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# A Novel Face Recognition Algorithm Based on Improved Retinex and Sparse Representation

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***Abstract***

*In recent years, face recognition technology has been widely used as a kind of important modern biological recognition technology. As one of the main factors that affect the recognition rate, the illumination variation has attracted the attention of many researchers. In order to improve the face recognition under illumination variation condition, a novel face recognition algorithm based on improved Retinex and sparse representation is proposed in this paper. Retinex algorithm can be used to solve the problem of face illumination variation in face recognition, but it is easy to produce 'halo' phenomenon. In order to improve the face recognition rate under the change of illumination condition. In this paper, firstly, in order to eliminate the interference of illumination on face recognition, we apply the Retinex that is improved by partial differential equations to face image processing. Then, sparse representation is used to extract face feature vector, and the voting method is used to realize the face recognition. Finally, the performance of the algorithm is tested by 3 standard face databases. The results show that the proposed algorithm can improve the face recognition rate under different illumination conditions, and has good robustness to illumination.*

***Keywords**: sparse representation; face recognition; Illumination-Robust; Retinex algorithm*

## 1. Introduction

Face recognition is one of the most important biological recognition technology, and now it has made great progress in face recognition. Robust principal component analysis [1], the robust sparse encoding algorithm which is based on Gabor features [2], iterative weighting regularized robust encoding algorithm [3], two-stage non-negative sparse representation algorithm [4] and a series of new algorithms have been successfully applied to face recognition. The related products have also been applied in such areas as public information security, finance and so on. However, there are still many problems in the application of face recognition, such as the illumination problem has been one of the key factors affecting the image quality. In recent years, researchers have proposed a variety of preprocessing algorithms to solve the problem of illumination in face recognition, such as histogram equalization [5], edge map [6], wavelet transform method [7], which are all used to extract illumination invariant facial feature. Although these algorithms can meet the real-time requirements, most of them can't solve the shadow problem, and they are difficult to achieve the desired results. The illumination compensation dictionary [8] has been proposed to achieve a very good illumination treatment effect, but the method requires the training image under the strict illumination control.

Some researcher proposed a face recognition method based on sparse representation (SR), the method can find a unique optimal sparse solution for face recognition, and

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exclude invalid test image doesn't belong to the training set by making full use of the sparsity of the face space. In the case of sufficient training samples, the SR algorithm can obtain better recognition results and have better robustness [9]. However the number of training samples are obtained under the real environment are usually less, and the linear relationship between the test samples and the training samples is destroyed when there are the large variation of pose, illumination variation and expressions variation. It is just for these reasons that the correct rate of face recognition of SR algorithm is low [10]. In recent years, some researchers have applied the Retinex algorithm based on the theory of retina to pre-process the face image. The algorithm can eliminate the interference of pose, illumination and facial expression to face recognition, which opens up a new way for face recognition under the constraint environment [11]. But the Retinex algorithm has some disadvantages, such as easy to appear "halo" phenomenon, which affect its application in face recognition.

In order to get a better effect of face recognition, we propose a face recognition algorithm based on improved Retinex and sparse representation, which is used to overcome some problems in the process of face recognition under the constraint environment. Firstly, the Retinex algorithm is improved by partial differential equations, and it is applied to face image preprocessing to eliminate the interference of illumination on face recognition. Then, sparse representation is used to extract face feature vector, and the voting method is used to realize the face recognition. Finally, the effectiveness of this method is tested by simulation experiment, simulation results show that the proposed algorithm can improve the recognition rate of human face and has good robustness.

