has a length of 56 n, where n is the σ number used (n = 3 in **Table 1**). The LDN parameters have the advantage of shortening the code length. However, LDN does not produce a high facial recognition rate, because the method cannot extract accurate facial features. Although the Gabor Global Phase Pattern (GGPP) method produces a recognition rate that is 1.62% higher than the LCP algorithm, it has a long code length. The code length of the GGPP method is 256 $n_s$, where $n_s$ranges from 1–5. Thus, the code can be up to 1,280 in length. This is long compared to the code length of 256 in LCP. A long code length results in what is called "the Curse of Dimensions", which is a well-known problem in facial feature extraction. The code of the proposed LCP is slightly longer than the 168 of $LDN^G$(when n = 3). However, although slightly longer, a code length of 256 is stable.

**Table 1.** Results of recognition rates bewteen proposed LCP algorithm and methods from other papers on images in FERET database.

| Method | fb | fc | dup1 | dup2 |
|---|---|---|---|---|
| LBP[10] | 80.90 | 84.69 | 64.90 | 48.62 |
| $LBP_w$[35] | 79.93 | 84.18 | 50.55 | 19.72 |
| LTP[18] | 84.30 | 36.22 | 52.26 | 22.94 |
| $LD_iP$[25] | 83.12 | 71.94 | 66.61 | 58.26 |
| $LD_eP$[19] | 85.10 | 79.35 | 63.45 | 61.21 |
| LPQ[28] | 84.89 | 88.79 | 63.34 | 46.79 |
| GGPP[27] | 87.60 | **92.86** | 70.67 | 66.97 |
| $LDN^K$[20] | 82.88 | 86.22 | 65.21 | 50.46 |
| $LDN^G_{0.3,0.6,0.9}$[20] | 87.84 | 84.69 | 72.86 | 69.27 |
| $LDN^G_{0.5,1.0,1.5}$[20] | 88.55 | 81.12 | 73.32 | 71.10 |
| $LDN^G_{1.0,1.3,1.6}$[20] | 88.43 | 78.06 | 72.08 | 70.18 |
| $LCP^{1.8}_{1,3,5}$ (3x3) | 95.98 | 91.24 | **76.73** | **74.79** |
| $LCP^{1.8}_{1,3,5}$ (5x5) | **97.41** | 86.08 | **76.73** | 69.66 |
| $LCP^{0.3}_{1,2,5}$ (9x9) | 94.56 | 77.84 | 70.36 | 65.81 |
| $LCP^{0.3}_{1,2,5}$ (11x11) | 94.14 | 77.32 | 70.50 | 66.67 |

**Fig. 8** illustrates the performance of the LCP algorithm proposed in this paper and the LDN algorithm of Ramirez Rivera et al. [20] for each type of image in the FERET database. The results confirm that the LCP algorithm has a higher recognition rate than the LDN algorithm.

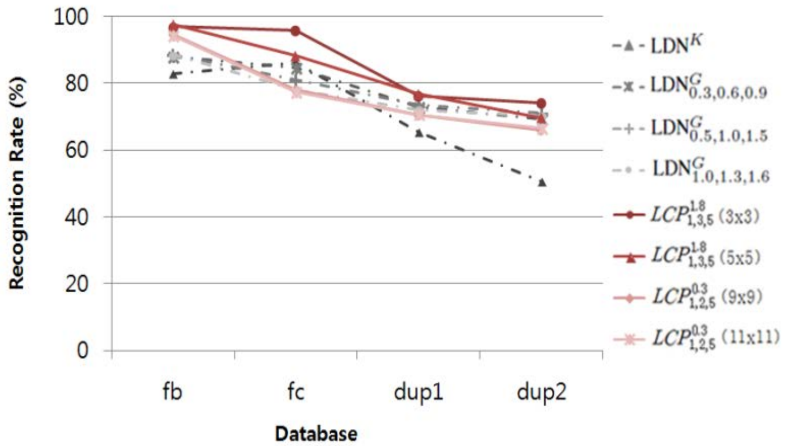



**Fig. 8.** Comparison of the recognition rate between proposed LCP algorithm and LDN Algorithm from Ramirez Rivera et al. [20]

### 4.2 Extended Yale B database Results

The Extended Yale B database [32-33] consists of a total of 38 people, with 28 people added to the Yale B database [33]. Each person is represented in a series of gray-level images with 64 types of illumination. In the Extended Yale B database, the position of the light source varies greatly according to the height and azimuth of the illumination; therefore, the illumination is highly influential. Thus, the Extended Yale B database is categorized five subsets according to the illumination variations. The five subsets are: sub 1 (0–12), sub 2 (13–25), sub 3 (26–50), sub 4 (51–77), and sub 5 (above 78). In this experiment, the gallery image was used for the sub 1 image, and probe images were used for the images influenced by illumination. To objectively evaluate the facial feature extraction technique with the Extended Yale B database, normalized images must be used. The Extended Yale B database was used because it provides gray-level images as well as normalized images of cropped facial areas.

