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Research Paper

Face Recognition using Color and Edge Orientation Difference Histogram

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Abstract

Face recognition is a challenging problem due to different illuminations, poses, facial expressions, and occlusions. In this paper, a new robust face recognition method is proposed based on the color and edge orientation difference histogram. Firstly, the color and edge orientation difference histogram is extracted using color, color difference, edge orientation, and edge orientation difference of the face image. Then the backward feature selection is employed in order to reduce the number of features. Finally, the Canberra measure is used to assess the similarity between the images. The color and edge orientation difference histogram shows the color and edge orientation difference between two neighboring pixels. This histogram is effective for face recognition due to the different skin colors and different edge orientations of the face image, which leads to a different light reflection. The proposed method is evaluated on the Yale and ORL face datasets. These datasets consist of gray-scale face images under different illuminations, poses, facial expressions, and occlusions. The recognition rate over the Yale and ORL datasets is achieved to be 100% and 98.75%, respectively. The experimental results demonstrate that the proposed method outperforms the existing methods in face recognition.

1. Introduction

Face recognition plays a major role in computer-aided identification. There are other ways of identification such as fingerprint identification [1–4], voice recognition [5,6], and iris recognition [7-9]. Identification using face recognition can be performed in a wider range due to an easier access to face images. For example, for the fingerprinting process, the finger must be placed on a device to be scanned; however, face images can be obtained easily using cameras without even paying attention to them. Different illuminations, poses, facial expressions, and occlusions influence the performance of face recognition systems [10,11]. Robustness to these problems is serious in the face recognition systems. Facial occlusion occurs when a person wears glasses, hats, and masks. It can also occur with moustaches, beards, and heavy makeups. Examples of facial occlusions are shown in figure 1. A lot of methods have been proposed for face recognition; these methods can be divided into two different categories: holistic approaches and local-based approaches. The holistic approaches use the whole face region for feature extraction, whereas the local-based approaches use specific regions of the face image for a local feature extraction. An example of a local feature can be the distance of the eyes, as it barely changes for a specific person.

Figure 1. Examples of facial occlusions.

In this paper, a new holistic method is proposed for face recognition. In this approach, the L*a*b* color space is used due to its good monotonousness. Firstly, the color and edge orientation difference histogram was extracted from the face image. This histogram contained the information of color, color difference, edge orientation, and edge orientation difference of the image. The color difference histogram has been proposed in [12] for image retrieval but it is not efficient enough for face recognition. In this paper, a new method of feature representation for a better content-based image analysis is introduced, namely the color and edge orientation difference histogram. In the proposed method, in addition to color difference, the edge orientation difference is introduced as another effective factor that has a great impact on the face recognition performance. The color information is fundamental to our perception. Each person has a different skin color as well as a unique facial structure. Edge orientation is one of the most effective features that can be used in order to determine the object boundaries and structures. As a result, the color and edge orientation difference histogram will be effective for face recognition. Although these features are mainly effective for face recognition, some of them maybe redundant. This may happen due to feature extraction from parts of the images that are not related to the face area. Hence, in the second step, the backward feature selection is utilized to select the best features for face recognition. This approach reduces the number of features and increases the recognition rate by removing the inefficient features. Finally, the optimized Canberra measure is used to measure the distance between the images.

The rest of this paper is structured as follows: the related works are reviewed in Section 2; the proposed method is described in Section 3; the evaluation of the proposed method is presented in Section 4; and the conclusions are drawn in Section 5.