## 2. Face Recognition Algorithm Based on Sparse Representation

The original objective of the sparse representation is to represent and compress the signal with lower sampling rates than the Shannon sampling theorem [12]. Inspired by the compressive sensing theory proposed by Candes [13], the sparse representation theory is widely used. Sparse representation theory is that the basic signal from the over-complete dictionary is used to linearly represent the input signal [14], and the linear combination (sparse representation coefficients) contains most of the information of the signal. When the sparse representation theory is applied to face recognition [15], the training sample set is used as an over-complete dictionary. If there are enough training samples for each class, the input samples can be expressed by a linear representation of the same training sample [16], and the design of over-complete dictionary is the key. Because the over-complete dictionary is made up of atoms, and the number of atoms is much larger than the number of signals. So it can be used in a wider range to select atoms for signal representation or approximation.

The problem of face recognition based on sparse representation is described as the sparse representation of the input image in the over complete dictionary. Firstly, $y = Ax$ ( $y \in R^m$ ) represents the face image, namely the image of $w \times h$ is extended to the dimension of the column vector of $m = w \times h$ . Secondly, we use training image database to build an over-complete dictionary $A \in R^{m \times n}$ , $n$ represents number of training images. Each training image is 1 column, which is called 1 atom. So, the over-complete dictionary is the $m \times n$ dimensional matrix. The $x \in R^n$ are the $n$ dimensional sparse representation of the input image in the over complete dictionary, namely the sparse coefficients. Most of these coefficients are 0, or close to 0. Solving the sparse representation of the input image in the over-complete dictionary is a sparse encoding problem, there are 2 solution methods [17].

Sparse encoding with sparse regularization constraints:

$$\hat{x} = \arg\min \left\| y - Ax \right\|_2^2 \quad s.t. \left\| x \right\|_0 \le t \tag{1}$$

 

Sparse encoding under error constraints:

$$\hat{x} = \arg\min \|x\|_0 \ \ s.t. \|y - Ax\|_2^2 \le \varepsilon \tag{2}$$

$\hat{x}$ is the optimal sparse representation of $y$ , $t$ represents sparse threshold, $\varepsilon$ represents error margin, $\|\bullet\|$ represents $l_0$ norm, what is the number of non-zero elements in the vectors.

Formula 1 and Formula 2 can be approached by different ways, such as orthogonal matching pursuit, Basis Pursuit [18], FOCUSS, gradient tracking, *etc*. At present, the $l_1$ norm is used to approximate solve the $l_0$ norm. When some researchers explain the reason for the similarity between the $l_0$ norm and the $l_1$ norm, Formula 2 can be converted to:

$$\hat{x} = \arg\min \|x\|_1 \ \ s.t. \|y - Ax\|_2^2 \le \varepsilon l_0 \tag{3}$$

The method is referred to as SRC (Sparse Representation-based Classification). Due to the sparse error, SRC uses face images alignment to form the over-complete dictionary $\mathbf{A} = \left[ A_1 \middle| A_2 \middle| \ldots \middle| A_i \middle| A_k \right]$, $k$ is the category number of training samples, so the Formula 1 can be converted to the problem to an optimum solution x such as:

$$\min_{x,e} \|x\|_1 + \|e\|_1 \quad s.t. Ax + e = y \tag{4}$$

In this formula, $A_i$ represents the $i$ th training sample set, $e$ represents the error between the input image and the training image when there is the ideal condition of no illumination change, no posture change, and occlusion. If $x_i$ is a sub vector of $x$ , and corresponding to the $i$ th sample, then the input image $y$ can be classified as the $\hat{i}$ th sample.

$$\hat{i} = \arg\min_i \|y - A_i x_i - e\|_2^2 \tag{5}$$

There are 2 problems in Formula 3:

1) Whether constraint $\|x_1\|$ of $l_1$ norm that is able to describe the characteristics of signal sparsity .

Whether $l_2$ norm $\|y - Ax\|_2^2 \le \varepsilon$ is able to describe the fidelity of signal. Especially when the input image $Y$ has noise or outliers (Caused by illumination change, occlusion, posture change, *etc*.,).