**Fig. 9** shows compares the results from the proposed LCP algorithm with those reported by Ramirez Rivera et al. [20] for various algorithms under identical settings. LDN uses the Kirsch compass mask's edge response, and is therefore robust to illumination variations. However, LDN did not extract accurate facial features, because patterns are only expressed using the largest positive and negative values of the edge response.

However, because the Extended Yale B database is largely influenced by illumination, positive results were obtained when the large mask (outstanding illumination variation) of $\mathrm{LCP}^{0.3}_{1,2,5}$ was applied. Furthermore, we obtained positive results with subsets 4 and 5, which are most influenced by illumination, when compared with other algorithms. However, when the small mask (outstanding contour extraction) of $\mathrm{LCP}^{1.8}_{1,3,5}$ was applied, results for subsets 2–4 were positive; however, for cases that received extreme illumination, as in subset 5, the face contour response could not be detected accurately, and therefore the results were not so good.

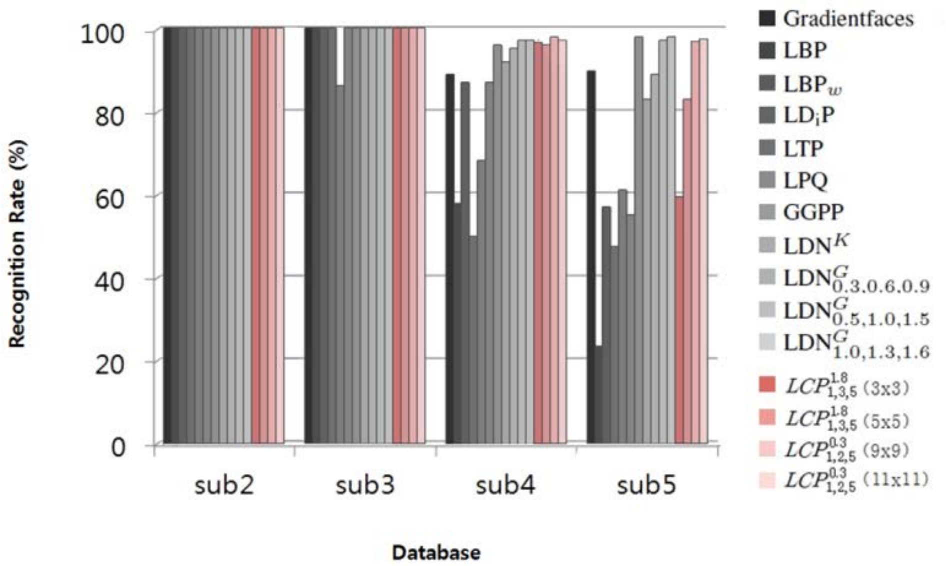



**Fig. 9.** Comparison of results from LCP with those from LDN [20].

### 4.3 CAS-PEAL-R1 Database Results

CAS-PEAL-R1 Database [36] is a partially disclosed data which consists of 30,900 images of 1,040(595 men, 445 women) persons. In this paper, in order to test LCP's Face Recognition Rate, as changing images of accessory, age, environment, direction and face. It consists of 6 images of facial change of 379 people, 6 accessory put-on image of 438 people, 10 to 31 light changing images of 233 people, 2 to 4 environment changing image of 297 people, image of time change of 66 people after 6months and 1 to 2 street change image. **Table2** presents a comparison of the LCP algorithm proposed in this paper with the results under identical conditions from other algorithms, as reported by Ramirez Rivera et al. [20] As indicated in **Table 2**, proposed LCP in this paper, gives good results for most of the data set and it is close to the best methods. Our proposed method outperforms Data sets of 2.4%, 0.6%, 9.7%, 6.7% in accessory, length, expression, lightness. One of the most problems in Face Recognition is light change. Light data set created in CAS-PEAL database has similar features to lights of actual environment.

In contrast to Yale B database which contains only images with shadows, the CAS-PEAL Lighting data set has dark (with shadows) and bright (with flashes) images.

As it is proved in conclusion regarding lightning change, proposed method can detect 47.22% of data set. Nevertheless, proposed method outperforms other methods in terms of face recognition rate and can obtain better result than GGPP and LPQ, which uses phase information.

The results yielded better recognition rates than human vision in images with less variation in illumination, noise, and aging, and exhibited better recognition rates on other image types compared with existing approaches [14].