2. Related Works

As mentioned earlier, there are two different kinds of approaches in the face recognition studies: holistic approaches and local-based approaches. The holistic approaches utilize the whole image for face recognition such as the Principle Component Analysis (PCA) [13], Linear Discriminant Analysis (LDA) [14], and Independent Component Analysis (ICA) [15]. The local-based approaches extract the local features from specific regions of the face image. The geometric features, which are considered as the local-based approaches, measure the distance between eyes, the width and length of the nose, and the mouth size [16]. These techniques are not inherently robust against variations in the facial pose and expression variations. Indeed, any change in the facial pose or expression may result in different facial geometric features. The Local Binary Patterns (LBP) [17], Gabor Wavelet [18], Scale-Invarint Feature Transform (SIFT) [19-21], and Speeded-Up Robust Features (SURF) [22] are some examples of the major approaches developed for the local-based face recognition. The approach in [23] proposed the Local Gabor Fisher Classifier (LGFC) for face recognition. In [24], a 2D Gabor Wavelet Transform (2DGWT) and a 2D Hidden Markov Model (2DHMM) have been utilized for face recognition. The proposed method in [25] uses both the Gauss-Laguerre and Log-Gabor filters for feature extraction. In [11], the SIFT descriptor has been utilized for feature extraction from the specific areas of the face image. In [26], the Kernel Discriminant Analysis (KDA) has been used to extract the features from the face image. The Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) methods are employed to classify the face images based on the extracted features. In [27], a formal description of granular computing has been proposed for face recognition. It uses a sequential decision process in order to minimize the misclassification cost. To describe the granular information of the face image, a series of image granulation methods are presented, which are based on the 2D sub-space projection methods including 2DPCA, 2DLDA, and 2DLBP. In [28], "Iterative weighted non-smooth non-negative matrix factorization" (IWNS-NMF) has been applied for feature extraction. This method extracts highly localized patterns of the face image. After that, the principle component analysis is used to reduce the dimension for classification by linear SVM. The approach in [29] uses the first derivative of the gaussian operator to reduce the impact of differences in illumination. Then Dual Cross Patterns (DCP) at both the holistic and component levels are extracted. In the recent years, the Convolutional Neural Networks (CNN) and deep learning based methods have been widely used for face recognition. It has been proved that a deep learning method can represent the concept of the image of a person by combining simpler concepts [30]. In [31], the spatial transformer layers have been inserted after the feature extraction layers in a CNN for face recognition. In [32], a novel deep neural net named Multi-View Perceptron (MVP) has been proposed, which has the ability to untangle the identity and view features in order to infer a full spectrum of multi-view images. The method proposed in [33] uses Deep Stacked Denoising Sparse Autoencoders (DS-DSA). This constructs a neural network that learns an approximiation of an identity functon by placing constraints to learn fine representations of the input. The method in [34] proposes an improved multi-scale CNN for face recognition. The features are extracted by convolution of each layer and then fed into softmax for classification.

3. Proposed Method

In this paper, a new face recognition method is proposed, which is robust against different illuminations, poses, facial expressions, and occlusions. First, the color and edge orientation difference histogram is extracted from the face image, and then the backward feature selection is applied to eliminate the redundant features. Finally, the optimized Canberra measure is used to evaluate the similarity between the images. Figure 2 illustrates a flow chart of the proposed face recognition method. In the following, the proposed method is described in more details.

3.1. Color and Edge Orientation Difference Histogram

The color and edge orientation difference histogram uses color, edge orientation, color difference, and edge orientation difference of the image. This histogram plays an important role in the image content analysis. The color information is fundamental to our perception. The humans can distinguish thousands of color shades but only two dozen gray shades [35]. The color quantization is used to extract the color information of the face image. The color quantization selects a limited set of colors to display a color image.

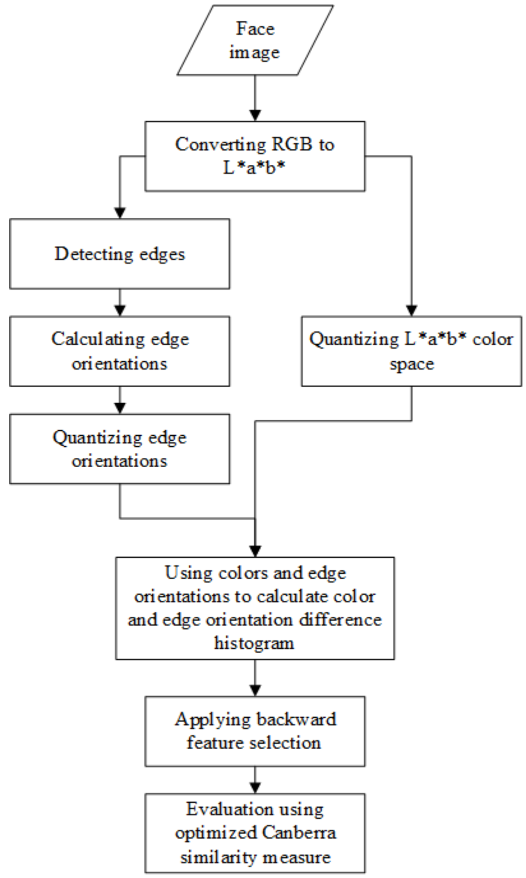

Figure 2. A flow chart of the proposed face recognition method.

