# Facial Expression Recognition with Pyramid Gabor Features and Complete Kernel Fisher Linear Discriminant Analysis*

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## Abstract

This paper presents a Facial Expression recognition [FER] approach using Pyramid Gabor features and Complete Fisher Kernel Linear Discriminant Analysis (CKFD). Based on the frequency locality of Gabor filters, we propose new pyramid Gabor features for FER, which can be extracted by two phases: multi-frequency channel decompositions and Gabor filtering with single frequency. Experiments show the proposed Pyramid Gabor features can reach better performance than traditional Gabor features in facial expression analysis and involve much less computations. Based on kernel principal component analysis (KPCA) and Fisher linear discriminant analysis (LDA), a complete Kernel Fisher Linear Disciminant Analysis was presented recently, which can carry out discriminant analysis in "double discriminant subspace". This paper expands the complete KFD to the field of facial expression recognition. We find the irregular information subspace is more dicriminant than the regular information subspace.

**Keyword**: Pyramid Gabor features, Kernel Method, Fisher Linear Discriminat Analysis

## I. Introduction

Gabor features have been widely applied in the field of computer vision because of its powerful analysis ability in the conjoint time-frequency domain. Some neurophysiological evidences [1,2] have been found that suggest the filter response profiles of human main class of linearly-responding critical neurons are best modeled as a family of self-similar 2D Gabor wavelet. The evidences confirmed the validity of Gabor features. Previous researches [3-6] have suggested the Gabor features analysis is one of most successful and affective methods in the fields of facial recognition, facial features extraction, and facial expression analysis.

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In the field of face analysis, principle component analysis (PCA) and linear discriminant analysis (LDA) are two classical tools widely used for data reduction and feature extraction. It is generally believed [7] that when it comes to solving problems of pattern classification, LDA outperform PCA, because LDA optimizes the low-dimensional representation of the objects with focus on the most discriminant feature extraction while the latter achieves simply object reconstruction. However, many LDA-based algorithms suffer from the so-called "*small sample size problem*" (SSS) [16] which exists in high-dimensional pattern recognition tasks, where the number of available samples is smaller than the dimensionality of the samples. The most famous solution to the SSS problem is to utilize PCA concepts in conjunction with LDA (PCA plus LDA)[7,8]. The effectiveness of the method has been demonstrated by [7,8,9,10]. However, to the problems with a highly nonconvex and complex distribution, like facial expression recognition (FER) problem, people believe a better solution to this inherent nonlinear problem could be achieved using nonlinear methods, such as the so-called kernel machine [11,19,20].

Recently, a complete Kernel Fisher Discriminant (CKFD) algorithm was presented by Jian Yang in [11], which can be used to carry out discriminant analysis in "double discriminant subspace". Unlike current kernel fisher linear analysis, it takes advantage of two kinds discrminant information: irregular information (in the null space of the within-class scatter matrix) and irregular information (outside of the null space)[11]. So this paper uses it to compare the performances of two kinds of information in FER.

In this paper, we present a new Pyramid Gabor features extraction method for the representation of facial expression. The pyramid Gabor features are integrated with the CKFD for facial expression recognition. Experiment shows that the proposed Pyramid Gabor feature can reach better performance and involve much less computations than the traditional Gabor features under the frame work of PCA+LDA and CKFD. We also found that the irregular information subspace of CKFD is more discriminant for facial expression recognition than regular features subspace.

## II. Feature Extraction

In computer vision, multi-frequency channel decompositions are interpreted through the concept of multi-resolution[17]. Generally, the targets that we want to recognize have very different spatial resolution. However, it is impossible to define a prior an optimum resolution to a given images. As to facial expression images, expression analysis maybe needs the different features corresponding with the different resolutions. On the other hand, a set of multi-frequency, different orientation Gabor features can supply the representation of spatial locality, frequency locality and orientation selectivity for a given facial images [5,6]. In fact the Gabor features is characterized with different resolution information. This is one of the reasons why Gabor feature can successfully be applied in face and facial expression recognition [3-6]. Inspired from the frequency locality of the Gabor features, in this paper, we proposed new Gabor features based on multi-frequency channel decompositions with pyramid algorithm. In each single frequency channel of a facial image, the features were extracted by a set Gabor filters with single frequency but different orientation. Experiments show that the features extracted by the method can reach better performance than the traditional Gabor features and involved much less computations.