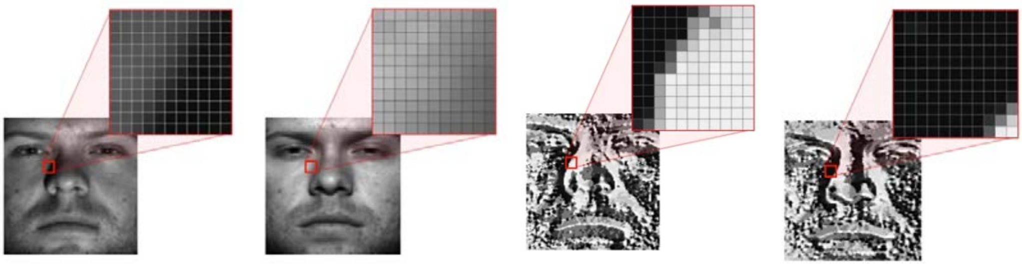
**Table 2.** Comparison of recognition accuracy with cas-peal database

| Method | Acc. | Age | Back. | Dist. | Expr. | Light. |
|---|---|---|---|---|---|---|
| LBP[10] | 75.06 | 89.39 | 98.73 | 97.45 | 87.45 | 14.62 |
| $LD_iP$[25] | 78.21 | 90.91 | **99.64** | 96.73 | 87.58 | 17.83 |
| LPQ[28] | 81.18 | 87.88 | 99.46 | 97.09 | 88.60 | 21.09 |
| GGPP[27] | 82.76 | **96.97** | 97.29 | 97.45 | 87.77 | 30.85 |
| $LDN^K$[20] | 80.00 | 95.45 | 97.83 | 98.18 | 84.20 | 27.99 |
| $LDN^G_{0.3,0.6,0.9}$[20] | 79.43 | 93.94 | 99.46 | 97.45 | 86.05 | 39.50 |
| $LDN^G_{0.5,1.0,1.5}$[20] | 81.66 | 92.42 | 99.46 | 97.45 | 87.39 | 40.57 |
| $LDN^G_{1.0,1.3,1.6}$[20] | 82.14 | 93.94 | 99.46 | 97.09 | 87.26 | 39.81 |
| $LCP^{1.8}_{1,3,5}$ (3x3) | **85.17** | 93.94 | 98.29 | 97.85 | **98.56** | **47.22** |
| $LCP^{1.8}_{1,3,5}$ (5x5) | 82.95 | **96.97** | 98.76 | **98.77** | **98.56** | 38.77 |
| $LCP^{0.3}_{1,2,5}$ (9x9) | 81.03 | 95.45 | 96.90 | 97.54 | 98.40 | 31.35 |
| $LCP^{0.3}_{1,2,5}$ (11x11) | 80.11 | 95.45 | 96.90 | 98.77 | 98.08 | 30.98 |

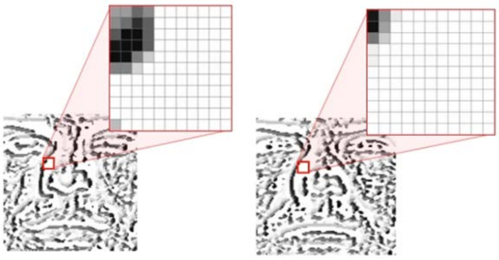
## 4.4 Noise Evaluation

Noise is generally undesirable; however, it was added to the probe image to test the robustness of the algorithm. In this paper, white Gaussian noise with the same variance value as used by Ramirez Rivera et al [20]. was applied to the FERET database probe image, followed by a measurement of the recognition rate. LBP uses a simple numerical difference; therefore, its recognition rate decreased dramatically as the noise level increased. **Fig. 10** shows the results of the proposed LCP and LBP using a simple gray-level value under the same illumination variance conditions. As shown in **Fig. 10(b)**, LBP is very sensitive to variations, and reacts in the same way to noise. Therefore, LBP could not extract a consistent pattern. On the contrary, LCP minimizes the impact of noise and illumination variations, as indicated in **Fig. 10(c)**.

$LD_i$ P [25] and LDN [20] use the edge response value of the Kirsch compass mask, thus achieving relatively robust results with regard to noise compared to LBP. We determined that the proposed LCP algorithm obtained more robust results in terms of the noise, because it uses the LoG mask, which is a combination of the Gaussian mask and Laplacian. Both the large mask of $LCP^{0.3}_{1,2,5}$ and the small mask of $LCP^{1.8}_{1,3,5}$use LoG; therefore, positive overall results were obtained, particularly when using the small mask of $LCP^{1.8}_{1,3,5}$, in which case the influence of noise was minimized and detailed edges were detected, yielding the best results.



