A LDP based Hyper-Spectral Face Recognition Algorithm Based on Gabor Filter

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Abstract: ***Face recognition algorithms finds applications in large domains. Especially face recognition has become an important authentication scheme. Due to high use in security, efficiency of these algorithms has become crucial. In this paper a technique is proposed for efficient face recognition based on LDP using Gabor filters. It is found that similarity index for the proposed technique is better as compared to hyper spectral block based approach.***

Keywords: Gabor filter, Local directional pattern, PCA

1. Introduction

As one of the most successful applications of image analysis and understanding, face recognition has been a rapid growing research area for many years. Face recognition addresses the problem of identifying or verifying a person by comparing his face with face images stored in the database. General procedures for face recognition including face detection, face normalization, feature extraction and recognition. Face detection can segment face from complicated background. Face normalization is used to normalize the face to ensure the input face and faces stored in the database are of the same size and position. Feature extraction is to represent the normalized face as low-dimensional vectors with discriminant power. Face recognition includes both identification and verification. Face identification is the process of providing a ranked listing of candidates whose faces best match with the input face. For face verification, a person presents an identity claim and his face to the system, and then the system either accepts or rejects his claim based on the result of comparing his faces with those stored in the databases. Although significant progress has been made in the area of face recognition during past few years, face recognition is still a challenging task. Face recognition in visible spectrum is influenced by variations in illumination, pose, facial expression, viewpoint, disguise and etc. Thermal infrared (IR) band, which consists of Mid-wave infrared (MWIR, 3-5), Long-wave infrared (LWIR, 8-14), can capture the emitted energy from an object, thus is more robust to illumination variation. The use of thermal IR imagery has great advantages over visible images for face recognition in variant illumination conditions. However, thermal IR imagery is sensitive to changes in body and ambient temperature and the existence of the glass. On the contrary, visible imagery is more robust to these factors. Considering the complementary information provided by visible and thermal IR images, fusion of them provides a viable way for face recognition.

2. Related Work

Starting from the booming low dimensional reconstruction of faces using KL or PCA [16] projections, Eigen pictures are one in every of the key driving forces behind face representation, detection, and recognition. it's renowned that there exist important statistical redundancies in natural pictures. Principal component Analysis (PCA)[15] is global structure conserving, the Eigen face technique uses PCA for spatiality reduction and maximize the overall scatter across all categories. PCA retains unwanted variations as a result of lighting and facial expressions. The PCA projects original data onto lower dimensional topological space spanned by Eigen vectors and corresponding largest Eigen values of the variance matrix for data of all categories. Eigen faces are the Eigen vectors of the set of the faces. Principal component analysis for face recognition relies on data theory approach during which the relevant information in an exceedingly face image is extracted as with efficiency as possible.

Shufu Xie projected that, block-based Fisher‟s linear discriminant (BFLD) [17] to cut back the spatiality of the projected descriptor and at identical time enhance its discriminative power. Finally, by using BFLD, fuse native patterns of Gabor magnitude and part for face recognition. The fusion of magnitude and phase additional enhance the recognition accuracy after they are encoded by native patterns and combined with BFLD.

3. Proposed Approach

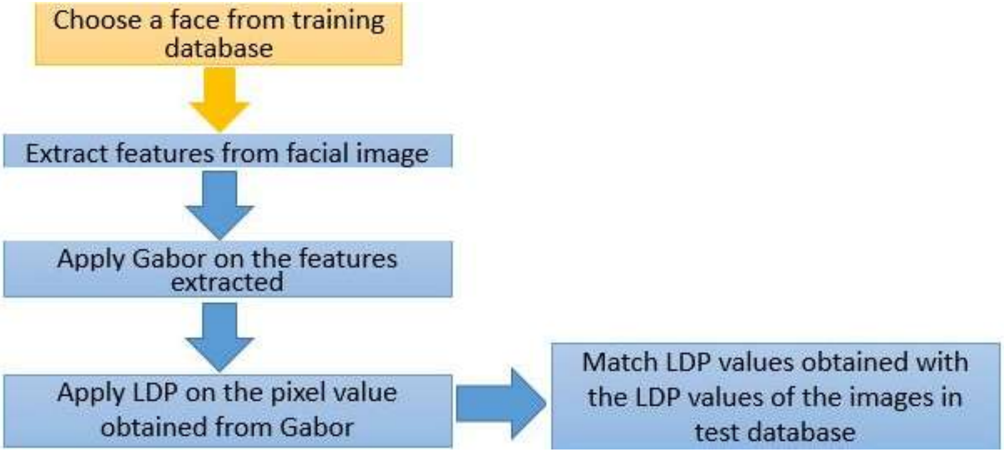
Gabor Filter: Face detection and feature extraction from facial image is done using Gabor filter. They are spatial filters which uses Gaussian function that apply sin/cos loacalization. Gabor filters are defined as :

Ψ_(μ,v) (z) = |(|k_(μ,v) |)|^2/σ^2 e^((-|(|k_(μ,v) |)|^2 |(|z|)|^2/ 2σ^2))[e^(ik_(μ,v) z)- e^(-σ^2/2)]

Where, μ defines orientation of Gabor kernel.
v defines scale of Gabor kernel.
Z = (x,y) and ||.|| denotes the normalization operator.