The L*a*b* color space is used for color description of an image due to its high monotonousness. A uniform quantization is used in the L*a*b* color space, in which the L* channel is quantized into 10 bins, and the a* and b* channels are quantized into 3 bins. As a result, 10 x 3 x 3 = 90 different color combinations are obtained. A color quantization is applied in order to define a threshold for changes in colors. By using the color quantization, the proposed method will be robust to different illuminations.

The edge orientation is another effective feature for the image content analysis. It is influential to determine the object boundaries and structures. After extracting the edges using gradient computation [36], the edge orientations are calculated. Some partial derivatives are required to calculate the edge orientations.

The sobel operator is robust to noise, and has a small computational burden; therefore, it will be a good solution to calculate the partial derivatives.

The procedure of the edge orientations calculation has been fully described in [12]. After calculating the edge orientations, these values are uniformly quantized into 18 bins. By quantizing the edge orientations, a thershold for the edge orientation difference will be defined; therefore, the proposed method will be robust to different poses and facial expressions.

Let H_{color} be a feature vector of 90 different color combinations and H_{ori} be a feature vector of 18 different edge orientations. In order to calculate the value for the color and edge orientation difference, each pixel is compared with its four main neighbors. If the two neighboring pixels have the same color or the same edge orientation, the color and the edge orientation difference of the two pixels will be calculated using equations (1) and (2):

$$H_{color}\big(C(x,y)\big) = \begin{cases} \sum\sum \begin{matrix}(\sqrt{(\Delta L^2 + \Delta a^2 + \Delta b^2)} \\ + \\ |\Delta O|)\end{matrix} \\ where\ \theta(x,y) = \theta(x',y') \end{cases} \tag{1}$$

$$H_{ori}\big(\theta(x,y)\big) = \begin{cases} \sum\sum \begin{matrix}(\sqrt{(\Delta L^2 + \Delta a^2 + \Delta b^2)} \\ + \\ |\Delta O|)\end{matrix} \\ where\ C(x,y) = C(x',y') \end{cases} \tag{2}$$

where $\Delta L, \Delta a,$ and Δb are, respectively, the color difference in the L* channel, a* channel, and b* channel. Also $\Delta O, \theta,$ and C are, respectively, the edge orientation difference, quantized edge orientation, and quantized color of a pixel. Finally, the color and edge orientation difference histogram is formed by merging H_{color} and H_{ori}. Accordingly, this histogram consists of 108 different features. Figure 3 shows two color and edge orientation difference histograms of a person in two different conditions. Figure 4 shows two color and edge orientation difference histograms of two different persons. The horizontal axis represents our color indices and edge orientations, and the vertical axis represents the color and edge orientation difference values. As one can see in figure 3, the color and edge orientation difference histograms of a specific person are similar, whereas in figure 4, the color and edge orientation difference histograms for two different persons are strongly different. Observing figures 3 and 4, it is clear that there are many features that are not effective for face recognition. These redundant features will be removed in the feature selection phase.

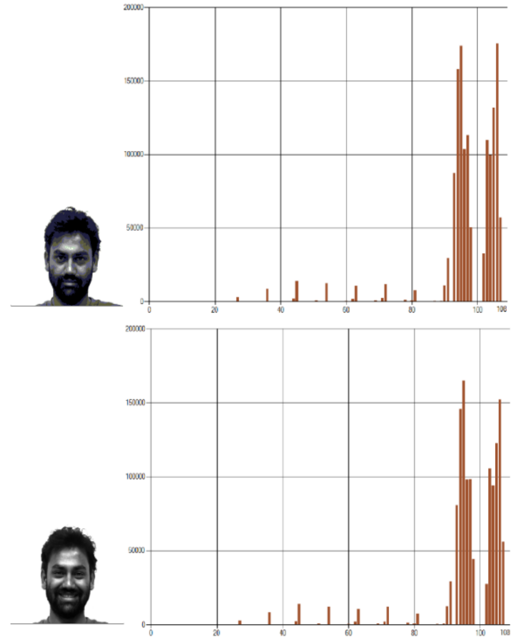

Figure 3. Two color and edge orientation difference histograms of a person in two different conditions.