### A. *Traditional Gabor Feature*

Gabor wavelet is a Gaussian function modulated by complex exponentials that provides the best trade-off between time -resolution and frequency-resolution. The general functional form of the 2-D Gabor filter is specified in [14] and [15], which is given by the following equation [14]:

$$\varphi_{u,v}(\vec{x}) = \left\|\vec{k}_{u,v}\right\|^2 \Big/ \delta^2 \exp(-\left\|\vec{k}_{u,v}\right\|^2 \left\|\vec{x}\right\|^2 \Big/ 2\delta^2)[\exp(i\,\vec{k}_{u,v}\,\vec{x}) - \exp(-\frac{\delta^2}{2})] \qquad \textbf{(1)}$$

where $\vec{x}$ denotes the pixel position in the spatial domain, $\vec{k}_{u,v}$ defines the width and the orientation of Gaussian window, which can be denoted as $\vec{k}_{u,v} = (k_v \cos\phi_u, k_v \sin\phi_u)'$ ,where $k_v = k_{\max} / f^v$ and $\phi_u = u\pi/8$, $\delta$ is the ratio between the width of the Gussia and the wavelength of the complex exponential wave, the term of $\exp(-\delta^2/2)$ compensates for the DC value because the cosine component has nonzero mean (DC response) while the sine component has zero mean.

The Gabor features of a face image $I(\vec{x})$ are extracted by convolving it with the family of Gabor filters:

$$G_{u,v}(\vec{x}) = \varphi_{u,v} * I(\vec{x}) \qquad \textbf{(2)}$$

where $G_{u,v}(\vec{x})$ denotes the corresponding Gabor features with orientation *u* and scale *v*. The image $I(\vec{x})$ can be thus represented by a set of Gabor coefficients $G_{u,v}(\vec{x})$. Figure 1 gives an example of the Gabor representations of a human face at different scales and orientations.

### B. *Multi-frequency Channels Decomposition with Pyramidal Algorithm*

A multi-resolution decomposition is also an image decomposition in frequency channels of constant bandwidth on a logarithmic scale [17]. The approximation of a signal at a resolution $r$ is defined as an estimate of derived from measurements $r$ per unit length. These measurements are computed by uniformly sampling at a rate [17]. The series of decompositions using pyramidal algorithm that can be illustrated in Figure 2.

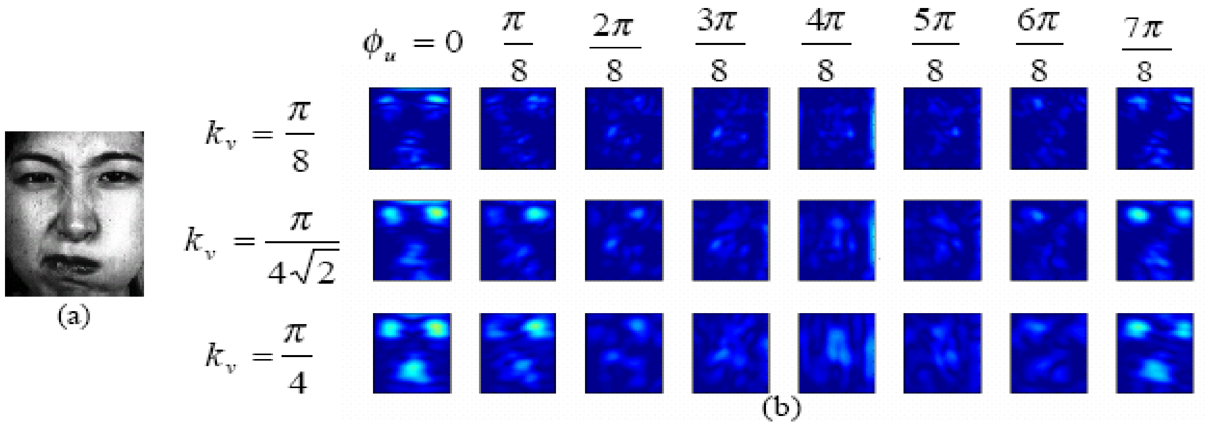


Fig. 1. (a). Input facial image (b). The magnitudes of the Gabor representationsof a face imagewith 3 scales and 8orientations, and the size of original face is 128×96