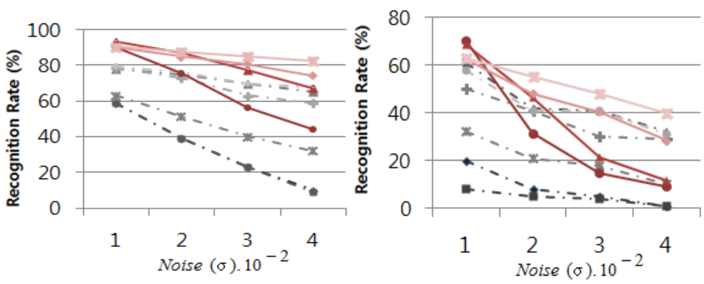
(a) (b)



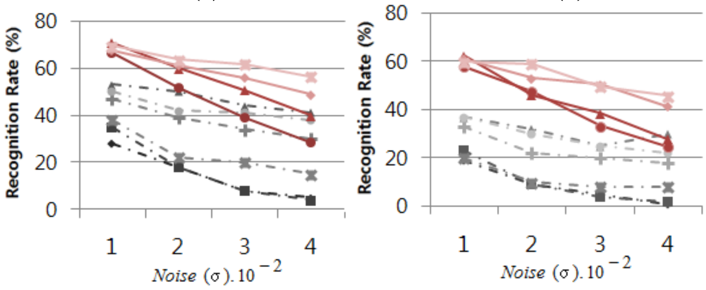
(c)

**Fig. 10.** Comparison of results from LBP and the proposed LCP algorithm with images containing illumination variations: (a) illumination changes in images; (b) LBP applied to images; (c) LCP applied to images.

**Fig. 11** shows a comparison between the proposed LCP algorithm and the results reported by Ramirez Rivera et al. [20] for different algorithms under identical settings. The results indicate that the proposed LCP algorithm is more robust with regard to noise than the LDN algorithms studied by Ramirez Rivera et al. [20]




(a) (b)




(c) (d)

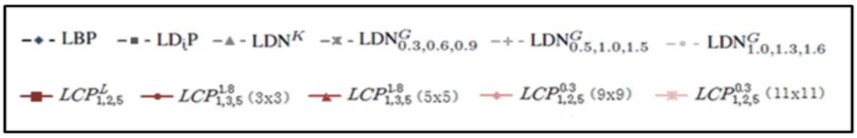



**Fig. 11.** Comparative results for proposed LCP algorithm and others in FERET database recognition with white Gaussian noise: (a) fb; (b) fc; (c) dup1; (d) dup2.

## 5. Conclusion

This paper has proposed a novel face recognition method that uses a new face descriptor and LCP. The proposed method extracts a face contour response using an LoG mask, and applies the LCP algorithm to represent it as a binary pattern. This approach achieved high recognition performance, even under the influence of illumination, noise, and aging. The proposed LCP algorithm uses LoG, which is similar to human vision, to extract the face contour response; therefore, it can effectively eliminate noise and other unnecessary information. Although the proposed method searches for the face contour response of most neighboring pixels, it applies a threshold value to the searched value, making it possible to express major facial features with only 8-bits. Thus, the proposed LCP used a reliable code length of 256 bits to accurately express facial features. Compared with other methods, the proposed approach can maintain a consistent code length, even under the influence of illumination, noise, and aging. To objectively evaluate the reliability of the proposed LCP, the recognition rate of frontal faces, changes in facial expression, illumination variations, and the passage of time were compared and evaluated with other methods using 3,451 gray-level images from the FERET database, and 2,414 gray-level images from the Extended Yale B database, and CAS-PEAL-R1 database is a partially disclosed data which consists of 30,900 images of 1,040(595 men, 445 women) persons.

The results yielded better recognition rates than human vision in images with less variation in illumination, noise, and aging, and exhibited better recognition rates on other image types compared with existing approaches. In particular, the proposed method yielded significantly higher recognition. Rates with frontal face images, illumination variations, and noise. However, in the case of the small mask of $\mathrm{LCP}^{1.8}_{1,3,5}$, a more detailed face contour was detected with a smaller mask size, and an increase in the σ value had the effect of reducing the noise; therefore, better results were obtained in the FERET database. In the case of the large mask of $\mathrm{LCP}^{0.3}_{1,2,5}$, as the mask size increased, it was more difficult to detect a detailed face contour response; however, it was possible to detect a face contour response under conditions with severe illumination variations. Therefore, positive results were obtained with the Extended Yale B database. The CAS-PEAL database results yielded better recognition rates than human vision in images with less variation in illumination, noise, and aging, and exhibited better recognition rates on other image types compared with existing approaches.

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