For the first problem, the coefficient constraint can be modified. We can increase 1 non-negative remainder sparse coefficient $\alpha$ ,or use 1 Laplace operator of sparse to represent coefficients or use the weighted norm $l_2$ to perform sparsity constraints. In addition, some researchers proposed the framework of general sparse model, and designed the sparse regularization operator. In addition to the literature 18, the $l_1$ norm is used for signal fidelity, and there are few literature related to the study of improving $\|y - Ax\|_2^2$ in this area.

SRC algorithm has a better effect when there are many training image inputs, the recognition is aligned, and when there is the ideal condition of no illumination change, no posture change, and occlusion. The algorithm is applicable to certain scenarios, such as secret locations or access control systems. Under ideal conditions, if the mirror reflection, projection and occlusion in the image local space can be seen, it can be regarded as a large scale sparse error processing. Posture change and alignment can result in a large number of nonlinear transformations, and they will destroy the low dimensional linear model, so posture change needs to use the coefficient error to correct, namely "robust PCA" removing the sparse error.

The actual face image is not ideal, but it is limited to the part of the image, just like the block is sparse for the entire image pixel, it can be expressed with an additional error $e$ . But the prerequisite must be already sparse, and then optimization problem can be converted to:

$$\min_{x,e} \|x\|_1 + \|e\|_1 \quad s.t.\ y = Ax + e \tag{6}$$

## 3. Retinex Algorithm

Retinex theory is a brightness perception and color constancy theory proposed by Land et al based on the theory of human visual system model. But according to the introduction of the color constancy theory of the previous section, we can know that the illumination value perceived by the human eye is determined by a relative value, which is obtained by comparing with the surrounding light. Therefore, Retinex algorithm uses irradiance model of the global light model to represent the imaging process of image. According to the model, the image B can be described by the Formula 7 as:

$$S(x, y) = R(x, y) \bullet L(x, y) \tag{7}$$

Among them, $R(x, y)$ is represented by the light independent reflection coefficient, which corresponds to the texture information of the material and the surface shape of the reflecting object. $L(x, y)$ represents all the light that is incident on the surface of the object. It can be obtained from Formula 7, Retinex theory holds that an image is composed of the incident image and the reflected image.

The Retinex theory is that the incident light irradiation in reflective objects, the reflection coefficient of the reflective object form reflected light entering the eye, this also forms the image that people see. Therefore, the focus of the algorithm based on Retinex theory is to use a variety of mathematical methods to remove the incident component L from the image S, and then we will obtain reflection component, which will be able to restore the original appearance of the object. In the calculation, there are two benefits as follows put Formula 7 in the log domain to process:

1) From the physiological point of view, the log curve is more close to the human visual system to the ability of the perception of light.
2) From a mathematical point of view, the complex product form can be transformed into simple addition and subtraction in the logarithmic domain, so that the algorithm can be simplified.

The Retinex algorithm in the log domain is shown as follows:

$$s(x, y) = r(x, y) + l(x, y) \tag{8}$$

And

$$s(x, y) = \log(S(x, y)), r(x, y) = \log(R(x, y)), l(x, y) = \log(L(x, y)) \tag{9}$$

By the Formula 7 we can know that $R(x, y)$ and $L(x, y)$ are unknown, in addition to the given original image $S(x, y)$ . Therefore, this is an indefinite equation for solving the problem to recover the reflection component and the luminance component from the original image. The following constraints can be got by the reflection theorem model of irradiance light: reflection coefficient $R \in [0,1]$ , $S \le L$ , $S$ close to $L$ .

Therefore, the general Retinex algorithm based on the above three constraints put forward different light estimation methods, first of all, the original image $s(x, y)$ from the log domain estimates the light component of the image $\hat{l}(x, y)$. Then we let $s(x, y)$ minus $\hat{l}(x, y)$ by using Formula 7, so we can get the image of the reflection component $\hat{r}(x, y)$. In the end, we can get the reflection image through the index operation. Figure 1 is the calculation process of Retinex algorithm.

