16th International Research/Expert Conference
"Trends in the Development of Machinery and Associated Technology"
TMT 2012, Dubai, UAE, 10-12 September 2012

FACIAL EXPRESSION ANALYSIS BASED ON OPTIMIZED GABOR FEATURES

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ABSTRACT
In this paper, a method analyzing the facial expressions by applying Gabor filters on face images is presented. To reduce the computational complexity and dimensionality, particle swarm optimization and the mRMR methods are used. 40 Gabor filters with changing parameters are generated and the optimum one from those is determined by applying particle swarm optimization. The dimension of the Optimized Gabor Features is reduced via mRMR method based on mutual information. The facial expression recognition is performed by using only the output of optimum parameter Gabor filter as well as the all 40 filter output feature set. The performance of the proposed method is presented by means of simulations.
Keywords: Facial Expression Recognition, Gabor Filters, Particle Swarm Optimization.

1. INTRODUCTION
Facial expression analysis is a challenging problem, even after technical advances in signal and image processing areas. Varying illumination, pose, and partial occlusion cause large changes on the face image. The local features representing facial expressions can be extracted via spatial-frequency analysis, since it is assumed that the local features of the face are invariant to changes specified [1-3]. It is seemed that Wavelet Analysis with well localized bases in space-frequency is an appropriate choice to extract the features. Gabor functions provide the best localization both in space and in frequency, among many other wavelets [4].
Filtering face images with a Gabor wavelet is the main part of feature extraction. A Gabor wavelet consists of complex values. Because of that, Gabor features obtained by filtering contain both real and imaginary parts.

Particle swarm optimization (PSO) is developed for the optimization of non-linear continuous functions, and it is inspired by bird flocking, fish schooling, and swarm theory [5]. To reduce the computational complexity and to find the optimum Gabor filter, PSO is applied on Gabor wavelet parameters.
In this study we deal with a facial expression recognition method based on Gabor filter features (consisting both real and imaginary parts), and present an optimization approach for the features by using the PSO algorithm and the mRMR (minimum Redundancy Maximum Relevance) method for the dimensionality reduction.

2. GABOR FILTERS

Gabor filters (also called Gabor wavelets or kernels) are used in the pre-processing, recognition and classification of images because of their well-behaved space-frequency characteristics. They have proven themselves to be a powerful tool for facial feature extraction and robust face recognition. They represent complex band-limited filters with an optimal localization in both the spatial as well as the frequency domain [6].

In general, the family of 2D Gabor filters can be defined in the spatial domain as follows [7,8]:

$$\psi_{u,v}(x,y) = {f_u^2}/{\pi\kappa\eta}\ exp\left(-((f_u^2/\kappa^2)x'^2 + (f_u^2/\eta^2)y'^2)\right)\ exp\ (j2\pi f_u x') \tag{1}$$

where $x' = x.cos\theta_v + y.sin\theta_v$, $y' = -x.sin\theta_v + y.cos\theta_v$, $f_u = f_{max} / 2^{(u/2)}$, and $\theta_v = v\pi/8$.

Each Gabor filter represents a Gaussian kernel function modulated by a complex plane wave whose center frequency and orientation are given by f_u and θ_v, respectively. The parameters κ and η determine the ratio between the center frequency and the size of the Gaussian envelope.

It is assumed that $\boldsymbol{p = (f, \kappa, \eta, \theta)}$ denotes the parameter set. In this study, 40 Gabor filters are chosen depending on various parameter sets. Then the PSO is used to find one optimum Gabor filter to extract the features, providing less computational complexity. To reduce the feature dimension, the mRMR method is used.

3. PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization (PSO) Algorithm is an evolutionary algorithm based on the idea of collaborative behavior and swarming in biological populations inspired by the social behavior of bird flocking or fish schooling [5].

PSO is an iterative method trying to find an optimum solution. Initial particle swarm is obtained randomly. Particle positions are updated at every iteration via two values; *pbest* and *gbest*. The first one *"pbest"* is the positions satisfying the best solution obtained by the particle up to that iteration. 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 a population consisting $\boldsymbol{n}$ particles having $\boldsymbol{D}$ parameters, the i'th particle is expressed as $x_i = [\ x_{i1}, x_{i2}, ...x_{iD}\ ]$. Velocity of the i'th particle (changing quantity 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:

$$v_i^{k+1} = v_i^k + c_1.rand_1^k.\left(pbest_i^k - x_i^k\right) + c_2.rand_2^k.\left(gbest^k - x_i^k\right) \tag{2}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{3}$$

$\boldsymbol{c_1}$ and $\boldsymbol{c_2}$ are learning parameters which are random acceleration terms that attract every particle towards *pbest* and *gbest* positions. $\boldsymbol{c_1}$ provides the particle to adjust its position according to its own experience, and $\boldsymbol{c_2}$ provides the particle to adjust its position according to the experience of the best one. ***rand1*** and ***rand2*** in the equation are normally distributed random numbers between 0 and 1.

4. mRMR (mINIMUM REDUNDANCY MAXIMUM RELEVANCE) METHOD

mRMR is a method achieving successful results and shortening the computation time and it is developed by Hanchuan Peng [9]. The aim of this method is to obtain maximum relevance by choosing features most related with the class information and to make the redundancy smaller by choosing the features less related with each other.

Features in the training set are assumed as random variables and dependency and redundancy values are obtained by calculating mutual information. Suppose that X and Y are two discrete random variables. Mutual information is obtained as;

$$I(X,Y) = \sum_{y \in Y} \sum_{x \in X} p(x,y) \log \left(\frac{p(x,y)}{p_1(x) p_2(y)} \right) \quad (4)$$

where $p(x,y)$ is the joint probability distribution function (pdf) of X and Y, $p_1(x)$ and $p_2(y)$ are the marjinal pdfs of X and Y, respectively.

