A fast face recognition based on image gradient compensation for feature description

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Abstract
To improve the efficiency of traditional face recognition techniques, this paper proposes a novel face recognition algorithm called Image Gradient Feature Compensation (IGFC). Based on the gradients along four directions in an image, a fusion algorithm and a compensation method are implemented to obtain features of the original image. In this study, gradient magnitude maps of a face image are calculated along four directions. Fusion gradients and differential fusion gradients are produced by fusing the four gradient magnitude maps of a face image in multiple ways, and they are used as compensation variables to compensate the appropriate coefficients on the original image and build IGFC feature maps of the original face image. Subsequently, IGFC feature maps are divided into several blocks to calculate the concatenated histogram over all blocks, which is in turn utilized as the feature descriptor for face recognition. Principal component analysis (PCA) is used to cut down the number of dimensions in high-dimensional features, which are recognized by the Support Vector Machine (SVM) classifier. Finally, the proposed IGFC method is superior to traditional methods as suggested by verification studies on YALE, ORL, CMU_PIE, and FERET face databases. When the LibSVM parameter was set to ‘-s 0 -t 2 -c 16 -g 0.0009765625’, the algorithm achieved 100% recognition on Yale and ORL data sets, 92.16% on CMU_PIE data sets, and 74.3% on FERET data sets. The average time for simultaneous completion of the data sets examined was 1.93 s, and the algorithm demonstrated a 70.71% higher running efficiency than the CLBP algorithm. Therefore, the proposed algorithm is highly efficient in feature recognition with excellent computational efficiency.

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1 Introduction

As computer graphics and image processing capability continue to develop, face recognition has become a popular field of research recently. Face recognition technologies can be generally classified into two categories [2, 39], one of which is based on global features, and the other is based on local features. Over the years, many excellent algorithms have been proposed for face recognition, such as principal component analysis (PCA) [38], linear judgment analysis (LDA) [6], two-dimensional PCA (2DPCA) [41], two-dimensional LDA (2DLDA) [16, 43], ICA [3], enhanced ICA [28], multiple feature subspace analysis (MFSA) [13], as well as several other classical global-feature-based algorithms. However, problems of small sample sizes or high dimensional data are commonly seen in face classification and recognition tasks. Therefore, most global-feature-based recognition methods are not available for direct use as the within-class scatter matrix is always singular.

In recent years, as deep learning technologies emerge and advance, many scholars began to study their applications in face recognition [10, 12, 22, 32–34]. Generally speaking, deep learning technologies extract data-driven features and obtain deep and dataset-specific feature descriptions by learning a large number of samples. Convolutional Neural Network (CNN) and Tensor Face are two of the most recognized deep learning face recognition methods. Deep learning technologies are advantageous because they express data sets more efficiently and accurately, but their results are highly dependent on the sample set and the computing power.

Researchers have done a lot of explorations on local-feature-based methods, most of which divide the global image into several parts and analyze the features of each part independently. Therefore, local feature extraction methods can demonstrate better robustness, and some of these methods include Local Binary Mode (LBP) [1], Local Gradient Pattern (LGP) [24], Center-Symmetric Local Binary Patterns (CS-LBP) [20], SIFT [7], HOG [14], and wavelet Gabor [29]. Specifically, LBP is the most classical local feature extraction method, which has been extended extensively from many aspects [1, 9, 20, 21, 24, 31]. Moreover, two very popular methods extended from LBP, namely LGP [24] and CS-LBP [20], have been widely used for face feature extraction. Wang et al. [40] proposed a face recognition algorithm named complete local binary mode (CLBP) and a classification recognition method based on LBP and the local difference values and gray values of the center pixel. Yang et al. [23] proposed a single sample face recognition algorithm based on bidirectional gradient centrosymmetric local binary mode (BGCSBP). This algorithm works by obtaining the horizontal and vertical gradient information of images, encoding it with a CS-LBP operator, and integrating BGCSBP feature descriptions of the formed face images for classification and recognition. In Zhang et al.’s work [45], LBP coding was performed on the pixels in the face image, which was in turn divided into several sub-regions. In each sub-region, LBP histogram features were calculated to describe the overall face image. LBP operator [1, 9, 21, 31] has been used to calculate the relationships of the differences between the center pixel and its surrounding pixels in an \( n \times n \) module to obtain a series of binary codes. However, as the number of neighboring pixels considered increases, remarkably high eigenvectors would be generated from the LBP operator. This problem could be solved by the centrosymmetric local binary
model [20]. Besides, Jun and Kim proposed an LGP descriptor [24], which considers the intensity gradient distribution and realizes local changes near key points.

