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A Galois Field based Texture Representation for Face Recognition

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Abstract

This paper presents a Galois field based texture representation for face recognition. A Galois field has been used to represent texture in images. The facial images are divided into several local regions. Each of these local regions is represented using a novel Galois field based method. The bin values of the normalized cumulative histogram forms the feature vector for the region. These local features are concatenated to form the face descriptor. Extensive experiments are performed on FERET face database and extended Cohn Kanade face database. The results clearly show that the proposed method is better and effective as compared to Rotation Invariant Local Binary Pattern and Log-polar transform.

Keywords: Galois Field, Texture, Face descriptor, Classification

INTRODUCTION

One of the properties that distinguish objects and images is texture, the other properties being shape and colour. Analysis of texture is one of the many aspects in image processing and computer vision. Texture analysis has been applied in the fields of visual inspection, remote sensing imagery, pattern recognition and image retrieval. Statistical [1], structural [2], model based [3] and signal processing models [4] are the common feature extraction methods. In [5], a survey of texture descriptors for texture classification is available. However, most of these approaches are sensitive to the changes of orientations and scales of the texture pattern. On the other hand, objects of interest under various orientations, scales, illumination and occlusion are often encountered in different applications, such as face recognition and signature verification. Therefore there arises a requirement to develop descriptors of texture which are insensitive or invariant to changes in rotation, scale, illumination and so on. There have been ongoing research activities to represent invariant texture. Many researchers have devoted their energies for representing texture in only rotation invariant environment. Some researchers have addressed the issue of scale invariance in images. Limited research is available on the area of rotation and scale invariant texture representation. The major existing approaches include psycho-physical transformation, multi-resolution simultaneous autoregressive (MRSAR) model [6], log-polar wavelet signatures [7], multichannel Gabor filtering [8] and the Wold model [9] for invariant texture analysis.

Biometrics is the study of human biological measurements for identification and verification. Biological measurements like face, voice and fingerprints qualify as a biometric characteristic because it has the properties of universality, distinctiveness, permanence and collectability. In recent times, more biological measurements have been considered as a biometric like gait, signatures and iris [10]. Based on physiological characteristics, biometric traits include face [12], fingerprints [13], finger geometry, hand geometry [14], hand veins [15], palm, iris [16], retina [17], ear [18] and voice. Based on behavioural characteristics, biometric traits include gait [19], signature [20] and keystroke dynamics [21][11]. A biometric system is similar to a texture pattern recognition system where the biometric data is obtained from an individual, a feature set is extracted from the acquired data and then this acquired feature set is compared against the template set in the database. A biometric system may either verify or identify an individual based on the type of application the biometric system is being used. A biometric system can be used for either identification or verification purposes. In verification application, a user's identity is validated by comparing the user's captured biometric features against the user's biometric features stored in the database. In identification application, a user is recognized by searching the templates of all the users in the database for a match [10].

Face recognition has emerged as a major ongoing research area in pattern recognition and computer vision. Face recognition is considered to be a difficult task than the usual pattern recognition problems due to the presence of few training samples (in some cases only one training sample) and numerous testing samples. The sources of variation in facial appearance can be categorized into two groups: intrinsic factors and extrinsic factors. Intrinsic factors are due to purely physical nature of the face and are independent of the observer. Extrinsic factors cause the appearance of the face to alter via the interaction of light with the face and observer like illumination, pose, scale and imaging parameters [11].

Current face recognition systems perform well under relatively controlled environments but tend to suffer when variations in different factors like rotation, scale, pose, illumination are present [24]. Thus finding good descriptors for the appearance of local facial regions is an open and ongoing issue. The researchers on texture analysis have developed a variety of different descriptors for the appearance of image patches. Heisele, Ho, Wu and Poggio developed a component-based method and two global methods for face recognition [22]. In the component system, facial components were extracted as features and classified using a Support Vector Machine. The two global systems recognize faces by classifying a single feature vector of gray values of the whole face image. Dai and Zhou extracted robust facial features by first applying Gabor wavelet transform and performing kernel principal component analysis in the second step [23]. These features were classified using a Support Vector Machine classifier. Ahonen, Pietikainen, Hadid and Maenpaa proposed a novel representation for face based on Local Binary Pattern (LBP) features [24]. The face images were divided into several regions from which the LBP features are extracted and concatenated into an enhanced feature vector as a face descriptor. Zhang, Shan, Gao, Chen and Zhang developed a face representation approach using a non-statistical method called Local Gabor Binary Pattern Histogram Sequence (LGBPHS) [12]. A histogram sequence is modelled by concatenating all histograms of the local regions of local Gabor magnitude binary pattern maps of the face image in this approach. Jafri and Arabnia presented a survey of face recognition techniques in [11].