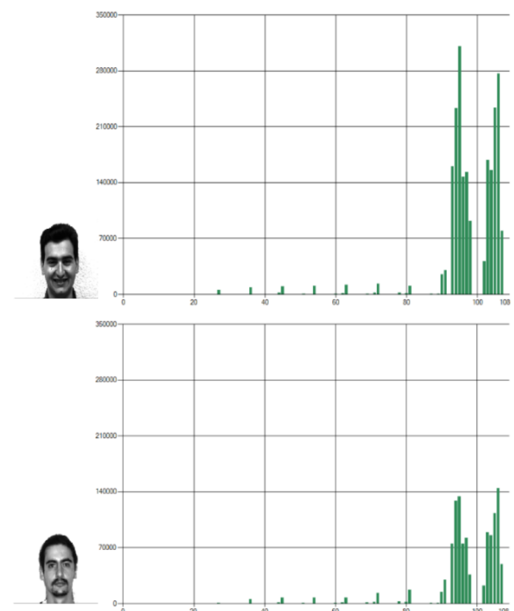

Figure 4. Two color and edge orientation difference histograms of two different persons.

3.2. Backward Feature Selection

As shown in both figures 3 and 4, there are lots of features whose values are equal or very close to zero; most of these features are redundant. Removing these features not only does not reduce the recognition rate but also will increase it. In this work, we used the backward feature selection to reduce the number of features effectively. First of all, the recognition rate for the initial 108 features was calculated; then each feature was temporarily eliminated and the recognition rate was calculated according to the remaining features. If removing a feature did not decrease the recognition rate, we considered that this feature was dispensable for classification and should be removed. Accordingly, the best recognition rate was updated. This procedure was continued until deleting a feature reduced the best recognition rate.

3.3. Optimized Canberra Measure

The proposed method was applied on all the training and test images. Then the similarity between a test image and each one of the training images was evaluated by the optimized Canberra measure. This measure is a weighted version of the Manhattan distance. The optimized Canberra measure is represented in equation (3):

$$D(T,Q) = \sum_{i=1}^{M} \frac{|T_i - Q_i|}{|T_i + u_T| + |Q_i + u_Q|} \qquad (3)$$

where D is the distance between T and Q, T is the test image feature vector, Q is the training image feature vector, M is the length of the feature vector, and u_T and u_Q are the averages of T and Q [12]. The recognized face is the one that has the lowest distance.

4. Experimental Results

In order to evaluate the performance of the proposed method in terms of the recognition rate and time complexity, the Yale [37] and ORL [38] face datasets were used. The Yale dataset consists of 165 face images of 15 different subjects with different facial expressions, illuminations, occlusions, and poses. The ORL dataset consists of 400 face images of 40 different subjects with different facial expressions, occlusions, and poses. In this section, the experimental results on these two datasets are examined.

4.1. Recognition Rate

The recognition rate is the percentage ratio of correct decisions to the total number of decisions. In order to evaluate the robustness of the proposed method against different facial expressions, illuminations, and occlusions, the Yale face dataset was examined. Figure 5 shows an example of a subject with different illumination, facial expression, and occlusions. The recognition rate of the proposed method on the Yale face dataset is shown in table 1.

Figure 5. An example of the Yale face dataset with different illuminations, facial expressions, and occlusions.

Table 1. Recognition rate on the Yale face dataset.

Number of training images per class	Number oft images per class	Recognition rate (%)
2	9	48.14
3	8	65
4	7	72.38
5	6	74.44
6	5	81.33
7	4	91.66
8	3	93.33
9	2	100
10	1	100

The ORL face dataset is used to evaluate the robustness of the proposed method against different facial expressions, occlusions, and poses. Figure 6 shows an example of a subject with different facial expressions, occlusions, and poses. The recognition rate of the proposed method on the ORL face dataset is represented in table 2.

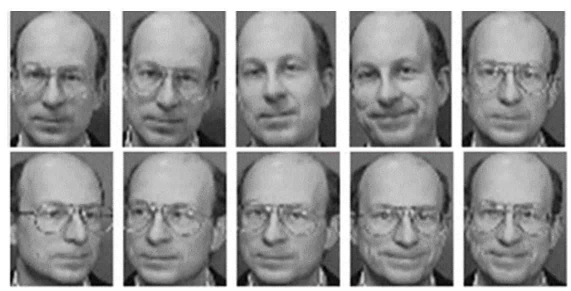

Figure 6. An example of the ORL face dataset with different facial expressions, occlusions, and poses.

Table 2. Recognition rate on the ORL face dataset.

Number of training images per class	Number of test images per class	Recognition rate (%)
2	8	68.75
3	7	70.35
4	6	79.58
5	5	89
6	4	95.62
7	3	95
8	2	98.75

4.2. Time Complexity

Our proposed face recognition method was implemented using the C# programing language.

