Infrared face recognition based on co-occurrence histogram of multi-scale local binary patterns

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Abstract: Different scales local binary patterns (LBP) extract different micro-structures, which contain important discriminative information for infrared face recognition. To capture the correlation between different scales, a new infrared face recognition method based on multi-scale LBP co-occurrence histogram was proposed in this paper. In traditional multi-scale LBP-based features, correlation in different micro-structures was ignored. To consider such correlation in infrared faces, co-occurrence histogram of multi-scale LBP codes was used to represent the infrared face. Multi-scale LBP co-occurrence histogram not only preserved great invariance to environmental temperature, but also greatly enhanceed the discriminative power of the descriptor as co-occurrence matrix of LBP code well captureed the correlation between different scale micro-structures around the same central point. The experimental results show the recognition rates of infrared face recognition method based on multi-scale LBP co-occurrence histogram can reaches 99.2% under same condition and 91.2% under variable ambient temperatures, outperform that of the classic methods based on LBP and multi-scale LBP histogram.

Key words: local binary pattern; infrared face recognition; multi-scale; correlation; co-occurrence histogram

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基于多尺度局部二元模式共生直方图的红外人脸识别

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摘　要: 不同尺度的局部二元模式(LBP)提取了红外人脸图中不同的微结构局部特征。为了挖掘不同尺度中局部特征的相关性,提出了一种基于多尺度 LBP 共生直方图的红外人脸识别方法。传统的多尺度 LBP 特征提取方法,丢失了对多尺度特征间相关性信息的提取。为了充分考虑微结构间的相关统计信息,提出了多尺度 LBP 共生直方图表示方法,以提取包含在红外人脸图像中的有用鉴别特征。多尺度 LBP 共生直方图特征表示方法不仅可以消除环境温度对红外人脸图像特征提取的影响,而且还可以增强对局部特征表示的鉴别性。实验结果表明:多尺度局部二元模式共生矩阵可以增强对红外人脸鉴别特征提取的有效性,提出的红外人脸方法的性能优于基于传统多尺度 LBP 和单尺度 LBP 方法,在相同环境情况下和在环境温度变化情况下可以达到 99.2%和 91.2%的识别率。

关键词: 局部二元模式; 红外人脸识别; 多尺度; 相关性; 共生直方图

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0 Introduction

Infrared face recognition, being light- independent, and not vulnerable to facial skin, expressions and posture, can avoid or limit the drawbacks of face recognition in visible light[1-2]. Therefore, infrared face recognition is an active research area of face automatic recognition. However, the challenges of infrared face recognition mainly come from the external environment temperature, low resolution and other factors[3-4]. Based on the property of infrared face image, exploring a robust feature extraction method is a key step in infrared face recognition system. Many feature extraction methods are proposed for infrared face recognition[5]. Most of the developed approaches make use of appearance-based methods, such as Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA) and Independent Component Analysis(ICA), which project face images into a subspace where the recognition is carried out[6]. Other reported infrared face recognition approaches are based on the use of local-matching: Local Binary Pattern(LBP)[5] and Gabor Jet Descriptors(GJD)[4]. Due to low resolutions of infrared face image, the local feature extraction is more appreciated for infrared face feature extraction, which can be used to get more local discrimination information. LBP histogram representation was applied to near infrared face recognition by Li et al[5], which get a better performance than statistical methods such as PCA and LDA. LBP-based facial image analysis has been one of the most popular and successful applications in recent years[7-9]. LBP encodes the relative intensity magnitude between each pixel and its neighboring pixels, which can describe the micro-patterns of the image such as flat areas, spots, lines and edges. The main advantage of this approach lies in the robustness of LBP to monotonic photometric changes and its computational simplicity[8]. Since the impact of external environment temperature on infrared face image is almost a monotonic transform, the LBP can extract robust features for infrared face recognition under different environment temperature situations. In 2013, considering the local discriminative features in infrared images, the method based on single scale local binary pattern was applied to far infrared face recognition by Xie et al[10], which gets a better performance than statistical methods such as PCA and LDA.

Due to robustness of LBP, LBP methodology has been developed recently with large number of variations for improved performance in different applications [11-15]. Recently, multi-scale strategy was introduced into texture classification. The LBP histograms in each scale are simply concatenated into a final representation. Since the multi-scale method always contributes to performance improvement, it can be introduced into infrared face recognition to achieve better performance than single scale method[13]. However, the classical multi-scale strategy ignores the correlation information between different scales. In fact, the correlation of the micro-structures in different scales consists of discriminative information.