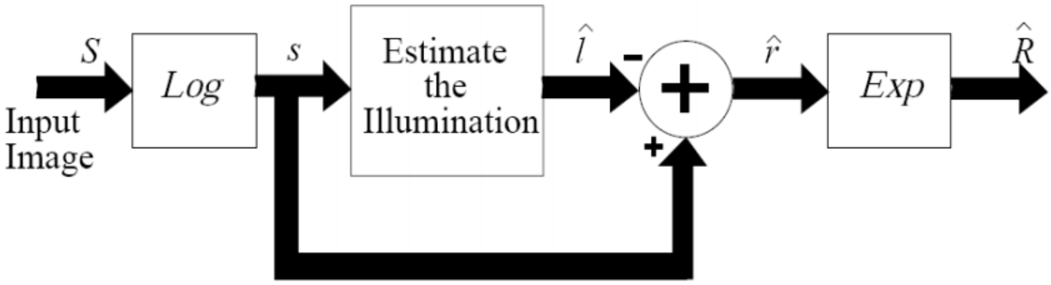


**Figure 1. Flow Chart of Retinex Algorithm**

In the color constancy theory, the reflection component is not affected by light intensity, so as the component that can cause the visual response, the reflection component should be different from the surrounding. Therefore the reflection component can be obtained by comparing each pixel in the image and the pixels in the other regions. However, different researchers have different views on how to understand "different from the surrounding components". From the other point view, there is a view that the light component is part of the slow change in the original image. Namely, the light is equal to each of the components in a region, if we can estimate this part, and then we can use the Formula 9 to calculate the reflection component. The light changes slowly, so it can be regarded as the low frequency part of the image. Therefore, the light component can be estimated by low pass filtering of the original image. So far, the problem of how to estimate the light component converts into how to design the low pass filter. According to the different form of the filter, ttere are different Retinex algorithms, such as Single Scale Retinex(SSR), Multi Scale Retinex(MSR).

## 4. Improvement of Sparse Representation

In this paper, we mainly analyze various kinds of illumination changes in the actual application of human face images such as reflected light, refraction light and scattered light. We first use partial differential equations to improve the Retinex theory, and then use the method to extract the invariant features of the input face, we can obtain the essential texture features of the image by the method, and reduce the influence of various light factors on the image. The extracted light invariant features are then transformed into the atomic library which is easy to be sparse representation. We can use the sparse matrix to make the face recognition quickly and accurately. The specific algorithm process is described as follows:

1) Assume that a face image can be represented by $I(x, y)$, then according to the Retinex theory, $I(x, y) = R(x, y)U(x, y)$, In this formula, the $R(x, y)$ is the texture profile that contains the image itself, while the $U(x, y)$ is the light in the image. For the realization of sparse said for light changing face image, we should minimize the light component. Instead, extracting the characteristic information.
2) In order to solve the reflection image $R(x, y)$, we first need to change the $I(x, y)$ to obtain the linear relation:

$$i(x, y) = u(x, y) + r(x, y) \tag{13}$$

3) Based on total variation model, it is estimated that $u(x, y)$ can get:

$$J_P[u] = \int_{\Omega} |\nabla u|^{p(|\nabla u|)} d\Omega \tag{14}$$

In this formula, $p(|\nabla u|)$ can be 1 or 2, when $|\nabla u| \to 0$, $p(|\nabla u|) = 2$. When $\nabla u \to \infty$ and $|\nabla u| \to \infty$, $p(|\nabla u|) = 1$. When the pixel is located at the edge of the image, the value of P is 1. In addition, the value of P is 2 in the flat area. We can use the following model to solve:

$$J_{\lambda}[u] = \int |\nabla u| dxdy + \lambda \int |u - i|^2 dxdy \tag{15}$$

The parameter $\lambda$ is a non-negative real number, and its selection is related to the edge preserving property after the model is smooth.

