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OPTIMIZATION OF THE FEATURES USED IN FACE RECOGNITION

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ABSTRACT
We present an optimization method for the features used in face recognition. The particle swarm algorithm is used to select the optimum parameters for the Gabor filter which is employed in our face recognition algorithm. We generate 40 Gabor filters and determine one optimum filter parameter set from those by using the particle swarm optimization. The face recognition is performed by using only the output of the Gabor filter with optimum parameter set as well as the all 40 filter output feature set. The performance of the proposed method is presented by means of simulations.
Keywords: Face Recognition, Gabor Filters, Particle Swarm Optimization.

1. INTRODUCTION

Face recognition remains to be a challenging problem even after technical advances in signal and image processing areas. Small changes on the mimics on the face, posing, and lighting effects cause large changes on the face image. However, it is assumed that the local features of the face are invariant to those changes and they can be extracted by using a spatial-frequency analysis [1-4]. In this respect, wavelet analysis with well localized bases in space-frequency becomes a natural choice. Among many other wavelets, Gabor functions provide the best localization both in space and in frequency. Hence, Gabor filters are widely used in pattern recognition applications to extract the local features of the image [5].

Particle swarm optimization (PSO) is developed for the optimization of non-linear continuous functions, and it is related to artificial life, bird flocking, fish schooling, and swarm theory [6].

In this study we deal with a face recognition method based on Gabor filter features and present an optimization approach for the features by using the PSO algorithm. The proposed method is tested on a face database.

2. GABOR WAVELETS

Since Gabor function have desirable local character, it is applied in the field of the image disposing, comprehending, and recognition. Gabor wavelet filter may distill local space and frequency domain information, which cannot be determined by Fourier analysis. The two dimensional Gabor function is given by,

$$g_{\sigma,\omega 0}(x,y) = \frac{1}{2\pi\sigma_x\sigma_y}\exp[-\frac{1}{2}(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y{}^2})]\exp[j\omega_0(x+y)] \tag{1}$$

where σ is the standard deviation, and ω_o is the space frequency of plural plane wave. If Gabor function is divided into odd (g^o) and even (g^e) parts, then we obtain,

$$g^e_{\sigma,\omega 0}(x,y) = \frac{1}{2\pi\sigma_x\sigma_y}\exp[-\frac{1}{2}(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y{}^2})]\cos(\omega_0(x+y)) \tag{2}$$

$$g^o_{\sigma,\omega 0}(x,y) = \frac{1}{2\pi\sigma_x\sigma_y}\exp[-\frac{1}{2}(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y{}^2})]\sin(\omega_0(x+y)) \tag{3}$$

If the equality $\sigma\,\omega_o \approx 1$ is achieved, then the even part of a Gabor function will be more useful for edge detection applications [11]. Gabor wavelets (filters) are obtained from Gabor function as;

$$\begin{aligned}\psi_n(x,y) = \exp\Bigg(-\frac{1}{2}\bigg(\Big[\frac{1}{s_x}\big((x-c_x)cos\theta-(y-c_y)sin\theta\big)\Big]^2 \\ +\Big[\frac{1}{s_y}\big((x-c_x)sin\theta+(y-c_y)cos\theta\big)\Big]^2\bigg)\Bigg) \\ \times \sin\Big(\frac{1}{s_x}\big((x-c_x)cos\theta-(y-c_y)sin\theta\big)\Big)\end{aligned} \tag{4}$$

Here, $\boldsymbol{n} = (\mathbf{c_x}, \mathbf{c_y}, \boldsymbol{\theta}, \mathbf{s_x}, \mathbf{s_y})$ shows the parameter set, where $\mathbf{c_x}$ and $\mathbf{c_y}$ denote the motion parameters on space, $\boldsymbol{\theta}$ is the steering parameter, and $\mathbf{s_x}$ and $\mathbf{s_y}$ are the scaling parameters. In our study, we choose 40 Gabor filters with various $\boldsymbol{\theta}$, $\mathbf{s_x}$ and $\mathbf{s_y}$ values. Then the PSO is used to find one optimum Gabor filter which is used for feature extraction and recognition of the faces.

3. PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization (PSO) Algorithm [7, 12] is a recently developed evolutionary algorithm. It is based on the idea of collaborative behavior and swarming in biological populations inspired by the social behavior of bird flocking or fish schooling [6 - 9].

PSO starts with a random solution (particle swarm) and tries to find the optimum solution by iterations. At every iteration particle positions are updated to optimize two values. The first; is the positions which satisfy the best solution obtained by the particle up to that iteration. This value is called *"pbest"* and must be stored in the memory. The other is the positions which satisfies the best solution obtained by all the particles in the population up to that iteration. This value is the global best and shown by *"gbest"*. Suppose that there is a population consisting $\boldsymbol{n}$ particles having $\boldsymbol{D}$ parameters. The i'th particle is expressed as $x_i = [\ x_{i1}, x_{i2}, ...x_{iD}\ ]$. Position of the i'th particle which satisfied the best latest solution is expressed as $pbest_i = [\ p_{i1}, p_{i2}, ...p_{iD}\ ]$. In the case where *gbest* is unique for all particles in every iteration, it is expressed as $gbest = [\ p_1, p_2, ...p_D\ ]$. Velocity of the i'th particle (changing quantity of its position for every dimension) is expressed as $v_i = [\ v_{i1}, v_{i2}, ...v_{iD}\ ]$. After finding two best values, particle velocities and positions are updated according to the following equations:

$$\begin{aligned}v_i^{k+1} = v_i^k + c_1.rand_1^k.\left(pbest_i^k - x_i^k\right) \\ +c_2.rand_2^k.\left(gbest^k - x_i^k\right)\end{aligned} \tag{5}$$