The frequency vetor k_(μ,v) is given as :

k_(μ,v) = k_v e^(iØ_μ)



Gabor kernel have 5 scales v ϵ {0,…,4}and 6 orientations µ ϵ {0,…,5}

Where $k_v = k_{max}/\lambda^v$ and $\emptyset_\mu = \Pi\mu/8.\lambda$ is the spacing factor between filters in the frequency domain and σ is variance of the Gabor filter image. The Gabor image is obtained by the convolution of the face image with the Gabor filter.

Local Directional Pattern [1]

The proposed study uses a local Directional Pattern concept, that overcomes the drawbacks of LBP and is additional strong for classification. The local descriptor LDP considers the edge response values altogether totally different directions rather than surrounding neighboring pixel intensities like LBP. As edge response magnitude is more stable than pixel intensity LDP provides a consistency in noise and illumination changes also. The LDP relies on LBP. Within the LBP operator, a gray-scale invariant texture primitive, has gained vital quality for describing texture of a picture. It labels each pixel of a picture by thresholding its P-neighboring values with the middle value by changing the result into a binary range by using Equation one.

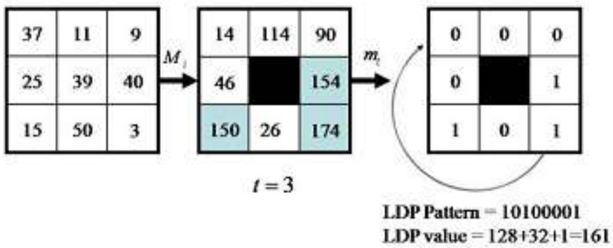
LDP considers the edge response values in each totally different direction. It's composed of 3 steps. First, eight directional edge response values (m_0… m_7) are obtained by applying kirsch masks in eight orientations (M_0…M_7).

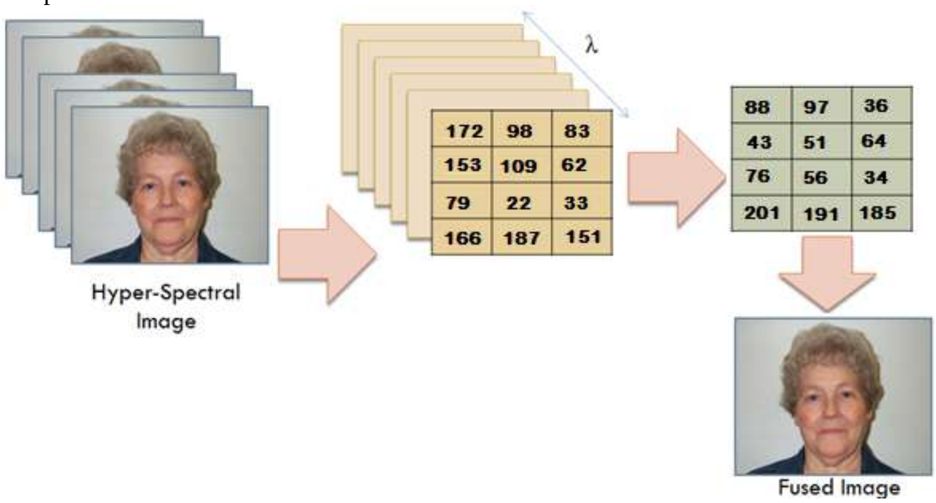
To encode Gabor magnitude pattern of a picture LBP also can be used, LBP is powerful to monotonic illumination changes in grey scale, however it's sensitive to non-monotonic illumination variation, random noise. Therefore its economical to use local Directional Pattern (LDP) to resolve these issues. Whereas the LBP considers neighboring pixel intensities. The LDP considers the edge response values in each totally different direction.

$$\begin{bmatrix}-3&-3&5\\-3&0&5\\-3&-3&5\end{bmatrix}\begin{bmatrix}-3&5&5\\-3&0&5\\-3&-3&-3\end{bmatrix}\begin{bmatrix}5&5&5\\-3&0&-3\\-3&-3&-3\end{bmatrix}\begin{bmatrix}5&5&-3\\5&0&-3\\-3&-3&-3\end{bmatrix}$$

$$\begin{bmatrix}5&-3&-3\\5&0&-3\\5&-3&-3\end{bmatrix}\begin{bmatrix}-3&-3&-3\\5&0&-3\\5&5&-3\end{bmatrix}\begin{bmatrix}-3&-3&-3\\-3&0&-3\\5&5&5\end{bmatrix}\begin{bmatrix}-3&-3&-3\\-3&0&5\\-3&5&5\end{bmatrix}$$