Additionally, Yang et al. [42] proposed an algorithm for face recognition based on the word bag model, which was established by integrating various features. By extracting local features in sample face images, a visual dictionary was trained offline and mapped to the corresponding high-dimensional and middle-level semantic space to extract descriptions of new face images. Ning et al. [30] proposed a BULPDA algorithm. They created a method to express similarity coefficients and proposed the vector space solution of singular value decomposition by integrating the concept of irrelevant space, which brought new insights on feature extraction. Fu et al. [8] proposed a face recognition algorithm based on the maximum value average, in which they used the template variance size to select different thresholds and extract more detailed information. Déniz et al. [17] proposed an approach to make robust use of HOG features for face recognition. Li et al. [26] used Gabor to transform images and extract features and realized some improvements in the face recognition rate. A. Bastanfard et al. [4, 5, 15] proposed some approaches to facial rejuvenation in adults image. It is helpful to solve the recognition rate of the condition of age change in face recognition process. In addition, there are other meaningful algorithms related to face recognition, such as literature [36], which have been deeply studied by Rituraj Sonil O et al.

Fast face recognition systems are face recognition systems that can recognize the identity of the person in the picture within a short time [10, 19, 25, 27, 33, 35, 37], which could significantly limit the time a recognized person stays in front of the camera and improve recognition efficiency. Specifically, Qu and Wei et al. [33] proposed a real-time face recognition method based on the convolution neural network with promising speed and accuracy. Cai and Lei et al. [10] proposed a fast and robust 3D face recognition approach with three component technologies: a fast 3D scan preprocessing, multiple data augmentation, and a deep learning technique based on facial component patches. Tang and Wu et al. [37] proposed a fast face recognition method based on the fractal theory that compresses the facial images to fractal codes and finishes face recognition with these codes. He Q and He B et al. [19] used the K-Mean clustering technology to improve the speed up robust features (SURFs), and their results were satisfactory.

Despite all of these advancements, a proper method for face recognition is still a challenge. Even though some reliable systems and advanced methods have been introduced with controlled conditions, their recognition rates, efficiencies, or speeds remain generally unfavorable. Many algorithms are very complex, which limits their recognition speed and efficiency significantly. To solve these problems, a novel concept called image gradient compensation (IGC) is proposed in this paper. Briefly, IGC uses a certain algorithm to strengthen the available salient features of the image and weaken the non-salient ones, thereby retrieving more valuable feature information during the feature extraction stage and improving the recognition rate. In this study, a fusion gradient and differential fusion gradient operator is used to generate fusion gradients and differential fusion gradients. An image gradient feature compensation (IGFC) algorithm is obtained by compensating the original image with appropriate compensation coefficients for fusion gradients and differential fusion gradients.

This study aims to improve the quality of extracted face image features, cut down the time and power spent on face recognition, and improve the recognition efficiency with the IGC strategy. Particularly, the IGC strategy is first used to enhance the available features of the image. Besides, the efficiencies of image feature extraction and face recognition are improved
as a result of simplified algorithms. Practical experiments proved that the algorithm is of good practical prospects.

The author’s main contributions are as follows: 1) A novel image gradient algorithm is proposed to extract image features with greater image recognition rates; 2) Image feature extraction is simplified remarkably with the image gradient fusion technology, and the operation efficiency of image recognition is improved markedly; 3) The proposed device needs comparably lower power to operate thanks to the improvements in image recognition efficiency.

The proposed algorithm can fit the needs of face identification systems and face recognition intelligent hardware systems in hotels, workplaces, community entries, etc. Unlike AI face recognition, this algorithm is still a traditional face recognition method. The image feature extraction process relies on the local-feature-based algorithm design, which evades the requirements of large samples and high computational power for face recognition training. Experimental results show that the algorithm has a good recognition rate with significantly higher efficiency.