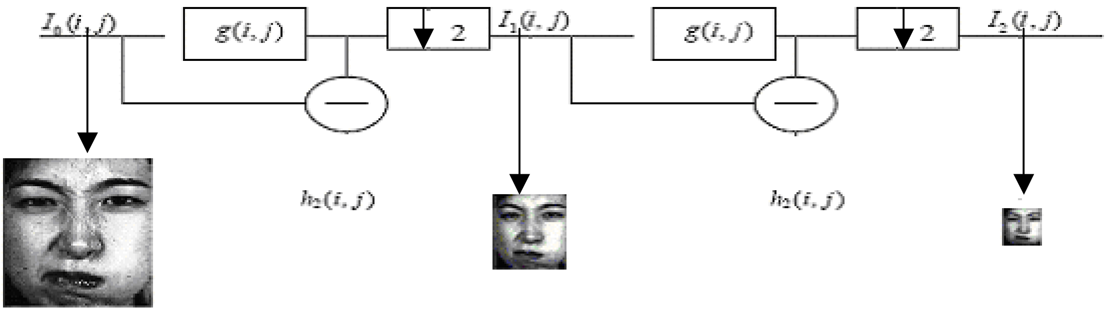


Fig. 2. Decomposition of $I_0(i,j)$ into different low resolution image $I_1(i,j)$ and $I_2(i,j)$ by Laplacian pyramid, where $I_0(i,j)$ is input image, $I_1(i,j)$ and $h_1(i,j)$ are the low and high frequency components of $I_0(i,j)$ respectively, $g(i,j)$ is a low-pass filter, $I_2(i,j)$ $h_2(i,j)$ have the similar meaning.

## C. *Pyramid Gabor Features*

The classical pyramidal implementation of multi-resolution transforms can be regarded as a kind of discrete wavelet decomposition in some sense. Therefore, it is reasonable that using the pyramidal algorithm to the extract Gabor features will not affect the essential of the feature. In equation (1), if giving a certain parameter $v$, the filter: $\varphi_{u,v}(\vec{x})$ only extracts the Gabor features centering frequency $k_v$. Because of the local frequency selectivity property of Gabor features, the Gabor features characterize $k_v$ can be extracted in the frequency channel as long as there is the information centering $k_v$ in the channel. As to an input image, $I_0(\vec{x})$, Gabor features characterize $k_i$ (where $i$ is a constant ) may be extracted in a component of $I_0(\vec{x})$ as long as the spectrum of the component encompasses the frequency scope localized by Gabor filter with centering frequency $k_i$.

Based on the above idea, we proposed a new pyramid Gabor feature extraction algorithm which is given as follows:

Step 1: Using the pyramidal algorithm to decompose the input image $I_0(\vec{x})$ to different channels: $I_1(\vec{x})$, $I_2(\vec{x})$ .... $I_n(\vec{x})$ as shown in figure 1.

Step 2: In every low frequency channel, extract the pyramid Gabor features by a set Gabor filters with single frequency but different orientation. $G_{u,i}(\vec{x}) = \varphi_{u,i} * I_i(\vec{x})$ where $i$ is constant and the spectrum of $I_i(\vec{x})$ should encompass the frequency scope localized by $\varphi_{u,i}(\vec{x})$.

Step 3: Downsample $G_{u,1}(\vec{x})$ $G_{u,2}(\vec{x})$ $G_{u,3}(\vec{x})$ ...by the different factor $r_i$, then normalize and Concatenate the corresponding pyramid Gabor features from different channel into a discriminative feature $X$.