In this paper, in order to represent the joint distribution of LBP patterns in different scales, we propose infrared face recognition based on the co-occurrence histogram of multi-scale LBP patterns (CMSLBP). Compared with single scale histogram, the multi-scale joint co-occurrence strategy can describe stronger local structures in infrared face images.

1 Local binary patterns representation

Local binary patterns were introduced by Ojala[8] which has a low computational complexity and a low sensitivity to monotonic photometric changes. It has been widely used in biometrics such as face recognition, face detection, facial expression recognition, gender classification, iris recognition and infrared face recognition[16-18]. In its simplest form, an LBP description of a pixel is created by threshold the values of the 3×3 neighborhood of the pixel against the central pixel and interpreting the result as a binary number. The parameters of the original LBP operator with a radius of 1 pixel and 8 sampling points are demonstrated in figure 1. LBP code for center point can be defined as:

$$\mathrm{LBP}_{P,R}(x_c,y_c)=\sum_{i=0}^{P-1}2^i\cdot S(g_i-g_c) \tag{1}$$

$$S(g_i-g_c)=\begin{cases}1,g_i-g_c\geqslant 0\\ 0,g_i-g_c<0\end{cases} \tag{2}$$

Where (x_c,y_c) is the coordinate of the central pixel; g_c is the gray value of the central pixel; g_i is the value of its neighbors; P is the total number of sampling points and R is the radius of the neighborhood. As shown in figure 1, the LBP patterns with different radiuses characterize different size local structures. In other words, a radius R stands for a scale. The parameters (P,R) can be (8,1), (8, 2), (16, 2) and (8, 3) etc.

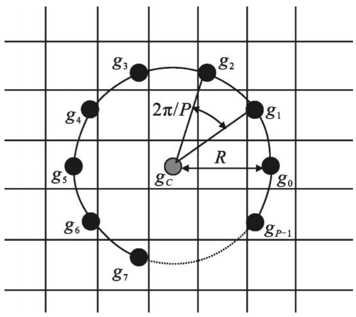
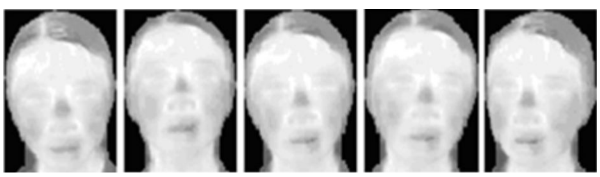


Fig.1 Parameters P and R of LBP

For the number of sampling points P, The dimension of histogram from LBP codes (LBPH) is 2^P. To reduce the dimension of the LBPH, "uniform patterns" is reserved for representation. An LBP code is defined as uniform if it contains at most two 0-1 or 1-0 transitions when viewed as a circular bit string. If P equals 8, only 59 of the 256 possible 8 bit LBPH bins come from uniform patterns histogram.



(a) Original infrared face

(b) LBP representation

Fig.2 LBP patterns image

Suppose the face image is of size $(M\times N)$. After identifying the LBP code of each pixel (x_c,y_c), by computing the LBP patterns histogram, traditional single scale infrared face recognition methods achieve the final features.

$$H(r)=\sum_{x_c=2}^{N-1}\sum_{y_c=2}^{M-1}f(\mathrm{LBP}_{P,R}(x_c,y_c),r) \tag{3}$$

$$f(\mathrm{LBP}_{P,R}(x_c,y_c),r)=\begin{cases}1,\ \mathrm{LBP}_{P,R}(x_c,y_c)=r\\ 0,\ \text{otherwise}\end{cases} \tag{4}$$

Where the value r ranges from 0 to 2^P-1.

The center-symmetric local binary patterns feature (CS-LBP)[19], which is a modified version of the LBP texture feature, inherits the desirable properties of both texture features and gradient based features. In addition, they are computationally cheaper and easier to implement. The basic coding principle of CS-LBP is shown in figure 3. In this paper, we use the CS-LBP to extract micro-structure features in infrared face recognition. In this paper, let P equal 8, the dimension number of CS-LBP is 16.