The remaining chapters of this paper are organized as follows. Section 2 introduces some concepts, important definitions, and the IGFC algorithm models. Section 3 gives the flow and implementation chart of the IGFC algorithm. Section 4 describes the experimental results on YALE, ORL, CMU_PIE face databases, and provides analyses to prove the superiority of our proposed algorithm. Finally, a conclusion will be drawn in Section 5.

2 Background

2.1 Image gradient

The first derivative of a one-dimensional function is defined as:

\[
\frac{df}{dx} = \lim_{\varepsilon \to 0} \frac{f(x + \varepsilon) - f(x)}{\varepsilon}
\]  

A gray image is considered as a two-dimensional function \( f(x, y) \), and the derivative of either \( x \) or \( y \) can be calculated as follows:

\[
\frac{\partial f(x, y)}{\partial x} = \lim_{\varepsilon \to 0} \frac{f(x + \varepsilon, y) - f(x, y)}{\varepsilon}
\]  

\[
\frac{\partial f(x, y)}{\partial y} = \lim_{\varepsilon \to 0} \frac{f(x, y + \varepsilon) - f(x, y)}{\varepsilon}
\]

Since an image is a discrete two-dimensional function by pixel, the smallest \( \varepsilon \) is 1 pixel. Therefore, eqs. 2 and 3 can be simplified to eqs. 4 and 5 (\( \varepsilon = 1 \)):

\[
\frac{\partial f(x, y)}{\partial x} = f(x + 1, y) - f(x, y) = gx
\]

\[
\frac{\partial f(x, y)}{\partial y} = f(x, y + 1) - f(x, y) = gy
\]
Equations 4 and 5 stand for the horizontal gradient (x gradient) and vertical gradient (y gradient) of a point \( g(x, y) \) in the image, respectively. When \( \epsilon = 1 \), the gradient of the image is equivalent to the difference between two adjacent pixels [46].

### 2.2 Related concepts

A pixel point in the image has two gradients in opposite horizontal directions, i.e. the left gradient and the right gradient. Let \( G_{rx} \) be the right gradient and \( G_{lx} \) be the left gradient, and they are calculated as follows:

\[
G_{rx} = \left| f(x+1, y) - f(x, y) \right| 
\]

(6)

\[
G_{lx} = \left| f(x, y) - f(x-1, y) \right| 
\]

(7)

Similarly, there are two gradients in the vertical direction, i.e. the upper gradient and the lower gradient. Let \( G_{uy} \) be the upper gradient and \( G_{dy} \) be the lower gradient, and we have:

\[
G_{uy} = \left| f(x, y-1) - f(x, y) \right| 
\]

(8)

\[
G_{dy} = \left| f(x, y) - f(x, y-1) \right| 
\]

(9)

**Definition 1:**

**Fusion gradient** The fusion gradient of image A is defined as the sum of left, right, upper, and lower gradients of image A, which is denoted as:

\[
G_{fusion} = G_{rx} + G_{lx} + G_{uy} + G_{dy} 
\]

(10)

**Definition 2:**

**Differential fusion gradient** The differential fusion gradient of image A is defined as the result of adding the subtracted values of the left and right gradients to the subtracted values of the upper and lower gradients, which is denoted as:

\[
G_{subfus} = (G_{rx} - G_{lx}) + (G_{uy} - G_{dy}) 
\]

(11)

**Definition 3:**

**Feature compensation** Feature compensation is defined as the operation of adding or subtracting the original image with the image’s feature operator. When a feature operator is added to the pixel value of the original image, **positive compensation** occurs. When a feature operator is subtracted from the pixel value of the original image, **negative compensation** occurs.
Definition 4: **Feature compensation coefficient** During image feature compensation, the feature operator can be added or subtracted several times on the original image. In this case, the number of times of such addition or subtraction is defined as the feature compensation coefficient. It is a real number for flexible adjustments of the feature compensation amplitude.