In our experiments, the pyramid Gabor features parameters we used are chosen as $\sigma = 2\pi$, $k_{\max} = \pi/4$, $f = \sqrt{2}$, $v \in (0,1,2)$, $u \in (0,1,...7)$, $n \in (0,1,2)$, $r_i \in (8,4,2)$ where $n$ is index of pyramid algorithm decomposition. In another word: there are three sets of Gabor filters respectively characterized by $k_v$, $\varphi_{u,0}(\vec{x})$, $\varphi_{u,1}(\vec{x})$, $\varphi_{u,2}(\vec{x})$, the input image $I_0(\vec{x})$ is decomposed to different channels:

$I_1(\vec{x})$, $I_2(\vec{x})$ and $h_1(\vec{x})$, $h_2(\vec{x})$. In fact the information of $h_1(\vec{x}), h_2(\vec{x})$ is encompasses in $I_0(\vec{x}), I_1(\vec{x})$, so the high-frequency components, $h_1(\vec{x}), h_2(\vec{x})$ don't be used to extract the features.

Since the computation of the convolution is much more than pyramid decomposition and $I_1(\vec{x})$, $I_2(\vec{x})$ have low resolution, therefore experiments show that the proposed pyramid Gabor features involve much less computations than traditional Gabor features.

## III. Introduction of Complete Fisher Kernel Linear Discriminant Analysis

In the field of high-dimensional pattern recognition, Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) are two classical linear approaches used to reduce the dimensionality of the features for good recognition performance. PCA can find a subspace whose vectors correspond to the maximum-variance directions in the original space. On the other hand, while LDA creates a linear combination of these which yields the largest mean differences between the desired classes. However, to the problems with complex distribution, like facial expression recognition (FER) problem, people believe that a better solution to this inherent nonlinear problem could be achieved using nonlinear methods, such as the so-called kernel machine. e.g. Kernel PCA.

KPCA was originally developed by [19], which overcomes many limitations of its linear counterpart by nonlinearly mapping the input space to a high-dimensional feature space. Based on Cover's theorem on the separatbility of patterns nonlinearly separable patterns in an input space are linearly separable with high probability if the input space is transformed nonlinearly to a high dimensional feature space [12]. Computationally, kernel PCA takes advantage of the Mercer equivalence condition and is feasible because the dot products in the high-dimensional feature space are replaced by those in the input space while computation complexity is related to the number of training examples rather than the dimension of the feature space.

Based on KPCA and LDA, a Complete Kernel Fisher Discriminnant Framework was presented recently [11]. The complete KFD algorithm based the framework can take advantage of two kinds of discriminant information: regular and irregular to classify the patterns [11].

### A. *Outline of KPCA* [11,20]

For a given nonlinear mapping $\Phi$, the input data space $IR^n$ can be mapped into the feature space $H$:

$$\Phi : IR^n \sim \mathrm{H}; \qquad x \to \Phi(x) \tag{3}$$

As a result, a pattern in the original input space $IR^n$ is mapped into a potentially much higher dimensional feature vector in the feature space $H$.

In fact, KPCA is to perform PCA in the feature space $H$. However, it is difficult to do so directly because it is computationally very intensive to compute the dot products in a high-dimensional feature space. Fortunately, kernel techniques can be introduced to avoid this difficulty.

Given a set of M training samples $(x_1, x_2, ...x_q)$ in $IR^n$, the within-class matrix on the feature space $H$ can be constructed by as following [11]:

$$S_t^\Phi = \frac{1}{M}\sum_{j=1}^{M}(\Phi(x_j) - m_0^\Phi)(\Phi(x_j) - m_0^\Phi)^T \quad (4)$$

Every eigenvector of $S_t^\Phi$ can be linearly expanded by $\beta = \sum_{i=1}^{M}\alpha_i\Phi(x_i)$. To obtain the expansion coefficients, denote $Q = (\Phi(x_1).....\Phi(x_M))$. Calculate the orthonormal eigenvectors $\gamma_1, \gamma_2, ...\gamma_m$ of $R$ corresponding to the $m$ largest positive eigenvlaues, $\lambda_1 \ge \lambda_2, ... \ge \lambda_m$, where $R = \tilde{R} - 1_M\tilde{R} - \tilde{R}1_M + 1_M\tilde{R}1_M$, where $\tilde{R} = Q^TQ$ and $1_M = (1/M)_{M\times M}$. The orthonormal eigenvectors $\beta_1, \beta_2 ... \beta_m$ of $S_t^\Phi$ corresponding to the m largest positive eigenvlaues, $\lambda_1, \lambda_2, ..., \lambda_m$, $\beta_j = Q\gamma_j / \sqrt{\lambda_j}$, $j = 1,2...m$.