The paper presents a novel Galois Field based texture representation for face recognition. The facial images are divided into local regions. Each of these local regions of the face is represented using a novel Galois Field based method. Then the bin values of the normalized cumulative histogram forms the feature vector for the region [26]. These local features are concatenated to form the face descriptor. Using this face descriptor, classification (recognition) is performed by the k-Nearest Neighbour classifier with Euclidean, Chi Square and Cosine similarity as distance metrics. The results of the proposed method are compared with Rotation Invariant Local Binary Pattern [24] and Log-Polar transform [7] which are applied for face recognition. Extensive experiments on the FERET face database [27] and extended Cohn Kanade face database [28] clearly demonstrate that the proposed method's features are effective for face recognition.

The rest of the paper is organized as follows. Section 2 explains the use of Galois Field for facial images. Section 3 provides the experimental setup for face recognition. Section 4 discusses the experimental results obtained. Section 5 concludes the study.

GALOIS FIELD-BASED FACE DESCRIPTION

Methodology

Galois Field have been used in computer science due to its ability to represent data in a finite field. The advantage of Galois Field is that the resultant value upon any arithmetic operation will be in the same range as that of the operands [29]. The Galois Field operator has been shown to be a good texture descriptor. It has been proven to be highly discriminative and its invariance to rotation and scale changes in texture images, make it suitable for demanding image analysis tasks [26]. The idea of using Galois Field based operator for face description is motivated by the fact that rotation and scale invariant descriptors are useful for robust matching.

Preprocessing reduces unwanted image variation by aligning face images. The face is cropped to eliminate the background. The cropped face images were resized to a fixed size of 150 x 130 pixel resolution. Further, the facial image is divided into 7 x 7 non-overlapping regions as shown in Fig. 1.

Figure 1. A facial image divided into 7 x 7 windows

The Galois Field based operator is applied to each region of the face image individually to generate the local descriptors and are combined to form a global descriptor. A Galois Field based operator on a face region is as described below:

Algorithm: Face region descriptors

Step 1: Consider a 3 x 3 neighbourhood of a pixel $I_{i,j}$ in an image region I as shown in Fig. 2.

$I_{i-1, j-1}$	$I_{i-1,j}$	$I_{i-1, j+1}$
$I_{i, j-1}$	$I_{i,j}$	$I_{i,j+1}$
$I_{i+1, j-1}$	$I_{i+1, j}$	$I_{i+1, j+1}$

Figure 2. 8-nearest neighbourhood of $I_{i,j}$

Step 2: Perform mod 2 addition of eight neighbouring elements along with center pixel $I_{i,j}$

$$I'_{i,j} = ((((((((I_{i,j} \oplus I_{i-1,j}) \oplus I_{i-1,j-1}) \oplus I_{i,j-1}) \oplus I_{i+1,j-1}) \oplus I_{i+1,j}) \oplus I_{i+1,j+1}) \oplus I_{i,j+1}) \oplus I_{i-1,j+1})$$

results in a 8-bit binary value $I'_{i,j}$

Step 3: Repeat Step 2 for all the pixels in the image region I, which results in a transformed image region I′.

Step 4: Construct the histogram with 50 bins for the transformed image region I′. The histogram is represented as a discrete function

$$h(r_k) = n_k$$

where r_k is the k^{th} value and n_k is the number of r_k values in the GF operated region.

Step 5: The cumulative histogram C_k is computed as

$$C_k = \sum_{j=0}^{k} h(r_j)$$

where k = 0, 1, 2, ..., 49.

Step 6: Normalized cumulative histogram of C_k is given by

$$NC_k = \frac{C_k}{||C||}$$

where

$$||C|| = \sqrt{c_0^2 + c_1^2 + \ldots\ldots + c_k^2 + \ldots. + c_{49}^2}$$

The bin values of normalized cumulative histogram forms the feature vector of a region. Such local normalized cumulative histograms are generated for all the 49 regions of the face image and are concatenated to form the global descriptor. This global descriptor forms a feature vector of the face image, which is used for training and classification purpose.

Classification

A nearest neighbour classifier is used for classification. In this study, the Euclidean distance, Chi-Square distance and Cosine distance are used for similarity measure. The weighted Euclidean distance metric [25] is

$$d(p,q) = \sum_{ij} \sqrt{\sum_{k=0}^{49} w_{ij}(p_{(ij)k} - q_{(ij)k})^2}$$

where $p_{(ij)k}$ is the k^{th} bin value of ij^{th} block of train sample and $q_{(ij)k}$ is the k^{th} bin value of ij^{th} block of test sample. The weight matrix w_{ij} is as given in Fig. 3.