### 2.3 IGFC algorithm model

The feature information of the image was extracted with the following steps:

1. Convert the image into a grayscale image in img. Format;
2. Obtain the fusion gradient and differential fusion gradient of the image;
3. Obtain image feature descriptions.

A fusion gradient image is a feature image with enlarged edge contours, and it can well display the rough facial contours. The fusion gradient image display of Lena head is shown in Fig. 1a. On the other hand, differential fusion gradient represents a more subtle and detailed description of edge contours (Fig. 1b).

The calculation of pixel value $A$ at row $i$ and column $j$ of image IMG is:

$$ a(i,j) = a0(i,j) + f_m^* g_{fusion}(i,j) - f_n^* g_{subfus}(i,j) $$

(12)

Where $a0(i,j)$ is the value of the pixel at the $i$th row and $j$th column of the original image, $f_m$ is the compensation coefficient of fusion gradient, $f_n$ is the compensation coefficient of differential fusion gradient, $g_{fusion}(i,j)$ is the fusion matrix of pixel point $a0(i,j)$, $g_{subfus}(i,j)$ is the differential fusion matrix of pixel point $a0(i,j)$.

![Fusion and difference fusion matrix](image-url)

*Fig. 1* The fusion and difference fusion matrix of Lena head, a fusion matrix, b difference fusion matrix
Figure 2 illustrates the workflow to calculate the IGFC value centered on \( a_0 \) (whose pixel value is 148) in image IMG, and the pixel values of its surrounding pixels concerned in the calculation are shown in Fig. 2a. The gradient amplitudes of the right, left, up, and low directions are calculated with Eqs. 6–9 (Fig. 2b). Therefore, \( g_{\text{fusion}} = g_{rx} + g_{lx} + g_{uy} + g_{dy} = 23 \) (Eq. 10), and \( g_{\text{subfus}} = (g_{rx} - g_{lx}) + (g_{uy} - g_{dy}) = -7 \) (Eq. 11). Let \( m = 1, n = 7 \), and we have the eigenvalue of pixel \( a_0 \) (Eq. 12):

\[
a = a_0 + g_{\text{fusion}} - g_{\text{subfus}} \times 7 = 220 \quad \text{(Fig. 2c)}.
\]

(4) In the Lena head with a specification of 200*200, we took area A(101:107,101:107) with clear outlines at the corner of the eye to find out the pixel values of the original image and the transformed feature image (Fig. 3).

The image appearance of Lena head after IGFC feature conversion is shown in Fig. 4:

### 2.4 Histogram statistics

Once the IGFC feature image of the original image is obtained, it is subjected to a histogram to extract its detailed feature vectors. The histogram statistics is implemented for statistical

![Fig. 2 Calculation process of IGFC eigenvalues, a the value of \( a_0(i,j) \), b the gradients of \( a_0(i,j) \), c the IGFC feature valued of \( a \)](image)

![Fig. 3 IGFC eigenmatrix of region A in Lena figure](image)
analysis of the grayscale images with pixel values between $0 \sim 255$ [14], and it returns a 256-dimensional array as the result, in which each value pair should be the statistic numbers of the corresponding pixel values in the image. The histogram statistics of Lena head is shown in Fig. 5.

In the field of face recognition, if a whole picture can be represented by histogram statistics, then the statistical results can represent the overall features of the whole image. However, different pictures may exhibit similar statistical results. To minimize the impact brought by such a situation, the whole image is divided into several subgraphs with a certain order, and the histograms of the subgraphs are calculated separately before being connected in a certain sequence to form the general feature vector of the overall image. Following that, a classifier is used to complete model training and vector testing and verify the image recognition and matching outcomes.

Fig. 4 The effect of Lena head’s IGFC feature

Fig. 5 Histogram of Lena head
Even if two different images are judged statistically similar by their integral histograms, it is highly possible to overthrow such a conclusion when comparing the histograms of their segmented sub-images. The Lena head is partitioned into a 3*3 array, and the histograms of each partitioned sub-graph are shown in Fig. 6 [17]:

As shown in Figs. 5 and 6, histograms with or without separate calculations are significantly different. Specifically, Fig. 5 is the global statistical result of Lena head, and the C2 block in Img1 of Fig. 6 corresponds to the local statistical result block G2 in Img2. Each histogram in Img2 corresponds to the subgraph that is located in the respective locations of the original image (e.g. E1 → A1, E2 → A2, etc).

