Best Wavelength Selection for Gabor Wavelet using GA in EBGM Algorithm

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Abstract—In this paper a new method for optimization of Elastic Bunch Graph Matching (EBGM) algorithm in frontal face recognition is presented. In EBGM algorithm, some pre-determined wavelength of Gabor wavelet is used to extract features from face image. For optimization of EBGM algorithm, Genetic Algorithm (GA) is used to select the best wavelengths of Gabor wavelet. For evaluation, algorithm has been tested on 300 classes of FERET face database. In training phase, only one image per class is trained. The recognition rate of optimized EBGM is about 91%. Also the optimized EBGM can run 1.5 times faster than original EBGM.

***Index Terms*—Wavelenth Selection, Face Recognition, Optimization, Genetic Algorithm (GA), Elastic Bunch Graph Matching (EBGM).**

I. Introduction

Facial image is the most common biometric characteristic used by humans to make a personal recognition, hence the idea to use this biometric in technology. Face identification involves extracting a feature set from a two-dimensional image of the face image and matching it with the templates stored in a database. This is a non intrusive method [1].

The applications of face recognition range from static (mug shots) to dynamic, uncontrolled face identification in a cluttered background (subway and airport). More applications of face recognition and its commercial products are discussed in [2].

Face recognition methods are divided to three categories: template based, feature based and hybrid method. Template based approaches such as Principal Component Analysis (PCA) and Independent Component Analysis (ICA), use template matching methods and use the whole face region as the raw input of recognition system to find the best matching. In other hand, feature based approaches such as EBGM, extract some local features from face image and compare features of facial images for recognition. Hybrid method such as human perception system, uses both template based and feature based approaches to recognize facial images. One can argue that this method could potentially offer the better of the two types of methods [1,2].

Manuscript received January 7, 2008.

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II. Related Works

Face recognition is an old challenging problem in pattern recognition research. Many of researchers focus his/her researches on this branch. Face recognition had been investigated from early 1970s to now. In this section, only some last researches about Elastic Bunch Graph Matching algorithm have been investigated.

First time, Wiskott et al [3] introduced Elastic Bunch Graph Matching (EBGM) algorithm for face recognition in 1997. In EBGM algorithm, faces are represented by graphs, which used Gabor wavelet transform for extracting features in each node of graph. The node of graphs has been named landmark and the Gabor coefficients of landmarks have been named as jet. In recognition phase, the algorithm recognizes novel faces by first localizing a set of landmark features using bunch graph model and then measuring similarity between these features.

Wiskott et al [4] compared EBGM algorithm with other high recognition rate algorithms on FERET and Bochum database in various face pose. They could show that EBGM algorithm is an accurate and robust method for face recognition. Their proposed system could achieve to 98% for recognition rate of frontal images on 300 samples set using only one training sample per class.

Bolme [5] has proposed a new EBGM algorithm for face recognition. The algorithm is modelled after the Wiskott's face recognition algorithm, but it is similar to Wiskott's EBGM algorithm in many aspects. In the thesis, a study of how accurately a landmark is localized using different displacement estimation methods was presented. Finally, he could achieve to 89.8% for recognition rate on FERET database. He has used only one sample per class in training phase.

Abrishami et al [6] have presented a hybrid method for face recognition using high order relationships among the image pixels and compress representation of the image. Their proposed algorithm analyzes local features, which are located by a meta-version of the sparsification algorithm in the context of Local Feature Analysis (LFA). The LFA sparsification chooses a subset of output points that are decorrelated as it possible, to reduce the dimensions of face representation. A set of points is determined for all images called fiducial points. A GA based method has been proposed to find these fiducial points on an image. Then, some Gabor coefficients are extracted from these points to identify faces. They could obtain 98.5% for recognition rate on ORL face database (40 face classes) using 10 training samples per class.

ISBN: 978-988-98671-8-8

It seems that high recognition rate of this method is indebted to large training samples for each class.

Tefas et al [7,8] in two similar papers, proposed a novel method to enhance the performance of elastic graph matching in face authentication using Support Vector Machine (SVM). The starting point is to weigh the local similarity values at landmarks according to their discriminatory power. Powerful and well-established optimization techniques were used to derive the weights of the linear combination. Also, they proposed a new approach that reformulates Fisher's discriminant ratio to a quadratic optimization problem subject to a set of inequality constraints by combining statistical pattern recognition and SVM. Both linear and nonlinear SVM were then constructed to yield the optimal separating hyper planes and the optimal polynomial decision surfaces, respectively. Experimental results indicated that the performance of morphological elastic graph matching was highly improved by using the proposed weighting technique. The Equal Error Rate (EER) of this system was 2.4% on a face database with 37 classes.