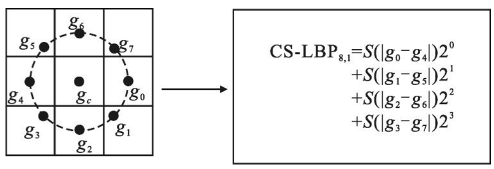
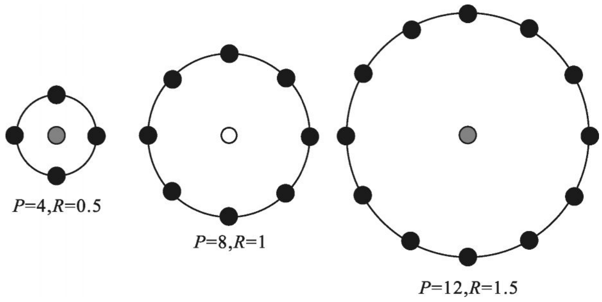


Fig.3 Basic principle of CS-LBP

2 Multi-scale LBP co-occurrence histogram

As shown in figure 1, each scale LBP depicts a local micro-structure in its small scale region. Therefore, single scale LBP can not represent rich local information with large described region. To extract the structure information in different resolutions, multi-scale strategy is usually used in texture classification task[13]. Multi-scale LBP operators are shown in figure 4.



R: radius of sampling circle P: total number of sampling points

Fig.4 Multi-scale LBP

Gray-level Co-occurrence Matrix[20] is firstly proposed to calculate co-occurrence of pixel values, but it is sensitive to monotonic photometric changes (external environment temperature impact for infrared face images). Fortunately, the external environment temperature change doesn't change the relative intensity magnitude in multi-scale LBP. However, the discriminative power of multi-scale LBP is limited by their simply histograms concatenation [21-22]. In order to represent the joint distribution of LBP patterns in different scales, we propose the co-occurrence histogram of multi-scale LBP patterns (CMSLBP) to represent infrared face images. Considering two scales $s1=(P1,R1)$ and $s2=(P2,R2)$, CMSLBP($s1$,$s2$) can be defined as follow:

$$\mathrm{CMSLBP}(s1,s2)=\mathrm{Co}(\mathrm{LBP}(s1),\mathrm{LBP}(s2)) \quad (5)$$

Where LBP($s1$) and LBP($s2$) are the LBP patterns on scales $s1$ and scales $s2$ individually, Co(LBP($s1$),LBP($s2$)) means the co-occurrence statistical operator. A visual illustration of CMSLBP has been shown in figure 5. The CMSLBP codes local features with the similar method of traditional LBP. As a result, CMSLBP also has the property: great invariance to variable environmental temperature.

In this paper, CS-LBP instead of LBP is operated to extract the single scale local patterns. So the dimension number of CMSLBP is 256.

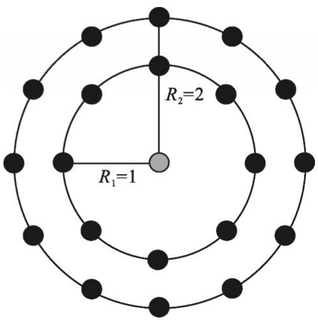


Fig.5 Spatial co-occurrence matrix of local binary patterns

3 Infrared face recognition method

In this section, the detail realization of infrared face recognition is introduced. The main steps in proposed method are listed as follow:

Stage one: Infrared face detection and normalization[1]. After normalization, the resolution of infrared face images is the same.

Stage two: The multi-scale CS-LBP is applied on the normalized infrared face image to get multi-scale LBP patterns.

Stage three: Multi-scale LBP Co-occurrence histogram proposed in Section III is applied to build the histogram representation by partitioning model.

Last stage: The nearest neighborhood classifier based dissimilarity of final features between training datasets and test face is employed to perform the classification task.

In this paper, we use the traditional metric based on chi-square statistic[8]. The dissimilarity of two histograms($H1$,$H2$) can be gotten by:

$$\mathrm{Sim}(H1,H2)=\sum_{bin=1}^{n}\frac{(H1(\mathrm{bin})-H2(\mathrm{bin}))^2}{H1(\mathrm{bin})+H2(\mathrm{bin})} \quad (6)$$

Where n is the dimension of co-occurrence histogram representation of multi-scale LBP.