The corresponding relationship of each histogram in Fig. 6 is as follows:

Fig. 6  Histogram of Lena head calculated with the 3 × 3 template

Fig. 7  Flow chart of the IGFC algorithm
a. E1 is the statistical histogram of A1, E2 is the statistical histogram of A2, E3 is the statistical histogram of A3;
b. F1 is the statistical histogram of B1, F2 is the statistical histogram of B2, F3 is the statistical histogram of B3;
c. G1 is the statistical histogram of C1, G2 is the statistical histogram of C2, G3 is the statistical histogram of C3.

3 Proposed method: IGFC

3.1 Algorithm process

The IGFC algorithm is executed with the following steps (Fig. 7). Firstly, image features are extracted. Secondly, the image features are decomposed into multiple subgraphs following the $3 \times 3$ template [17]. Thirdly, each subgraph is subjected to histogram calculations to obtain the feature vector. Fourthly, PCA is used to reduce dimensionality. Finally, SVM classification is used to train and recognize image classifications.

3.2 Implementation of the algorithm

When implementing the algorithm, an image is loaded and converted into a grayscale one to obtain an $m\times n$ matrix $A$.

Step 1: Calculate the differences between pixel point $a0(i,j)$ in matrix $A$ and its up, down, left and right adjacent pixel points, take the absolute values of the differences (where $1 < i < m-1$, $1 < j < n-1$), and obtain the upper gradient $g_{uy}$, lower gradient $g_{dy}$, right gradient $g_{rx}$, and left gradient $g_{lx}$.

Step 2: Calculate $g_{fusion}$ (Eq. 10);

Step 3: Calculate $g_{subfus}$ (Eq. 11);

Step 4: Calculate the pixel value $a(i,j)$ of the pixel point $a0(i,j)$ (Eq. 12).

Step 5: Repeat Step1 ~ Step4 until all pixels in matrix A are converted into a feature matrix $B$ of $(m-2)\times(n-2)$.

![Fig. 8](image-url) Comparison of recognition rate of different compensation coefficient $fn$ in ORL and CMU_PIE library (%)
Step 6: Use adjacent value filling (fill null positions in the matrix with the mean of their immediate adjacent values) to transform matrix B into a new matrix $B'$ of $m \times n$ (identical to matrix A).

Step 7: Use a specific template to block matrix B [17], and calculate the histograms for each image block. Connect the histograms for each block in a specific order to obtain the feature vector of the image. In this paper, the specific template is $3 \times 3$.

Higher dimension numbers of the image feature vector mean more time and storage resources needed for model training and recognition. Therefore, PCA, as one of the most commonly used dimensionality reduction methods, is used to reduce the number of dimensions of feature vectors [44]. After PCA processing, high-dimensional data are removed, and only the most important feature information remains.

### 3.3 Vector machine SVM

The support vector machine (SVM) method is a tool to discriminate and classify test samples by extracting limited sample information based on statistical theory. It can minimize the structural risks, evade the problems of overfitting and local minimization commonly seen in traditional methods, and provide strong and generalized results. The kernel function is adopted in SVM to map the high-dimensional space with low calculation complexity and bypass the Curse of Dimensionality. Therefore, SVM has been widely used in face recognition [16], and this paper adopts LIBSVM, a sub-model of SVM, developed by Professor Chih-Jen Lin and his colleagues [11]. Matlab 2016a was used for the classification experiments of face recognition.

### 4 Experiment and result analysis

#### 4.1 Experimental environment

In this section, we will illustrate the effectiveness of our proposed operator. Specifically, we evaluated the performance of our proposed method on three public face image databases, which are Olivetti Research Laboratory (ORL), YALE face database, and CMU_PIE face database.

The tests were performed on a 2.4GHz CPC, 8GB memory (including 1G video memory), and a 64-bit Windows 7 operating system.