After the projection of the mapped sample $\Phi(x)$ onto the eigenvector system $\beta_1, \beta_2 ... \beta_m$, we can obtain the KPCA transformed feature vector $y = (y_1, y_2, ...y_m)^T$ by $y = P^T\Phi(x)$ where $P = (\beta_1, \beta_2 ... \beta_m)$.

### *B. Extraction of two Kinds of Discriminant Features by LDA* [11]

CKFD presents a new method to perform LDA in the KPCA transformed space $IR^m$. The standard LDA algorithm [18] remains inapplicable since the within-class scatter matrix $S_w$ is still singular in $IR^m$. CKFD take advantage of this singularity to extract more discriminant information than avoid it by means of the previous regularization techniques, which splits the space $IR^m$ into two subspaces: the null space and the range space of $S_w$, then derive the regular discriminant vectors from the range space and derive the irregular discriminant vectors from the null space.

In the KPCA transformed space $IR^m$, construct the between-class and within-class scatter matrices $S_b$ and $S_w$. Calculate $S_w$ 's orthonormal eigenvectors, $\alpha_1, \alpha_2, ...\alpha_m$, assuming the first $q$ ones are corresponding to positive eigenvalues.

To extract the regular dicriminant vectors, $\tilde{S}_b = P_1^TS_bP_1$ and $\tilde{S}_w = P_1^TS_wP_1$ are defined where $P_1 = (\alpha_1, \alpha_2, ...\alpha_q)$. It is easy to verify that $\tilde{S}_w$ is invertible, thus the standard LDA algorithm can be used to extract the regular discriminant vectors by maximizing the ratio $\det|\tilde{S}_b| / \det|\tilde{S}_w|$.

To extract the irregular dicriminant vectors, $\hat{S}_b = P_2^TS_bP_2$ is defined where $P_2 = (\alpha_{q+1}, \alpha_{q+2}, ...\alpha_m)$. Calculate $\hat{S}_b$ 's orthonormal eigenvectors $v_1, v_2, ...v_d$ ($d \le c-1$,where $c$ is the number of classes) corresponding to the $d$ largest eigenvalues. Let $V = (v_1, v_2, ...v_d)$, the irregular discriminant feature vector then is defined $z^2 = V^TP_2^Ty$ in [11] where y is the KPCA transformed feature vector.

### *C. Summary of CKFD* [11]

In summary of CKFD, it is a two-phase algorithm: KPCA and LDA. The algorithm can be described by the following:

***Step 1.*** Use KPCA to transform the input space $IR^n$ into an $m$ -dimensional space $IR^m$, where $m = rank(R)$ . $R$ is the centralized Gram matrix. Pattern $x$ in $IR^n$ transformed to be KPCA-based feature vector in $IR^m$ .

***Step 2.*** In $IR^m$ , construct the between-class and within-class scatter matrices $S_b$ and $S_w$ . Calculate $S_w$ 's orthonormal eigenvectors, $\alpha_1, \alpha_2, \ldots \alpha_m$ , assuming the first $q$ ones are corresponding to positive eigenvalues.

***Step 3.*** Extract the regular discriminant features: Let $P_1 = (\alpha_1, \alpha_2, \ldots \alpha_q)$ . Define $\tilde{S}_b = P_1^T S_b P_1$ and $\tilde{S}_w = P_1^T S_w P_1$ and calculate the generalized eigenvectors $u_1, \ldots u_d$ ( $d \le c-1$ ) of $\tilde{S}_b \varepsilon = \lambda \tilde{S}_w \varepsilon$ corresponding to the $d$ largest positive eigenvalues Let $U = (u_1, u_2, \ldots u_d)$ . The regular discriminant feature vector is $z^1 = U^T P_1^T y$ .