In equation (5), c_1 and c_2 are $x_i^{k+1} = x_i^k + v_i^{k+1}$ learning parameters which are random acceleration terms that attract every particle towards *pbest* and *gbest* positions. c_1 provides the particle to move according to its own experience, whereas c_2 provides the particle to move according to the experience of other particles. Choosing small values for these parameters when we are far from the target region causes the particles to move away from the solution, hence the time to reach the target will be longer. On the other hand, choosing larger values accelerates to convergence, but it may cause unpredictable movements and skipping the target region. Experiments of researchers on this algorithm yielded that choosing c_1 and c_2 as 2 is a good trade-off. ***rand1*** and ***rand2*** in equation (5) are random normally distributed numbers between 0 and 1, where k is the iteration number.

4. METHOD

In our study, the face images of the *Olivetti Att – ORL* database are used to generate the training set and the test set. The *Olivetti Att – ORL* database composes of 400 face images, 10 different face images for each of 40 people. The training set is generated by 48 face images, 3 different poses for each of 16 people. The test set is generated by 48 face images, 3 different face images for each of the same 16 people. The optimization of Gabor wavelets used in feature vector extraction by using PSO is explained in the following steps:

1. Parameters for 5 different scales and 8 angles are selected.
2. Using these parameters, 40 Gabor Wavelets are obtained according to equation (5).
3. The images in the training set are filtered by those 40 filters.
4. For each pose, the differences between filtered images are calculated by the Euclidean Distance.
5. The parameter making the difference value for each pose larger is used to update *pbest*. (It is assumed that the optimum filter obtained differs the filtered images from each other, so it will be distinctive in face recognition)
6. The parameter providing the largest difference value from the beginning up to this iteration updates *gbest*.
7. Velocity and position are updated by the equations (7) and (8).
8. Go to step 2, and repeat.

When the maximum iteration number is reached, the Optimum Gabor Wavelet is generated by the last parameter $(c_x, c_y, \theta, s_x, s_y)$ obtained. The feature vectors for each of the images in the training set and the test set are extracted by the Optimum Gabor Wavelet. Face recognition by using feature vectors is applied in two different ways:

- By calculating the distances between the vectors using the Euclid distance, it is decided that the image in the test set belongs to which individual in the training set.
- Feature vectors of the individuals in the training set and the test set are subjected to Principal Component Analysis for identification.

5. RESULTS

40 Gabor Wavelets with 5 different scales and 8 different orientations used for feature extraction. At the first stage, feature vectors for all images in the training set and the test set are extracted by using all 40 Gabor filters. The images in the sets have 112 x 92 dimension. The feature vector of an image has a length of 412160 values, since it is filtered by 40 filters making the computations time consuming. The filtered images are scaled and the length of the vector is decreased to 25760. Face recognition is performed by calculating the Euclid distance betweeen the feature vectors. 28 of 48 face images are identified correctly, at the same time 12 of 16 individuals are determined correctly. At the second stage of our study, by the help of optimization of Gabor Wavelet parameters with PSO, the feature vectors' (filter responses) optimization is performed. As a result, a parameter set is obtained which provides the best distinction for each of three poses. The parameters obtained by the PSO method are as $c_x = 0.3921$, $c_y = -0.1919$, $\theta = 5.2234$, $s_x = 5.0472$, $s_y = 3.319$. The optimum Gabor filter generated by this parameter set is shown in Figure 1. The feature vectors are obtained by filtering all the images in the training set and the test set with the optimum Gabor filter. Face recognition is performed by calculating the Euclid distances between feature vectors. In this case, 24 of 48 face images are identified correctly, at the same time 9 of 16 individuals are determined correctly.

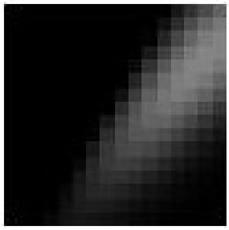

Figure 1. The Optimum Gabor Filter.

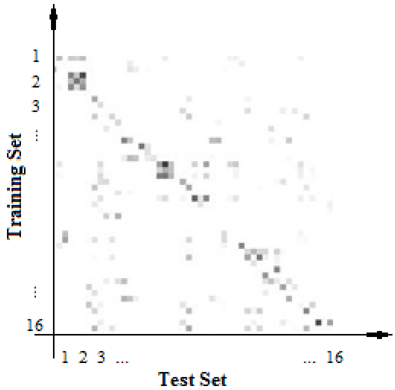

Figure 2. Performance with using only one optimized parameter set

After extracting feature vectors, Principal Component Analysis (PCA) is performed, besides the Euclid distance, to determine the image in the test set that belongs to which person in the training set. The result for PCA is shown in Figure 2. The dark colored regions in the figure shows that difference for that indices is minimum. The dark diagonal line corresponds to overlap between the traning set and the test set.

During the first stage of our study, feature vectors were obtained by using 40 Gabor wavelets and the face recognition performance was seen as 60%. At the second stage the feature vectors were calculated by using the optimum Gabor filter obtained by the help of PSO, and the face recognition performance was seen as 50%. To decrease the number of Gabor wavelets from 40 to 1 made the data volume smaller than the previous by 97.5%. And the loss in the performance of face recognition was limited to 10%. Our study is going on to increase the recognition performance by the help of preprocessing methods.

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