#### 4.2 Parameter settings

##### 4.2.1 Compensation coefficients $f_m$ and $f_n$

As indicated by Eq. 12, compensation coefficients $f_m$, $f_n$ will affect the accuracy of algorithm recognition. Therefore, these coefficients were analyzed to find out their impacts on test results and obtain the most reasonable values.

Since $f_m$ is the compensation coefficient of fusion gradient calculated by accumulating gradients in multiple directions, it is expected to be large. However, if $f_m$ is too large, too many pixel values will be equal to or greater than 255, which is not favored for image feature
extraction. Therefore, \( fm \) is set to 1 in this algorithm, and we focused on the influences of different \( fn \) values on the algorithm recognition rates (Fig. 8).

For the ORL database set, most experimental results on the impact of different \( fn \) values reached 100% accuracy thanks to the \( 3 \times 3 \) image separation method. To further understand the influence of \( fn \) on the recognition rates, the \( 1 \times 2 \) template was used instead of \( 3 \times 3 \) in another set of experiments, and the impacts of different \( fn \) values on the recognition rates became more significant (Fig. 8).

The experimental results show that greater \( fn \) does not mean better recognition. For ORL and CMU_PIE face libraries, when \( fm = 1 \), the recognition rates obtained when \( fn = 7, 8, \) and \( 9 \) are relatively stable and high compared to the other situations. Therefore, in the remaining parts of this paper, we chose \( fm = 1 \) and \( fn = 7 \).

4.2.2 Other parameters

The image block template adopted in this paper is \( 3 \times 3 \), and the classifier used is the LibSVM classifier[11] developed by Professor Chih-Jen Lin and his colleagues, and the corresponding parameters are set as ‘-s 0 -t 2 -c 16 -g 0.0009765625’.

4.3 Experimental results

Our proposed algorithm was compared with five excellent algorithms (classic LBP [1], CLBP [40], WLCGP [18], LGP [24], and FNDC [37]) on four face databases (YALE, ORL, CMU_PIE, and FERET) for their recognition rates and operation efficiencies.

4.3.1 Recognition rates

For all the algorithms referenced, experimental parameters in each original document were used; if the experimental parameters were not provided in the original document, the parameter settings in this paper were used. The recognition rates generated by each algorithm were compared, and 30%–80% of all the images of a certain individual on the databases were used for training.

Fig. 9  Samples on the Yale database
4.3.2 YALE database results

The Yale Face Dataset was created by Yale University. It consists of 11 images for each of the 15 different people, who were shot with different poses, expressions, and light conditions. Each image is 80 × 80 pixels in size, and a sample set of one person is shown in Fig. 9.

In this experiment, the first 3–8 images in each sample set were used for training, and the remaining images were tested. The test results are described in Table 1.

| Algorithms   | Training image number |
|--------------|-----------------------|
|              | 3        | 4        | 5        | 6        | 7        | 8        |
| Classic LBP | 68.33    | 67.62    | 75.56    | 72.00    | 90.00    | 88.89    |
| CLBP         | 70.83    | 77.14    | 84.44    | 82.67    | 98.33    | 97.78    |
| LGP          | 68.81    | 60.81    | 73.21    | 70.07    | 88.53    | 86.75    |
| WLCGP        | 70.25    | 75.15    | 76.95    | 81.25    | 85.45    | 95.56    |
| FNDC         | 74.82    | 76.19    | 76.89    | 78.25    | 94.21    | 97.52    |
| Proposed Algorithm | **77.50** | **75.24** | **77.78** | **78.67** | **95.00** | **100.00** |

Table 1 Recognition rate comparison of different number of training images on YALE database /%

4.3.3 ORL database results

ORL face database was created by Olivetti Research Laboratory, The University of Cambridge, UK. This dataset involves 400 92*112 pictures of 40 people (10 pictures each), and the facial expression changes, small gesture variations, and scale changes among the pictures of
In this experiment, images No.10 to No.18 for each person in the database were taken for training, and the remaining images were tested. The test results are displayed in Table 3.

### 4.3.4 CMU_PIE database results

The CMU_PIE face database was created by researchers at Carnegie Mellon University. The original database contains pictures of 68 people taken under 13 poses, 43 light conditions, and 4 expressions, and the total number of photos is 40,000. In this paper, 1632 64 × 64 grayscale face images in the CMU_PIE database were tested, and 24 images of each person were included in one sample set. An example sample set is given in Fig. 11.

