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Fusing Local Patterns Of Gabor Magnitue For Recognition System

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ABSTRACT

Face recognition is a process of analyzing (or) comparing face with the previously stored face images. Training phase involves the collection of images and checking it for the presence of noise. A testing phase is a selection of particular image and testing with predefined images and the result shows whether the person is authorized (or) not. Histogram equalization is a process of minimizing the contrast of the image and normalizing which smoothens the image pixels. A Gabor feature extraction is an orientation process which gets the image based on head position changes and it can seen through discrete fourier transform. Pixel selection is the process of selecting 8 neighbourhood pixels based on the center pixels, and it is represented on the blocks. Image is tested (or) compared with predefined images stored on the database and selects corresponding correct image. Compared with previous technique it provides better performance.

Key words- histogram, face recognition, Gabor feature extraction.

INTRODUCTION

GABOR: In image processing, a Gabor filter, named after Dennis Gabor, is a linear filter used for edge detection. Frequency and orientation representations of Gabor filter are similar to those of human visual system, and it has been found to be particularly appropriate for texture representation and discrimination. In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave. The Gabor filters are self-similar – all filters can be generated from one mother wavelet by dilation and rotation.

Its impulse response is defined by a harmonic function multiplied by a Gaussian function. Because of the multiplication-convolution property (Convolution theorem), the Fourier transform of a Gabor filter's impulse response is the convolution of the Fourier transform of the harmonic function and the Fourier transform of the Gaussian function. The filter has a real and an imaginary component representing orthogonal directions. The two components may be formed into a complex number or used individually.

Gabor filters are directly related to Gabor wavelets, since they can be designed for a number of dilations and rotations. However, in general, expansion is not applied for Gabor wavelets, since this requires computation of bi-orthogonal wavelets, which may be very time-consuming. Therefore, usually, a filter bank consisting of Gabor filters with various scales and rotations is created. The filters are convolved with the signal, resulting in a so-called Gabor space. This process is closely related to processes in the primary visual cortex. Jones and Palmer showed that the real part of the complex Gabor function is a good fit to the receptive field weight functions found in simple cells in a cat's striate cortex.

The Gabor space is very useful in image processing applications such as optical character recognition, iris recognition and fingerprint recognition. Relations between activations for a specific spatial location are very distinctive between objects in an image. Furthermore, important activations can be extracted from the Gabor space in order to create a sparse object representation.

Gabor methods deal with non stationary in seismic signals by decomposing a signal into roughly stationary parts, processing each part separately, and assembling the results into a global final. In numerical wave field propagation, a complex geological region is broken up into small regions of nearly constant velocity, and the wave field is propagated through each region separately. In frequency slicing, a signal is broken up into separate frequency bands, each processed separately, and the results assembled for the final, complete result.

Previous work on automatic facial expression processing includes studies using representations based on: optical flow estimation from image sequences principal components analysis of single images and physically based models. This paper describes the first study that uses Gabor wavelets to code facial expressions. Our findings indicate that it is possible to build a automatic facial expression recognition system based on a Gabor wavelet code which has a significant level of psychological plausibility.

Face recognition is a challenging problem in pattern recognition research. Many face recognition methods have been proposed in the past few decades. A great number of methods are appearance based. Face recognition can be essentially considered as determining whether two face feature vectors are from the same individual or different individuals. Both the Gabor features and the Bayesian algorithm have the property of reducing transformation difference. The Bayesian algorithm can learn from the training set and decouple *T* and *I* on the second order statistical dependency. Gabor analysis is insensitive to transformation variation perhaps on higher order dependency by the elastic graph model and the wavelet transformation. By integrating the two complementary approaches, our new method achieves a better performance.

PROPOSED SYSTEM

To investigate the potential of Gabor phase and its fusion with magnitude for face recognition, we introduce,

Local Gabor XOR patterns(LGXP):

It encodes Gabor phase by using local XOR pattern(LXP) operator.

Block Based Fischer's linear discriminant(BFLD):

To extract discriminative low-dimensional features. Finally by using BFLD, we fuse local patterns of Gabor magnitude and phase to utilize their complementary information for face recognition.Conducting comparative experimental studies of different local Gabor patterns, their combination with BFLD as well as their fusion with the databases. Experimental results shows that the proposed phase-based methods achieves better results than magnitude-based methods in many cases and the introduction of BFLD greatly improves the performances. In addition the proposed fusion approaches achieves results comparable to the best known ones.