4) In order to solve the problem, the above problem can be changed into a function optimization problem:

$$J = \arg\min \|\nabla u\|_1 + \lambda \|u - i\|_2 \tag{16}$$

Among them, the first one is the total variation of the image, which shows the spatial smoothness of the image, and the latter shows the edge preserving of the image, while adjusting the parameters of the whole model. Through the forward difference and backward difference iteration, the optimal equation can be used to obtain the final illumination estimation $\hat{u}$.

5) Using $\hat{u}$ to restore the reflection coefficient model $R(x, y)$, then $R(x, y)$ is used for sparse representation in the dictionary of atoms.

6) If the training samples set has K class samples, and each class has $n_k$ samples, then the dictionary R can be expressed as:

$$R = \left[ R_{11}, R_{12}, \ldots, R_{1n_1}, R_{21}, \ldots, R_{2n_2}, \ldots, R_{kn_k} \right] \tag{17}$$

$R_{ij}$ represents the column vector , which is converted from a sample library image $R(x, y)$. Each column corresponds to a reflection model image. But with the sparse representation classification of samples requires very high dimension. This paper uses PCA to extract the main components of the $R$ dictionary, and filters out the unnecessary information. At the same time, we use different dimensions due to the different number of samples in different databases.

7) The test sample $y_1$ can be expressed as a linear combination of the dictionary $y_1 = Ax_1$. When the number of training samples reaches a certain degree, $x_1 = [0, 0, \ldots., 0, x_{i1}, \ldots, x_{in_i}, 0, \ldots, 0]^T \in R^m$ is a very sparse coefficient vector. That is, we can use the $L_0$ norm to solve the non-zero elements in the equation:

$$\hat{x}_0 = \arg\min \|x\|_0 \tag{18}$$

And then according to the position of non-zero elements, we can distinguish the categories of samples.

 

8) The former solving process is a NP problem. The research on atomic tracking, compressed sensing and sparse representation shows that when the number of samples is sparse, the above problem can be transformed to solve by $l_1$ norm:

$$\hat{x}_1 = \arg\min \|x\|_1 \tag{19}$$

This problem can be solved by standard linear programming method.

9) For each category *i*, let the $\delta_i : R^n \to R^n$ be the characteristic function of the coefficient vector $x \in R^n$ on the class *i*. That $\delta_i$ only copies the elements corresponding to the *i*th class on $x \in R^n$, while the other elements are zero. Using this $\delta_i$, we can approximate the reconstruction of the test samples $y$:

$$\hat{y}_i = A\delta_i(\hat{x}_1) \tag{20}$$

So the sample can be classified according to the minimum residual error between $y$ and $\hat{y}$:

$$\min_i r_i(y) = \left\| y - A\delta_i\left(\hat{x}_1\right)\right\|_2 \tag{21}$$

The final classification result can be expressed as the corresponding value of the parameter which minimizes the result of the above formula:

$$identity(y) = \arg\min_i r_i(y) \tag{22}$$

# 5. Experiment and Analysis

## 5.1. Experimental Conditions and Data Source Description

This experiment compares the improved method with the SSR in the literature 20 and the MSR in the literature 19, the recognition rate of face images is obtained by experiments shows that the method has a significant improvement in the processing of light image. The results show that this method is suitable for the large illumination changes. In order to verify the performance of the face recognition method, the configuration of the computer we choose is as follows: CPU: Intel PIV, 3.0GMHz; RAM: 8G; OS: windows XP. We use MATLAB 2013 to do simulation test, the simulation object is Yale B face database, CMU-PIE face database and AR database.

(1) Yale B is an extension of the face database, there are 38 people, and each person has 64 light conditions positive image, 5 subsets respectively corresponding to different illumination conditions. As shown in Figure 2.

**Figure 2. Illumination Condition of One of the 5 Subsets of Yale B**

(2) CMU-PIE face database has 68 persons; each person has 13 entire right sides of the figure and the left sides of the figure of different posture as well as 43 different light conditions of the image. 21 of the 43 images are in the background of lighting off or on. Each person has 3 subsets, some images of a person in the face database are shown in Figure 3.