In this experiment, images No.10 to No.18 for each person in the database were taken for training, and the remaining images were tested. The test results are displayed in Table 3.
For the CMU_PIE face database, when the number of training is 10, the proposed algorithm demonstrates higher recognition rates compared to other reference algorithms except for the classical LBP. Besides, the recognition rate of the proposed algorithm rises steadily from 42.86% to 92.16% as the number of training increases from 10 to 18.

### 4.3.5 FERET database results

Face Recognition Technology (FERET) engineering was launched by the US Department of Defense’s Counterdrug Technology Transfer Program (CTTP). The resulting FERET database includes a general face library and universal test standards, in which variations in facial expressions, illuminations, gestures, and ages are all represented by 1400 images of 200 people (7 images each person). An example sample set is given in Fig. 12.

In this experiment, images No.3 to No.5 for each person in the database were taken for training, and the remaining images were tested. The test results are displayed in Table 4.

| Algorithms          | Number of Training |
|---------------------|--------------------|
| Classic LBP        | 41.24              |
| CLBP                | 40.67              |
| LGP                 | 40.12              |
| WLCGP               | 39.45              |
| FNDC                | 42.25              |
| Proposed Algorithm  | 41.34              |

For the CMU_PIE face database, when the number of training is 10, the proposed algorithm demonstrates higher recognition rates compared to other reference algorithms except for the classical LBP. Besides, the recognition rate of the proposed algorithm rises steadily from 42.86% to 92.16% as the number of training increases from 10 to 18.

### Table 3  Recognition rate comparison of different number of training images on CUM_PIE database /%

| Numbers of Training | Algorithm   | Classic LBP | CLBP | LGP | WLCGP | FNDC | Proposed Algorithm |
|---------------------|-------------|-------------|------|-----|-------|------|-------------------|
| 10                  | Classic LBP | 45.38       | 32.14| 23.56| 40.36 | 42.98| **42.86**         |
| 11                  | Classic LBP | 49.66       | 45.48| 31.42| 51.49 | 47.15| **51.81**         |
| 12                  | Classic LBP | 46.81       | 40.44| 29.15| 47.81 | 50.12| **49.63**         |
| 13                  | Classic LBP | 45.72       | 37.83| 28.34| 44.26 | 48.25| **48.13**         |
| 14                  | Classic LBP | 44.41       | 36.18| 31.58| 45.86 | 47.56| **48.97**         |
| 15                  | Classic LBP | 56.05       | 44.61| 38.72| 61.56 | 65.58| **66.83**         |
| 16                  | Classic LBP | 57.17       | 57.35| 39.86| 65.95 | 73.15| **74.26**         |
| 17                  | Classic LBP | 72.27       | 66.81| 52.36| 76.84 | 78.51| **79.83**         |
| 18                  | Classic LBP | 88.48       | 78.92| 59.94| 91.87 | 91.58| **92.16**         |

### Table 4  Recognition rate comparison of different numbers of training images on the FERET database. /%

| Algorithms   | 3   | 4   | 5   |
|--------------|-----|-----|-----|
| Classic LBP  | 41.24| 55.87| 70.43|
| CLBP         | 40.67| 62.67| 73.6 |
| LGP          | 40.12| 59.65| 69.8 |
| WLCGP        | 39.45| 61.87| 70.65|
| FNDC         | **42.25**| **65.4**| **73.3**|
| Proposed Algorithm | **41.34**| **66.34**| **74.3**|

Fig. 12  Samples on the FERET database
For the FERET face database, when the number of training is 3, the proposed algorithm demonstrates higher recognition rates compared to other reference algorithms except for the classical FNDC. Besides, the recognition rate of the proposed algorithm rises steadily from 41.34% to 74.3% as the number of training increases from 3 to 5. Generally speaking, the proposed algorithm demonstrates higher recognition rates than other algorithms when the number of training is 5.