The main contribution of the work lies in two aspects:

- The LGXP descriptor for Gabor phase encoding
- LGXP fusion with local patterns of Gabor magnitude by BFLD.

The latter work associated with these is,

- Gabor wavelet representation : Convolution of the image with Gabor kernels
- Local binary patterns: It assigns label to every pixel of an image by thresholding the 3 x 3 neighborhood of each pixel with the center pixel value and considering the result as a binary number.

The basic idea of BFLD is to divide the high-dimensional LGXP descriptor into multiple feature segments, then apply FLD to each segment, and finally combine the decisions of all the block-wise FLD. Then for each face image, calculate its multiple LGXP maps. Then divide these pattern maps into multiple non overlapping blocks and calculate the block based representations. The FLD matrices are used to calculate the low-dimensional features for each block.

Block Partition Strategy:

Each pattern map is divided into M blocks and each block is further partitioned into k sub blocks. For BFLD, this strategy preserves the spatial relations of different sub-blocks, and obtains better representation than using only one histogram. In some sense, one block in BFLD can be viewed as the combination of some sub-blocks in LGXP. To make the sub-block partition clear, adopt "a x b" to denote the number of sub-blocks, where "a" is the number of sub-blocks in horizontal direction and "b" that in vertical direction.

In contrast with current human-computer interaction, face-to-face human communication uses a variety of modes, including facial gestures and expressions. It would be desirable to make use of more natural communication modes in human-computer interaction and ultimately computer facilitated human interaction. The automatic recognition of natural facial expressions is a necessary step towards this goal. Several classes of perceptual cue to emotional state are displayed by the face: relative displacements of features (opening the mouth); quasi-textural changes in the skin surface (furrowing the brow); changes in skin hue (blushing);and the time course of these signals.

GABOR MAGNITUDE AND PHASE FOR FACE RECOGNITION

In order to facilitate the recognition of a particular face in a picture, we re-parameterize a query picture to a basis of "Eigen faces", or the vectors produced from performing singular value decomposition on a set of training faces. Each of these vectors, when rearranged into a two dimensional image, has the appearance of a ghostly face, and tends to accentuate certain characteristics. Once the query image has been projected to this new coordinate system, in figure 2.1 we can compare it against existing images, in order to recognize a face.

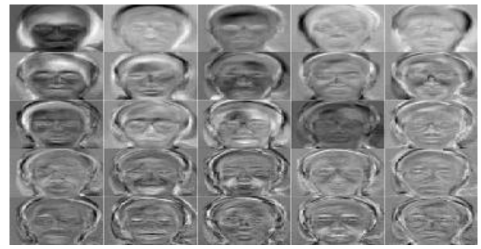

Figure 2.1 : Face recognition

The following picture is partitioned into testing set (~30%) and training set (~70%). For each entry in the test set, in figure 2.2 the best match from its closest class of faces. Black lines separate different test examples is shown.

Figure 2.2 : Best Match from its closest class of faces

The assignment asks several questions that we are to answer in regards to the Yale database of images:

1. How many principle components are required to obtain human-recognizable reconstructions?

In the following figure 2.3, each new image from left to right corresponds to using 1 additional principle component for reconstruction. As you can see, the figure becomes recognizable around the 7th or 8th image, but not perfect.

Figure 2.3: Principal component for reconstruction

In this next image figure 2.4, we show a similar picture, but with each additional face representing an additional 8 principle components. You can see that it takes a rather large number of images before the picture looks totally correct.

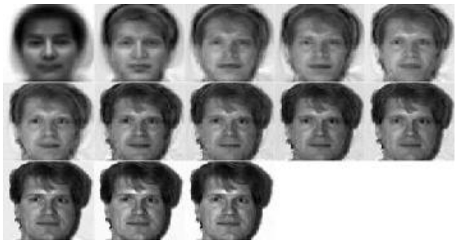

Figure 2.4: Additional principle component for reconstruction

3. How do the results change when excluding the images with glasses?

The images converge to the correct face slightly faster, but not by much as shown in figure 2.5.