The second step is top t values of the edge response values m_i (i=0-7) are selected and set them to 1. The other (8-t) bit of 8 bit LDP pattern is set to 0, thus we can obtain information about significant directional edge responses. Finally, we convert the binary code into a decimal number as shown in fig below :





4. Experimental Setup & Results

MATLAB (matrix laboratory) could be a multi-paradigm numerical computing atmosphere and fourth-generation programing language. A proprietary programing language developed by MathWorks, MATLAB permits matrix manipulations, plotting of functions and information, implementation of algorithms, creation of user interfaces, and interfacing with programs written in alternative languages, as well as C, C++, C#, Java, fortran and Python. though MATLAB is meant primarily for numerical computing, an elective tool case uses the MuPAD symbolic engine, permitting access to symbolic computing talents. a further package, Simulink, adds graphical multi-domain simulation and model-based style for dynamic and embedded systems. In 2004, MATLAB had around one thousand thousand users across business and domain. MATLAB users return from varied backgrounds of engineering, science, and political economy.

Image Database

In this work two databases of images are created namely training database and testing database shown in figure.

Figure: Training and testing database

The computed result in the form of similarity index between proposed method and base method is given below in tables. The similarity index is having values in range from 0 to 1. Closer the value to 1 greater is the similarity of the two images. One means exact match is found.

Table 1: Proposed method result

Source Image	SIMILARITY INDEX									
	TARGET IMAGES									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	1	0.6230	0.5438	0.7118	0.5703	0.6893	0.5044	0.2831	0.4249	0.3693
2	0.6230	1	0.5041	0.7267	0.6555	0.4446	0.3895	0.4503	0.3355	0.3293
3	0.5438	0.5041	1	0.6680	0.5093	0.4615	0.4733	0.4461	0.4529	0.3509
4	0.7118	0.7267	0.6680	1	0.7392	0.5412	0.5286	0.6314	0.4658	0.4189
5	0.5703	0.6555	0.5093	0.7392	1	0.5199	0.3899	0.4648	0.3407	0.3767
6	0.6893	0.4446	0.4615	0.5412	0.5199	1	0.4954	0.1900	0.3756	0.2667
7	0.5044	0.3895	0.4733	0.5286	0.3899	0.4959	1	0.3241	0.6791	0.5771
8	0.2831	0.4503	0.4461	0.6314	0.4648	0.1900	0.3241	1	0.3268	0.2470
9	0.4249	0.3355	0.4529	0.4658	0.3407	0.3756	0.6791	0.3268	1	0.5763
10	0.3693	0.3293	0.3503	0.4189	0.3767	0.2667	0.5771	0.2470	0.5763	1

The proposed approach results are shown in table above. It is clear from the above table that exact match is found for the image in test and train database. While for base paper approach shown in table 2 it is clear that values are closer to

1 but not exact 1.

Table 2: Base paper method result

Source Image	SIMILARITY INDEX									
	TARGET IMAGES									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	**0.9970**	0.6277	0.5487	0.7184	0.5756	0.6977	0.5098	0.2867	0.4282	0.3779
2	0.6296	**0.9963**	0.5099	0.7352	0.6636	0.4502	0.3936	0.4550	0.3383	0.3372
3	0.5515	0.5109	**0.9924**	0.6774	0.5167	0.4673	0.4784	0.4512	0.4569	0.3587
4	0.7161	0.7305	0.6719	**0.9976**	0.7437	0.5483	0.5339	0.6383	0.4697	0.4289
5	0.5772	0.6634	0.5156	0.7482	**0.9957**	0.5260	0.3939	0.4702	0.3435	0.3855
6	0.6951	0.4498	0.4679	0.5445	0.5255	**0.9962**	0.5005	0.1925	0.3786	0.2731
7	0.5093	0.3943	0.4803	0.5316	0.3945	0.5019	**0.9963**	0.3275	0.6843	0.5908
8	0.2861	0.4557	0.4527	0.6351	0.4707	0.1927	0.3273	**0.9980**	0.3293	0.2531
9	0.4288	0.3397	0.4598	0.4688	0.3449	0.3806	0.6860	0.3302	**0.9978**	0.5896
10	0.3726	0.3334	0.3553	0.4213	0.3810	0.2701	0.5829	0.2499	0.5802	**0.9869**

5. Conclusion

Performance of face recognition algorithms can be compared in terms of accuracy of matching. Accuracy of face recognition is also termed as similarity index. So if similarity index is greater than a specific threshold a match is found. In this paper proposed technique obtains a higher similarity index as compared to hyper spectral approach.

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