2	1	1	1	1	1	2
2	4	4	1	4	4	2
1	1	1	0	1	1	1
0	1	1	0	1	1	0
0	1	1	1	1	1	0
0	1	1	2	1	1	0
0	1	1	1	1	1	0

Figure 3. Weight matrix

The weighted Chi Square distance [25] can be defined as

$$\chi^2(p,q) = \sum_{ij} \sum_{k=0}^{49} w_{ij} \frac{(p_{(ij)k} - q_{(ij)k})^2}{p_{(ij)k} + q_{(ij)k}}$$

The Cosine similarity is the angle between the two feature vectors, irrespective of its magnitudes. The larger the *cos* value, the more similar the corresponding images. The weighted Cosine distance [25] is defined as

$$\cos(p,q) = \sum_{ij} \sum_{k=0}^{49} w_{ij} \frac{\sum p_{(ij)k}\, q_{(ij)k}}{\sqrt{\sum p_{(ij)k}^2}\sqrt{\sum q_{(ij)k}^2}}$$

Further, test sample is classified using the K-Nearest Neighbour classifier.

EXPERIMENTAL SETUP

The FERET database

The Face Recognition Technology (FERET) [27] program has addressed the issues of large database of facial images and a testing procedure to evaluate face recognition systems by creating a large database of facial images and the establishment of FERET tests. The database consists of images of 1199 individuals which is divided into development and sequestered portions of the database. The images contain variations in lighting, facial expressions, pose, angle, etc.

The gallery set is a collection of images of known individuals, known as 'fa' set which consists of frontal images of 1196 people. The image of the individual to be identified is called a probe set or probe, identified by 'fb' set which consists of alternative facial expression than in the 'fa' photograph. In our experiments, there are 1749 images of 1009 individuals as the gallery set i.e. 'fa' set. The probe set or 'fb' set consisted of 1503 images of 1009 individuals. The sample cropped facial images of the FERET dataset are shown in Fig. 4.

Figure 4. Sample cropped face images from FERET Face dataset. First row contains the gallery 'fa' images. Second row shows the probe set 'fb' images

The extended Cohn Kanade database

The Cohn Kanade (CK) database has become one of the most widely used test-beds for algorithm development and evaluation for automatically detecting individual facial expressions. Later the CK database was extended as the Extended CK [28] where the number of sequences is increased by 22% and the number of subjects by 27%.

For our experiments, the database included 2172 image sequences from 123 subjects. The image sequence vary in direction from 10 to 60 frames and incorporate the onset (i.e. neutral frame) to peak formation of the facial expressions. The gallery set is the set of neutral images of all the 123 individuals. The remaining images form the probe set, which is 2049 images. The sample cropped facial images of the extended Cohn Kanade database are shown in Fig. 5.

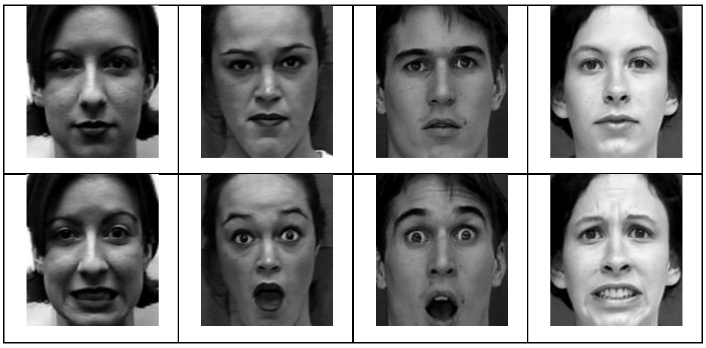

Figure 5. Sample cropped face images from Extended Cohn Kanade Face dataset. First row contains the gallery 'neutral' images. Second row shows the probe set 'peak expression' images

EXPERIMENTAL RESULTS AND DISCUSSION

The experiments are conducted with the proposed method on FERET and extended CK face databases. The Galois Field operator is applied on each facial image which is divided into non-overlapping regions. The normalized cumulative histogram of each local region is generated. The bin values of these normalized cumulative histograms are concatenated which forms the feature vector. The k-Nearest Neighbour classifier is trained with the features extracted from the training images and then the test images are classified based on three distance metrics i.e., Euclidean, Chi Square and Cosine. The test images are classified based on unit weights and weighted distance metrics i.e. weighted Euclidean, weighted Chi Square and weighted Cosine metrics. The experiments are also performed on two state of the art methods, Rotation Invariant Local Binary Pattern (RILBP) and Log-Polar transform. The results of the experiments performed are presented below.