Ω states all the features in the training set, S states the selected feature subset. Maximum dependency and minimum relevance values are obtained as shown below

$$max_{S \subset \Omega} D(S,c), D = \frac{1}{|S|} \sum_{x_i \in S} I(x_i, c) \quad (5)$$

$$min_{S \subset \Omega} R(S), R = \frac{1}{|S|^2} \sum_{x_i, x_j \in S} I(x_i, x_j) \quad (6)$$

$|S|$ is the number of features in the selected subset, and $I(x_i,c)$ is the measure of relation between every features and class labels. $I(x_i, x_j)$ is the measure of relation between features. The most suitable feature set is obtained by optimizing equations (5) and (6) according to difference ($max(D - R)$) and quotient ($max(D / R)$) criterions.

5. METHOD

In this study, *The Japanese Female Facial Expression (JAFFE)* [10] database is used to evaluate the performance of the proposed method. The JAFFE face database used at this study contains 144 images of 6 basic facial expressions (Happy, Sad, Angry, Disgust, Fear, Surprise) posed by 10 Japanese female models. Images are cropped to increase the useful information. Image size is 160x128. 85% of the database is used as training set and the rest as test set.

To obtain an optimum Gabor filter for feature extraction PSO is applied in an iterative manner:

1. 40 particles are generated randomly $\boldsymbol{p_i = (fu_i, \kappa_i, \eta_i, \theta_i)}$.
2. Using these particles 40 Gabor filters are obtained according to equation (1).
3. Face images in the training set are filtered with each filter.
4. Filtered images are sampled by 16 to reduce the dimension. Images reshaped as an array with a dimension of 80. 80 real and 80 imaginary values copmpose the feature vector.
5. K-fold cross validation is applied on training set and K-NN classifier is used to evaluate each filters' performance. The parameter making this value better is used to update *pbest*.
6. The parameter providing the best classification performance for training set from the beginning up to this iteration updates *gbest*.
7. Velocity and position are updated according to the equations (2) and (3).
8. Control the iteration number. If it is not reached to the maximum, go to step 2 and repeat.

The optimum Gabor filter is generated by *gbest* $\boldsymbol{(f, \kappa, \eta, \theta)}$. The feature vectors are obtained as a result of filtering with the optimum filter. To reduce the dimensionality mRMR is applied on training set feature vectors according to two different criterion as mentioned earlier. Feature vector dimension is chosen as 20, 40, 60, 80, and 120. Facial expression recognition is processed by classifying test set feature vectors via two different classifiers (K-NN classifier and Support Vector Machines).

6. RESULTS

Since the particles' initial values are generated randomly, classification problem is simulated more than one time and the average classification rates are obtained. Table 1 shows the optimum Gabor filter parameters obtained for three simulations.

Table 2 shows two different classifiers' performances for varying feature vector dimensions. Selection of 40 features by applying mRMR makes the performance better and the dimension smaller. Filtered image size was 160x128. So the feature vector composes of 20480 values without dimensionality reduction. As a result of three experiments the proposed method provides at least 75% dimensionality reduction and a considerable increment at performance.

Table 1. Optimum Gabor parameters

	F	κ	η	Θ
E1	-44665983,4135709	-2046624212,82303	1390774112,13132	-4172115230,77643
E2	0,0883883476483185	2125868,43474943	-364605,473468680	0,392699081698724
E3	-5742401563,43466	93563726519,9782	7991100697,17061	153338084370,488

Table 2. Facial expression classification rates

Feat Dim.	**Exp1**		**Exp2**		**Exp3**		**Average**	
	KNN	**SVM**	**KNN**	**SVM**	**KNN**	**SVM**	**KNN**	**SVM**
160	*61.9%*	*66.6%*	*57.89%*	*68.42%*	*63.16%*	*57.89%*	*64,30%*	*60,98%*
120 (Dif)	*66.6%*	*66.6%*	*52.63%*	*73.68%*	*66.6%*	*57.89%*	*66,06%*	*61,94%*
120 (Quot)	*66.6%*	*71.43%*	*52.63%*	*63.16%*	*66.6%*	*63.16%*	*65,92%*	*61,94%*
80 (Dif)	*76.19%*	*71.43%*	*68.75%*	*68.42%*	*66.6%*	*63.16%*	*67,67%*	*70,51%*
80 (Quot)	*71.43%*	*71.43%*	*68.75%*	*63.16%*	*66.6%*	*63.16%*	*65,92%*	*68,93%*
60 (Dif)	*71.43%*	*76.19%*	*68.75%*	*66.6%*	*72.22%*	*57.89%*	*66,89%*	*70,80%*
60 (Quot)	*66.6%*	*76.19%*	*52.63%*	*68.42%*	*66.6%*	*63.16%*	*69,26%*	*61,94%*
40 (Dif)	*71.43%*	*71.43%*	*68.75%*	*68.42%*	*77.7%*	*73.68%*	***71,18%***	***72,63%***
40 (Quot)	*76.19%*	*71.43%*	*68.75%*	*68.42%*	*77.7%*	*68.42%*	***69,42%***	***74,21%***
20 (Dif)	*80.9%*	*66.6%*	*47.37%*	*57.89%*	*57.89%*	*57.89%*	*60,79%*	*62,05%*
20 (Quot)	*76.19%*	*71.43%*	*68.75%*	*50%*	*61.1%*	*57.89%*	*59,77%*	*68,68%*

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