To sum up, the algorithm described in this paper was compared with five algorithms (classic LBP, CLBP, WLCGP, LGP, and FNDC) on four databases (YALE, ORL, CMU_PIE, and FERET), and the comparison results suggest the proposed algorithm to offer greater recognition rates than the other algorithms in general.

### 4.3.6 Time complexity analysis

In order to compare the operation efficiencies of each algorithm in terms of image feature extraction and image recognition, the times spent by the proposed algorithm and five other algorithms (classical LBP, CLBP, WLCGP, LGP, and FNDC) to complete the image feature extraction and image recognition tasks were recorded (Tables 5 and 6).

For image recognition, we performed model training and image recognition as two independent experiment sessions. The times each algorithm spent from the beginning of image processing to the end of recognition were recorded (measured number of images in each image set: 3 for Yale, 2 for ORL, and 6 for CMU_PIE).

Judging from the tables, FNDC and CLBP algorithms are comparably more efficient for YALE, spending 1.68 s and 1.54 s to extract feature information from 165 80 × 80 images, respectively. However, the proposed algorithm exhibited much more superior performance (0.55 s) in that aspect.

For ORL, CLBP, LGP, WLCGP, and FNDC algorithms all demonstrate promising running efficiency, spending 3.71 s, 3.94 s, 3.96 s, and 2.26 s to extract feature information from 400 92*112 images. Nevertheless, these numbers are still longer than that of the proposed algorithm (1.97 s).

For the CMU_PIE database, CLBP, WLCGP, and FNDC algorithms exhibit good performance, using 14.54 s, 15.32 s, and 5.25 s to extract feature information from 1632 64 × 64

| The database (consume /s) | Classic LBP | CLBP | LGP | WLCGP | FNDC | Proposed Algorithm |
|--------------------------|------------|------|-----|-------|------|-------------------|
| YALE                     | 3.46       | 1.54 | 1.83| 1.68  | 0.78 | 0.55              |
| ORL                      | 14.00      | 3.71 | 3.94| 3.96  | 2.26 | 1.97              |
| CMU_PIE                  | 21.89      | 14.54| 34.25| 15.32 | 5.25 | 3.26              |
| Average                  | 13.12      | 6.59 | 13.34| 6.98  | 2.76 | 1.93              |

| The database (consume /s) | Classic LBP | CLBP | LGP | WLCGP | FNDC | Proposed Algorithm |
|--------------------------|------------|------|-----|-------|------|-------------------|
| YALE                     | 0.95       | 0.41 | 0.52| 0.48  | 0.22 | 0.152             |
| ORL                      | 2.8        | 0.75 | 0.81| 0.8   | 0.45 | 0.39              |
| CMU_PIE                  | 6.81       | 5.62 | 8.72| 3.83  | 1.33 | 0.82              |
| Average                  | 3.52       | 2.26 | 3.35| 1.7033| 0.67 | 0.454             |
images, respectively. However, the total time spent by the proposed algorithm to finish the identical task is merely 3.26 s. On average, the time spent by the proposed algorithm to extract image features from the three databases remains obviously shorter than the other algorithms.

5 Conclusion

In this article, we propose a new face recognition algorithm (IGFC algorithm) capable to extract features from the original image by fusion and compensation. The algorithm calculates the gradient values in four directions for each pixel in the original image and uses the fusion gradient and differential fusion gradient to compensate for the original pixel value. Following the pixel value compensation, a feature graph that can accurately describe the original features can be obtained. Subsequently, the feature graph is divided into several blocks and each block is subjected to histogram calculations. The histograms obtained are connected in a given sequence to generate a feature vector that describes the image features, and the dimensionality of the feature vector is reduced by principal component analysis. Finally, the SVM classifier is used to classify and identify the original image. Experiments show that the IGFC algorithm can produce good recognition rates in YALE, ORL, CMU_PIE, and FERET databases with excellent operational efficiency.

The proposed algorithm mainly focuses on the image recognition effect in a specific environment, but the face recognition effect in the case of complex background is not very ideal. The face recognition effect in complex background is not very ideal, which will be the focus of the later work. The author will strengthen the research on this aspect of technology, and try to put forward an algorithm that can better solve the face recognition effect in complex background.

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Declarations

Competing interests The authors declare they have no competing no financial interests.

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