Figure 2.5 : Images excluding glass

However, in this next image figure 2.6, we show images where the dataset excludes all those images with either glasses or different lighting conditions. The point to keep in mind is that each new image represents one new principle component. As you can see, the image converges extremely quickly.

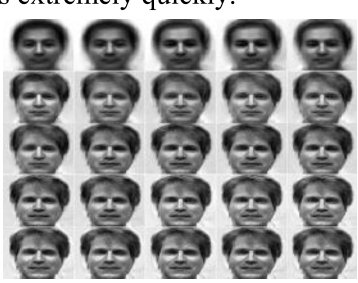

Figure 2.6: Images with glass and different lighting condition

The next example image shows recognition without the glasses-wearing individuals. The results are slightly better, but overall, it seems that glasses do not make a major impact in recognition.

Then another example of recognition is shown in figure 2.7, where only the normal lighting and no glasses images are used (except for the three people that are always wearing glasses). The recognition is perfect.

Figure 2.7: Normal lighting and no glasses images

4. Try some recognition experiments on subsets of the database corresponding to changes in lighting and changes in expression as shown in figure 2.8. Which category of variations is easier to accommodate? It is much easier to accommodate a change in expression. Presumably this is because the relative intensities of the pixels are very similar between images of different expressions, while those with different lightings display very different intensities. Put another way, the Eigen faces technique is robust against local changes, but not to global changes. Consider the following examples, where the lighting has been varied.

Figure 2.8: Lighting varied

About half of all of the classifications are wrong (9 of 16 correct). Compare this to the following image, where the expressions are different, and almost all of the classifications are correct (23 of 26 correct) as in figure 2.9.

Figure 2.9 : Expressions are different

5. Can you recognize non-faces by projecting to orthogonal complement?

Yes, we can. The key is that when non-face images are projected to the Eigen faces subset, and then reconstructed, they will not resemble the original images (they will look like faces). Images that are faces, however, will resemble the original face to some degree as shown in the following figure 2.10.

Figure 2.10 : Non-faces by projecting to orthogonal complement

The two face images on the left clearly resemble their corresponding reconstructions below. The others, which are not faces (real human faces, at least) do not have reconstructions that match the original. This allows us to distinguish faces and non-faces.

MODULE DESCRIPTION:

Testing Phase:

The image which is to be tested is selected from the large number of images.

Checking Portion:

To check whether authorized (or) unauthorized person.

Both the terms "authentication and authorization" are used for the security purpose, usually in the computer software. Authentication in broad sense is some type of operation of c verifying something as valid; by authentication we mean that what is correct and valid thing. Object authentication and person authentication is a different thing; the object authentication is that, we verify that object's origin, while the person authentication is that, we verify the person's identity. While in terms of security of computer, authentication is some sort of procedure via which the identity of an individual who is the initiator of the communication is verified . For example when the person logs-in into any thing either the computer application software, or logging to the computer then the person authentication is required.

In general authentication is a way to guarantee that the user individual who is using the computer applications, so that individual is authorized or not. While the term authorization is used mostly in the networking, authorization is that when the compute administrator of the network gives the right to a person to use the pc also gives the facility to do work on it along with his data storage facility. The administrator give the password of that particular system in the network, to the user, that he can use that computer independently, and use the recourses attach to that computer.

Histogram equalization : Pixel enhancement.

The histogram manipulation, which automatically minimizes the contrast in areas too light or too dark of an image, consists of a nonlinear transformation that it considers the accumulative distribution of the original image; to generate a resulting image whose histogram is approximately uniform. On the ideal case, the contrast of an image would be optimized if all the 256 intensity levels were equally used. Obviously this is not possible due to the discrete nature of digital data of the image. However, an approximation can be achieved by dispersing peaks in the histogram of the image, leaving intact the lower parts. This process is achieved through a transformation function that has a high inclination where the original histogram has a peak and a low inclination in the rest of the histogram.

Normalized image : To smooth the pixels

Image normalization method which can overcome illumination effects effectively. The proposed method is based on intensity distribution transformation. However, instead of applying it globally, transformation in intensity distribution is performed for each column independently using one frontal mean face as a reference image. Since it does not require image processing such as image segmentation, the computational complexity is very low and it can circumvent boundary discontinuity caused by region segmentation. Extensive experimental results using Ferret database and extended Yale B database demonstrate the competence of the proposed method.