**Figure 3. Partial Face Images of 3 Sub Sets of CMU-PIE Library**

(3) AR database origin contains 126 positive images, a total of 4000 images, for each individual, 26 images were extracted from two separate parts, divided into 2 subsets. As shown in Figure 4.

**Figure 4. Face Images of 2 Sub Sets of AR Library**

### 5.2. Experimental Results and Analysis

**5.2.1. Results and Analysis of Face Recognition Based on Yale B:** The average recognition rate of SSR, MSR and the method of this paper is shown in Table 1. We can clearly see from the table, with respect to SSR, MSR face recognition method, the face recognition rate of this method has been improved. In the first subset, the method achieve 100% recognition accuracy, the recognition rate is also significantly improved on several other subsets, especially in subset 5, the recognition rate of SSR is less than 90%, and the recognition rate of the proposed algorithm is still 95%. The comparison results show that this method is more robust.

**Table 1. Comparison of Different Methods for the Recognition Rate of Yale B Database**

| | SSR | MSR | Paper algorithm |
|---|---|---|---|
| Subset 1 | 97.5% | 98.5% | **100%** |
| Subset 2 | 95.5% | 95.0% | **99.0%** |
| Subset 3 | 94.5% | 94.5% | **97.0%** |
| Subset 4 | 92.0% | 94.0% | **96.5%** |
| Subset 5 | 88.5% | 92.5% | **95.0%** |

**5.2.2. Results and Analysis of Face Recognition Based on PIE:** The average recognition rate of SSR, MSR and the method of this paper on CMU-PIE face database is shown in Table 2. We can see from the table, in the experiment of subset 1, the recognition rate of this method is 0.5% lower than that of MSR algorithm, but in the other two sub sets, this method is obviously better than the other two methods. The recognition accuracy of SSR method in subset 3 is only 85% or so, which is obviously lower than the other two methods, so as to prove the superiority of the method in this paper.

**Table 2. Comparison of Different Methods for the Recognition Rate of PIE Database**

| | SSR | MSR | Paper algorithm |
|---|---|---|---|
| Subset 1 | 95.5% | **97.5%** | 97% |
| Subset 2 | 91.5% | 93.0% | **95.5%** |
| Subset 3 | 85.5% | 90.0% | **92.5%** |

**5.2.3. Results and Analysis of Face Recognition Based on AR:** The average recognition rate of SSR, MSR and the method of this paper on AR face database is shown in Table 3. The recognition accuracy of the three methods on the AR subset is relatively high. In the two sub sets, the recognition accuracy of the proposed method reaches 99%, this accuracy is at least 1% percentage points ahead of the other two methods, basically close to 100%.

**Table 3. Comparison of Different Methods for the Recognition Rate of PIE Database**

| | SSR | MSR | Paper algorithm |
|---|---|---|---|
| Subset 1 | 97.7% | 98.0% | **99.5%** |
| Subset 2 | 98.0% | 97.5% | **99.0%** |

## 6. Conclusions

In this paper, we first analyze the problem of human face recognition in the presence of uneven illumination. We first classify and introduce the existing methods to solve the problem. We focus on the advantages and disadvantages of Retinex theory and partial differential equations, what are used to solve the problem of illumination. Through the research of sparse representation method and the complex illumination problem in face image, we propose a face recognition method based on sparse representation and partial differential equations. The Retinex algorithm is improved by partial differential equations, and the algorithm can effectively reduce the reflection coefficient in halo phenomenon, and then obtain the illumination invariant atomic library. Finally, we use sparse representation to complete the face recognition under complex illumination. The experimental results show that the algorithm can effectively improve the recognition performance of sparse representation in dealing with complex illumination.

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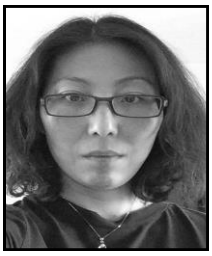

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