The experiments were run on a computer with an Intel Core i7 5500U CPU and 16GB of RAM. The time complexity of the proposed method was evaluated using both the Yale and ORL face datasets. The evaluation was done using three different measures. The first measure was the feature extraction time (FET), which was the time required to extract features from a face image. The second measure was the feature selection time (FST), which was the time required to select the effective features from the extracted features. The last measure was the average testing time (ATT), which was the time required to recognize the most similar image with the test image. The consuming time of the proposed face recognition method in terms of FET, FST, and ATT is shown in table 3.

Table 3. Time complexity of the proposed method (in seconds)

Dataset	FET	FST	ATT
Yale	0.232	0.103	0.002
ORL	0.044	0.248	0.063

The results obtained indicate that the proposed method has a low execution time.

4.3. Comparison with Other Works

The proposed method was evaluated on the Yale and ORL face datasets, and its performance was compared with the performance of a number of well-known methods [26,28,33,34]. The methods in [26,28] are based on machine learning, whereas the methods in [33,34] are based on CNN and deep learning.
In order to achieve the most accurate comparison, we compared the proposed method with the state-of-the-art on the best results reported in their papers. The results obtained are shown in table 4. The comparison result shows that the proposed method has a higher recognition rate compared to the traditional machine learning methods as well as deep learning. It is also very competetive compared to the CNN approach in [34] and outperforms it on Yale dataset.

Table 4. Comparison of the proposed method with different approaches on the Yale and ORL datasets.

Method	Yale	ORL
Proposed method	100%	98.75
[26]	95.25%	96%
[28]	96.6%	97.5%
[33]	98.16%	98%
[34]	98.9%	99.4%

5. Conclusions

In this paper, a new effective method for face recognition was proposed. First, the color and edge orientation difference histogram was calculated from the face images. Then the backward feature selection was used to remove the redundant features and increase the recognition rate of the proposed method. Finally, the optimized Canberra measure was used to compute the similarity between the face images. The proposed method was evaluated on the Yale and ORL face datasets. The experimental results showed that the proposed method was robust against different illuminations, facial expressions, occlusions, and poses. Also the results obtained attest the superiority of the proposed method to the sate-of-the-arts in terms of recognition rate.

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تشخیص چهره با استفاده از هیستوگرام تفاوت رنگ و جهت لبه

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چکیده:

تشخیص چهره به علت وجود شرایط نوری، حالات چهره، زوایای صورت و پوشش‌های مختلف، یکی از مسائل چالش برانگیز در علم پردازش تصویر می‌باشد. در این مقاله، یک روش تشخیص چهره مقاوم بر پایه هیستوگرام تفاوت رنگ و جهت لبه ارائه شده است. در ابتدا، هیستوگرام تفاوت رنگ و جهت لبه با استفاده از المانهای رنگ، اختلاف رنگ، جهت لبه و اختلاف جهت لبه، از تصویر چهره استخراج می‌گردد. سپس، انتخاب ویژگی به صورت عقبگرد جهت کاهش تعداد ویژگی‌ها مورد استفاده قرار می‌گیرد. در پایان، از معیار کانبرا جهت اندازه گیری میزان شباهت دو تصویر چهره استفاده می‌شود. هیستوگرام تفاوت رنگ و جهت لبه، اختلاف رنگ و اختلاف جهت لبه‌ها را بین دو پیکسل همسایه نشان می‌دهد. این روش به علت تفاوت در رنگ پوست‌ها و همچنین لبه‌های هر چهره و بازتاب متفاوت نور از چهره‌های مختلف، رویکردی مناسب برای تشخیص چهره دارد. جهت ارزیابی روش ارائه شده در این مقاله، از دیتاست‌های Yale و ORL استفاده شده است. این دیتاست‌ها شامل تصاویر چهره خاکستری با شرایط نوری، حالات چهره، زوایای صورت و پوشش‌های مختلف می‌باشند. نتیجه ارزیابی‌ها نشان می‌دهد که نرخ تشخیص در دیتاست‌های Yale و ORL به ترتیب ۱۰۰ و ۹۸,۷۵ درصد می‌باشد. در نتیجه، روش ارائه شده در تشخیص چهره، عملکرد بهتری را نسبت به سایر روش‌ها به نمایش می‌گذارد.

کلمات کلیدی: تشخیص چهره، هیستوگرام تفاوت رنگ و جهت لبه، اختلاف رنگ یکنواخت، اختلاف جهت لبه.