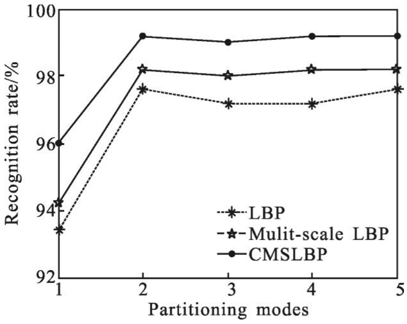
4 Experimental results

There's no standard database for infrared face recognition. To verify the effectiveness of proposed method and other ones, all experiments are done under an infrared face database built by ourselves with a ThermoVisionA40 infrared camera. It contains 1 000 photos taken under the same condition. There're 50 persons, and 20 photos for each person. All photos are kept according to the original temperature. To check the robustness of the recognition system, there're 165 photos taken under variable ambient temperature in database. The temperature varies from 24.3 ℃ to 28.4 ℃. The original size for each image is 240 ×320. After preprocess and normalization, it becomes 80×60. Experiments take Euclidean distance for final classifier.

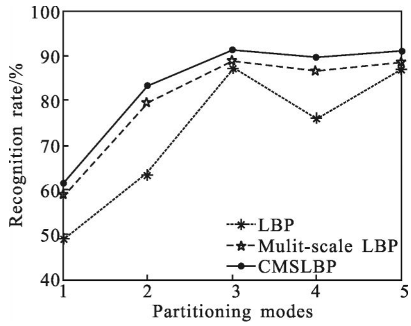
Fig.6 Part of infrared face database

In experiments, CS −LBP operator is implemented, parameters of two scales are $s1$ (8,1) and $s2$ (8,2). The dimension number of histogram extracted by the CMSLBP is 256. To make full use of the space location information, the partitioning is applied to get final features. Five modes of partitioning are used: 1 is non−partitioning, 2 is 2×2, 3 is 4×2, 4 is 2×4, and 5 is 4×4. The recognition results by using LBP, Multi-scale LBP and CMSLBP features with different partitioning modes are demonstrated in figure 7.

It can be seen from figure 7 that the recognition performance of the method based on CMSLBP outperforms that of the method based on traditional multi-scale LBP and traditional LBP both under same condition and under variable ambient temperature condition. This is because that CMSLBP extracts more local structural features in relatively larger region, which contributes better discriminative ability in infrared face representation.



(a) Under same condition



(b) Under variable ambient temperature

Fig.7 Recognition results with different partitioning modes

To verify the effectiveness of the proposed features extraction method for infrared face recognition, the three existing features extraction algorithms are used for comparisons include traditional LBP histogram [10], traditional multi-scale LBP histogram[13] and PCA+LDA[6]. All the experiments are executed on Think Centre workstation (CPU: Intel Core 3.2 GHz, RAM: 3.47 GB) running MATLAB 2007 on Windows XP (32−bit) platform. The running times include total training and test times.

Tab.1 Best recognition rates and running times of different methods

Methods	Date type	Time/s	Recognition rate
CMSLBP histogram	Same condition	12.58	99.2%
LBP histogram	Same condition	12.43	97.6%
Multi−scale LBP histogram	Same condition	24.89	98.2%
PCA+LDA	Same condition	23.04	92.4%
CMSLBP	Variable ambient temperature	11.96	91.2%
LBP histogram	Variable ambient temperature	11.89	87.4%
Multi-scale LBP histogram	Variable ambient temperature	23.80	88.6%
PCA+LDA	Variable ambient temperature	20.39	33.6%

The best recognition results and ru nning times for the same-session data and elapse-timeare demonstrated in table 1. It can be seen from the table 1 that co-occurrence histogram of multi-scale LBP can improve the recognition performance of traditional LBP histogram. It is also revealed from table 1, compared with traditional multi-scale LBP histogram, proposed CMSLBP can extract more relative information in multi-scale LBP patterns, which contributes to better recognition performance. Regarding the running time, the CMSLBP is faster than traditional multi-scale LBP histogram and is a little slower than traditional LBP. In conclusion, the multi-scale LBP co-occurrence histogram presentation is a simple and effective feature extraction method for infrared face recognition.

5 Conclusions

The conventional LBP-based feature as represented by the LBP histogram still has room for performance improvements. Correlation among different scales around the center point could enrich the descriptive power and boost the discriminative power of the descriptors. In this paper, a simple and effective feature is proposed for infrared face recognition. The proposed feature is based on considering co-occurrence of multi-scale LBP patterns. Co-occurrence histogram of two scales LBP patterns could provide much more information than their simple concatenation. Experiments illustrate that the CMSLBP histogram is effective in extraction the discrimination information and the performace of the proposed infrared face recognition method outperforms the muti-scale LBP histogram and traditonal LBP histogram.

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