Table 1 presents the results of the experiments conducted on the FERET face database. In the first set of experiments, unit weights are used for classification. The Galois Field facial descriptor has been able to classify the facial images with an accuracy of 84.63% using the Euclidean distance as the similarity measure in the k-Nearest Neighbour with k set to 1. Using the Chi Square distance in the place of Euclidean distance, the recognition rate of 83.76% is obtained. The recognition rate of 83.36% is achieved when the Cosine distance is used as the dissimilarity measure. For RILBP, recognition rates of 65.2%, 68.79% and 66.93% were recorded for Euclidean, Chi Square and Cosine distance metrics respectively. In the case of Log-Polar transform, recognition rates of 81.69%, 81.63% and 82.49% were obtained for Euclidean, Chi Square and Cosine distance metrics respectively. With weights for local regions being applied (as shown in Fig. 3) in the next set of experiments, the recognition rates of 82.1%, 82.5% and 82.36% were obtained using the proposed method for Euclidean, Chi Square and Cosine distance metrics respectively. RILBP produced recognition rates of 56.88%, 58.54% and 58.01% with weighted Euclidean, weighted Chi Square and weighted Cosine distance metrics, whereas Log-Polar transform generated recognition rates of 80.1%, 80.76% and 80.9% with weighted Euclidean, weighted Chi Square and weighted Cosine distance metrics.

Table 1: Face Recognition rates using the proposed method, RILBP method and Log-Polar transform method for FERET database

		Percentage (%) of correct classification		
	Distance Measure	**Galois Field operator**	**RILBP**	**Log-Polar Transform**
With unit weights	Euclidean	84.63	65.20	81.69
	Chi Square	83.76	68.79	81.63
	Cosine	83.36	66.93	82.49
With weights	Euclidean	82.10	56.88	80.10
	Chi Square	82.50	58.54	80.76
	Cosine	82.36	58.01	80.90

The experimental results indicates that the Galois Field operator along with Euclidean distance metric in the k-Nearest Neighbour with k value set to 1, is an efficient facial descriptor with unit weights being applied. This shows that the weights prescribed for the facial image hardly make much difference to the Galois Field based facial descriptor. The results demonstrate the efficacy of the Galois Field based descriptor for face recognition.

In order to evaluate the proposed approach, the experiments are also conducted on the extended Cohn Kanade face database, the results of which are presented in Table 2. The Galois Field based face descriptor yielded 99.7%, 98.82% and 98.63% classification rates for Euclidean, Chi Square and Cosine distance metric with unit weights being applied for the local regions in the k-Nearest Neighbour with k set to 1. Similarly, recognition rates of 78.77%, 85.55% and 82.33% were obtained for RILBP with unit-weighted Euclidean, unit-weighted Chi Square and unit-weighted Cosine distance metrics. Recognition rate of 97.9% was recorded in the case of Log-Polar transform for unit-weighted Euclidean and 97.56% recognition rate was recorded for both unit-weighted Chi Square and Cosine distance measures. When prescribed weights were applied to the local regions, the values were obtained as follows. The Galois Field face descriptor classified the images with an accuracy of 95.16%, 93.99% and 93.65% for Euclidean, Chi Square and Cosine distance metrics, respectively. RILBP classified images with an accuracy of 76.91%, 81.5% and 79.3% using Euclidean, Chi Square and Cosine distance metrics, in that order. Log-Polar transform classified the test images with an accuracy of 94.97% using both the distance metrics, Euclidean and Chi Square, whereas Cosine distance yielded a recognition rate of 94.77%.

Table 2. Table 2: Face Recognition rates using the proposed method, RILBP method and Log-Polar transform method for extended CK database

		Percentage (%) of correct classification		
	Distance Measure	**Galois Field Operator**	**RILBP**	**Log-Polar Transform**
With unit weights	Euclidean	99.70	78.77	97.90
	Chi Square	98.82	83.55	97.56
	Cosine	98.63	82.33	97.56
With weights	Euclidean	95.16	76.91	94.97
	Chi Square	93.99	81.50	94.97
	Cosine	93.65	79.30	94.77

It clearly indicates that the proposed method results are comparable to the two state of the art methods, Rotation Invariant Local Binary Pattern and Log-Polar transform. Consistent with the results in the previous experiments, the proposed method with Euclidean distance metric is efficient in itself without the weights being applied for the local regions. The classification rates are higher in the case of extended CK face database than the FERET database indicating that the less number of training samples leads to better classification.

CONCLUSION

In this paper a Galois Field based texture representation has been successfully used for face recognition. The facial images are divided into local regions. Each of these local regions is represented using the Galois field method. The bin values of the normalized cumulative histogram forms the feature vector for the local region. These local features are concatenated to form the face descriptor. The performance of the proposed methodology is evaluated for face recognition on standard face databases, FERET and extended Cohn Kanade. The results obtained are comparable to two state of the art methods, Rotation Invariant Local Binary Pattern and Log-Polar transform. Future work includes using the proposed Galois Field based method for different applications such as offline signature verification, Content based image retrieval, script identification, etc.,

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