III. EBGM Algorithm

EBGM algorithm contains three main phases: modelling phase, training phase and recognition phase. But before these main phases, pre-processing is performed on whole database to equalize facial images.

First phase of EBGM is creation of bunch graph from a modelling set using localizing landmarks manually and computing jets in each landmark location. After face modelling, system is trained by some training samples. In training phase, only one sample per class is used. The algorithm recognizes novel faces by first localizing a set of landmark features on face using bunch graph model and then measuring similarity between input features and all training samples to find the most similar face.

A. Bunch Graph Creation

The first step of EBGM algorithm is modelling. EBGM algorithm needs examples of what the landmark jets look like to locate the landmarks in a novel face. Jets are defined as Gabor coefficients in a landmark location computing by convolution between Gabor wavelet filters and subimage around each landmark location. In modelling phase, the jets are extracted from facial images with manually selected landmark locations. Both Wiskott [3] and Bolme [5] have used 70 faces to create bunch graph.

The jets of all modeling images are collected in a data structure called a bunch graph. The bunch graph has a node for every landmark on the face. Every node is a collection of jets for the corresponding landmark. The bunch graph serves as a database of landmark descriptions that can be used to locate landmarks in novel imagery.

B. Training

After the face is modelled using bunch graph, only one sample per class is used for training. First, landmarks of each face are localized using bunch graph, and then jets are computed in landmarks to extract facial features and save them. In localization, jets are extracted from image and matched to jets extracted from a set of modelling jets in bunch graph.

Locating a landmark has two steps. First, the location of the landmark is estimated based on landmark location of bunch graph, and second, that estimate is refined by extracting a Gabor jet from that image and comparing that jet to one of the models. Estimation and refinement of landmark location has been discussed by Wiskott et al [4].

C. Recognition

In recognition phase, image graph of new face is built by an elastic graph matching process, and then its features are compared with all classes in training set by a simple similarity function. Both localization and comparison uses Gabor jets extracted at landmark positions. Similarity between novel images is expressed as function of similarity between localized Gabor jets corresponding to facial landmarks. In this paper, we used similarity function that proposed by Wiskott et al [3].

D. Gabor Wavelet

Gabor wavelet has been used to extract feature from landmark locations. 2-dimensional Gabor wavelet filter in point (x, y) has five parameters and is defined as below [5]:

$$w(x, y) = \exp\left(\left(x'^2 + \gamma^2 y'^2\right) / 2\sigma^2\right) \cos(2\pi x'/\lambda + \varphi) \tag{1}$$

That x' and y' are computed using equation (2) and (3) respectively.

$$x' = x\cos\theta + y\sin\theta \tag{2}$$

$$y' = -x\sin\theta + y\cos\theta \tag{3}$$

λ specifies the wavelength of the cosine wave, or inversely the frequency of the wavelet. Wavelets with a large wavelength will respond to gradual changes in intensity in the image. Wavelets with short wavelengths will respond to sharp edges and bars.

θ specifies the orientation of the wavelet. This parameter rotates the wavelet about its center. The orientation of the wavelets dictates the angle of the edges or bars for which the wavelet will respond. In most cases θ is a set of values from 0 to π. Values from π to 2π are redundant due to the symmetry of the wavelet.

φ specifies the phase of the sinusoid. Typically, Gabor wavelets are based on a sine or cosine wave. In the case of this algorithm, cosine wavelets are thought to be the real part of the wavelet and the sine wavelets are thought to be the imaginary part of the wavelet. Therefore, a convolution with both phases produces a complex coefficient. The mathematical foundation of the algorithm requires a complex coefficient based on two wavelets that have a phase offset of $\pi/2$.

σ specifies the radius of the Gaussian. The size of the Gaussian is sometimes referred to as the wavelet's basis of support. The Gaussian size determines the amount of the image that effects convolution. In theory, the entire image should effect the convolution; however, as the convolution moves further from the center of the Gaussian, the remaining computation becomes negligible. This parameter is usually proportional to the wavelength, such that wavelets of different size and frequency are scaled versions of each other, i.e. $\sigma = c\lambda$.