Gabor Feature Extraction:

Orientation process is carried here. To get the image based on the head position changes.

Discrete Fourier Transform:

To see the pixel changes. Here the pixel changes in the image given is seen.

Local binary pattern:

To get the number of pixels based on centre pixels with 8 neighborhood pixels. The 8 neighborhood pixels are top, left, right, bottom, topmost left, topmost right, bottommost left, bottommost right.

Gabor Local Binary Pattern:

Orientation + Neighborhood.

Here the neighborhood pixels points are taken and they are combined together.

LG X Pattern:

Gabor + LBP.

Here the Gabor process and local binary pattern process is carried together.

BB Representation:

Block Representation. 8 pixel wise division of image.

Face Recognition:

Giving the corresponding image number and the system selects the related matches of the particular image.

Gender Identification:

Identifying the gender of the particular image.

Exit: Getting out of the main window.

DATA FLOW DIAGRAM:

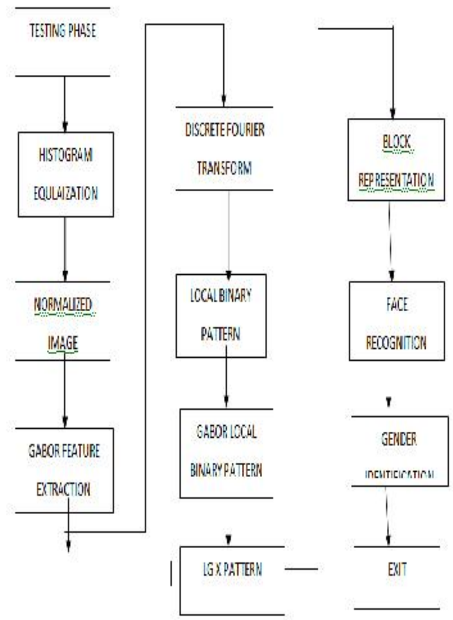

Figure 2.11 Modules of face recognition system

From the following figure 2.11, for testing phase the image is entered for testing to check the entered person is an authorized (or) an unauthorized person. Then the histogram equalization process is carried out to check the clear view of the image. From the normalization smoothening of pixels is carried out. The Gabor Feature Extraction process is used to get the image based on the head position changes.

The Discrete Fourier Transform(DFT) is used to see the pixel changes in the image. From the Local Binary Pattern(LBP) the number of pixels based on the centre pixel with 8 neighborhood pixels is checked. The Gabor Local Binary Pattern(LGBP) is the combination process of Gabor process and the LBP pattern.The block representation process shows the block representation of the image. It also shows the 8 pixel wise direction of image. Finally from the face recognition the related faces of the image which is selected for testing is done. Next the gender identification process shows the gender of the particular image.

CONCLUSION

Thus to exploit effectively the Gabor phase information, as well as its fusion with Gabor magnitude. Under the framework of local pattern encoding, we propose the so-called Local Gabor XOR Patterns (LGXP) to encode locally the Gabor phase. Additionally, by one “divide and conquer” strategy, we introduce the BFLD method, and study the fusion methods of different local patterns of Gabor feature. These methods are extensively evaluated and compared with previous methods on the FERET and FRGC 2.0 datasets, which indicates that our fusion method achieves better or comparable results than the best known ones.

FUTURE WORK

We also experimentally reveal that methods based on local Gabor patterns, both the proposed LGXP and existing LGBP/LGPP, work reasonably well under relatively simple testing scenarios, for instance, FERET Fb, Fc, and Experiment 1 of FRGC 2.0. But, they all degrade abruptly when the testing is challenging with large variations due to unconstrained imaging conditions, e.g., FERET DupI, DupII, especially Experiment 4 of FRGC 2.0. This observation might imply that these local pattern methods are sensitive to large extrinsic variations. Finally, as expected, the fusion of magnitude and phase further enhance the recognition accuracy whey they are encoded by local patterns and combined with BFLD. In the current score-level fusion, we simply combine component classifiers by sum rule. It is evidently not optimal, and as a future work we will exploit better statistical fusion schemes. We need more future efforts to improve its performance for out of sample problem.

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