γ specifies the aspect ratio of the Gaussian. Most wavelets tested with the algorithm use an aspect ratio of 1.

In each landmark location, jet features are computed by convolution of subimage around landmark and Gabor filters. Wiskott et al [3,4] assumed $\lambda \in \{4, 4\sqrt{2}, 8, 8\sqrt{2}, 16\}$, $\theta \in \{0, \pi/8, 2\pi/8, 3\pi/8, 4\pi/8, 5\pi/8, 6\pi/8, 7\pi/8\}$, $\varphi \in \{0, \pi/2\}$, $\sigma = \lambda$ and $\gamma = 1$ for Gabor wavelet parameters. Bolme [5] has proposed $\varphi \in \{-\pi/4, \pi/4\}$ and $c = 3/4$ instead of corresponding parameters in Wiskott's algorithm. In both proposed algorithm, the wavelengths of wavelet are predefined.

IV. EBGM Algorithm Optimization

Genetic Algorithm (GA) is a powerful tool for optimization that is proposed by Holland [9] in 1975. GA is a stochastic algorithm and it has been inspired from natural evolution. GA has three operators: selection, crossover and mutation. Schematic of an ordinary GA is demonstrated in Figure 1.

We proposed a GA based algorithm to optimize wavelength of Gabor wavelet in EBGM algorithm. Both Wiskott and Bolme assumed 5 wavelengths in range 4-16. In proposed GA, integer representation and 6 genes per chromosome are used. The integer values of genes can select from 0-25. Each zero value in chromosome decreases the number of wavelength by one. Therefore, GA can select the best number and values for wavelengths of Gabor wavelet transformation.

In each generation, the size of population is 50 and all parents are replaced by new offspring, except the best parent of last generation (elitism). Parents are selected using tournament selection.

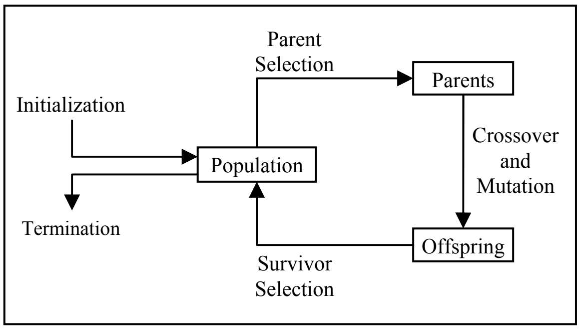

Figure 1: Genetic algorithm scheme

Crossover and mutation for proposed GA are uniform crossover and random noise respectively. The crossover probability is 0.8 and mutation probability is 0.1. GA continues its search until the number of generation reached to 100. Fitness function is equal to corresponding recognition rate. To evaluate a wavelength set, a recognition process is done on model set. Our model set contains 70 arbitrary faces.

Wiskott [4] and Bolme [5] have used 30 and 25 landmarks per face respectively. Some of these landmarks are around the face and have little effects on recognition. To decrease the computational complexity, we reduced number of landmarks by ignoring some redundant landmarks seeming have not important information. In our proposed method only 14 landmarks are used per image that most of them are located around eyes. Landmarks around lip may be disturbed by beard or toilet. Also, other facial points have smooth region that have not important information for face recognition. Figure 2 shows the proposed landmark locations on a sample face.

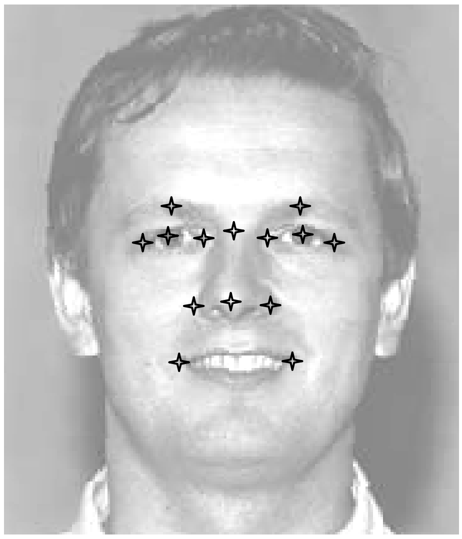

Figure 2 - Landmark locations on face

V. Experimental Result

For evaluation, the first 300 face classes of FERET database were selected. Only two first frontal images per face class were used: first frontal image (fa) for training and second frontal image (fb) for test. We select all eye points of image manually.

For pre-processing phase, all facial images were normalized using eye points. After normalization, distance of eye points in all images is 50 pixels. Then, redundant pixels of around images were cropped to resize them to 120 x 140.

70 different facial images are selected to create bunch graph. Bunch graph has 14 nodes and 70 layers, but initially, all nodes of bunch graph are empty. They will be filled by Gabor coefficients using the best Gabor wavelengths.

Bunch graph is created in optimization step. In other words, for each individual of population in all generations, a bunch graph is created and finally, the best bunch graph will be obtained after optimization completion.

GA starts its search and a bunch graph is created per individual using modelling set. After bunch graph creation, the model is tested on the modelling set. The fitness of individual is equal to obtained recognition rate. Figure 3 shows diagram of mean fitness changes during generations.

After 100 generations of GA, the best bunch graph model using the best Gabor wavelengths is achieved. The best recognition rate on modelling set (70 images) was 97.1% using the best wavelengths set. The best wavelength set consists of 6 elements that are 3, 6, 9, 13, 17 and 21. Now, all nodes of final bunch graph are filled by best jets.

For evaluation of proposed method, after optimization of wavelengths, algorithm was tested on 300 frontal facial images of FERET dataset. In training, only one face per class is used and finally 90.7% is obtained for recognition rate.

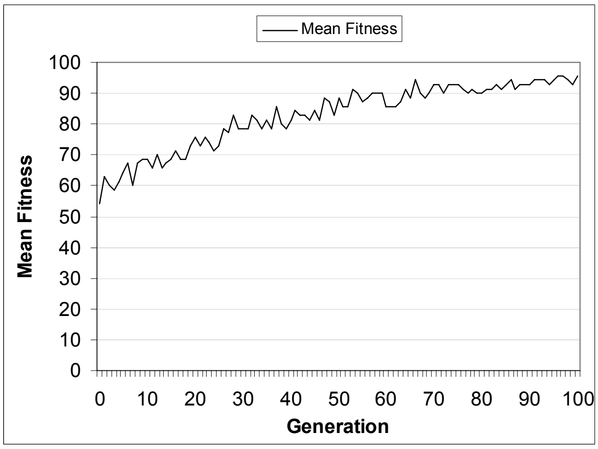

Figure 3 - Diagram of Mean Fitness Changes during Generations

Wiskott's EBGM algorithm and proposed optimized EBGM were implemented using MATLAB 6.5 on an Intel Pentium IV 2 GHz with 512 MB RAM. Wiskott's EBGM algorithm with 30 landmarks took about 18 seconds for each face. But optimized EBGM took about 12 seconds, because of fewer landmarks. So, optimized EBGM is 1.5 times faster than Wiskott's EBGM, although optimized EBGM has 7.3% lower recognition rate.

When 14 landmarks that depicted in Figure 2 is used in Wiskott's EBGM algorithm, it will recognize each face in 9 seconds and the recognition rate will be 83%.

A comparison between Wiskott's EBGM, modified Wiskott's EBGM and optimized EBGM algorithms with is shown in Table I. It seems that using 14 landmarks instead of 30 landmarks in original EBGM algorithm can decrease the recognition rate about 15%. But optimized EBGM can obtain higher recognition rate with same landmarks.

Table I - Comparison of EBGM Algorithms

Algorithm Name	Number of Landmarks	Recognition Rate	Execution Time
Wiskott's EBGM	30	98%	18 seconds per image
Modified Wiskott's EBGM	14	83%	9 seconds per image
Optimized EBGM	14	90.7%	12 seconds per image

VI. Conclusions and Future Works

In this paper, an optimized EBGM algorithm is presented for face recognition. Optimized EBGM uses the base EBGM algorithm and a genetic algorithm to select the best wavelengths for Gabor wavelet. Also, only 14 landmarks were used to extract feature for face recognition. Because of these modifications, the optimized EBGM is 1.5 times faster than original EBGM. But the recognition rate of optimized EBGM reduced to 90.7%. In other word, Wiskott's EBGM algorithm is 7.3% more accurate than proposed algorithm.

In proposed algorithm, the objective of optimization was increasing recognition rate, therefore, fitness function set to recognition rate. For optimization of both recognition rate and computational complexity, fitness function of GA has to change. Increasing the recognition rate and decreasing the computational complexity are two contrary objectives. So, for increasing the recognition rate and decreasing the computational complexity simultaneously, Multi Objective GA (MOGA) can be used.

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