***Step 4.*** Extract the irregular discriminant features: Let $P_2 = (\alpha_{q+1}, \alpha_{q+2}, \ldots \alpha_m)$ Define $\hat{S}_b = P_2^T S_b P_2$ and calculate $\hat{S}_b$ 's orthonormal eigenvectors $v_1, v_2, \ldots v_d$ $(d \le c-1)$ corresponding to the d largest eigenvalues. Let $V = (v_1, v_2, \ldots v_d)$ .The irregular discriminant feature vector is $z^2 = V^T P_2^T y$ .

***Step 5.*** Fuse the regular and irregular discriminant features using summed normalized-distance for classification.

The algorithm of fusing the two kinds of information can be found in [11].

## IV. Experiments

In this paper, the fusion coefficient of CKFD is chosen as $\theta = 0.6$. In addition, the kernel function is chosen a fractional power polynomial function that was applied successfully in face recognition [13]:

$$k(x, y) = (x \bullet y)^d \tag{5}$$

$d$ is chosen as 0.6 in our experiments. In our experiments, we used the JAFFE database [3] to train and test the system. The database contains 200 images of ten Japanese females expressing one of seven facial expressions (happy, sad, angry, fearful, surprised, disgusted, and neutral). Every expression of each person has three samples, indexed by 1, 2 and 3. Let us denote them as $T_1$, $T_2$ and $T_3$. The experiment uses two of them to train a 1-NN classifier, the rest one is used as testing data. We repeat the experiment three times by changing the train samples and test samples according the index. All facial images are firstly preprocessed by some common methods and scaled to fixed size of 128×96 pixels. Secondly the Gabor features and Pyramid Gabor features of all images are extracted. At last, the nearest neighbor rule is used to classify the facial expression images. The experiment results of computation time and recognition accuracy comparison between traditional Gabor features and the proposed pyramid Gabor features are given in table 1, 2, and table 3.

From the table 1, we see that the computation involved for Pyramid Gabor features extraction is much less than traditional Gabor feature extraction. From table 2 and table 3, it can be seen that: 1). The proposed Pyramid Gabor features can reach the better performance than traditional Gabor feature for facial expression recognition. 2). CKFD can be applied in the field of FER successful. And it is found that the irregular information is more dicriminant for facial expression recognition than regular features.

**Table 1.** The time-consuming comparison between
Gabor features extraction and Pyramid Gabor features extraction

| | Gabor features | Pyramid Gabor features |
|---|---|---|
| All images | 11minutes and 44 seconds | 5 minutes and 32 seconds |
| One image | 3.52 seconds | 1.66 seconds |

**Table 2.** Gabor features-Based methods recognition rate

| | Linear method | | | CKFD | | | |
|---|---|---|---|---|---|---|---|
| Testing set | 1-NN classifier | PCA | PCA+LDA | KPCA | Regular features | Irregular features | Fusion |
| T1 | 75.76% | 83.33% | 92.42% | 86.36% | 89.39% | 93.94% | 92.42% |
| T2 | 82.81% | 92.19% | 98.44% | 85.94% | 95.31% | 98.44% | 98.44% |
| T3 | 76.11% | 83.58% | 95.52% | 83.58% | 88.06% | 95.52% | 95.52% |
| Average | 78.22% | 86.37% | 95.46% | 85.29% | 90.92% | 95.97% | 95.46% |

**Table 3.** Pyramid Gabor features-Based methods recognition rate

| | Linear method | | | CKFD | | | |
|---|---|---|---|---|---|---|---|
| Testing set | 1-NN classifier | PCA | PCA+LDA | KPCA | Regular features | Irregular features | Fusion |
| T1 | 66.67% | 78.79% | 93.94% | 75.76% | 90.91% | 93.94% | 95.45% |
| T2 | 76.56% | 90.62% | 98.44% | 93.75% | 96.88% | 100% | 100% |
| T3 | 73.13% | 80.60% | 94.03% | 82.09% | 88.06% | 98.51% | 97.01% |
| Average | 72.12% | 83.34% | 95.46% | 83.87% | 91.95% | **97.48%** | **97.48%** |

## V. Conculsion

This paper presents new pyramid Gabor features for facial expression recognition that can reach better performance than traditional Gabor features and involve less computations. We expand the CKFD algorithm to the field of FER with the pyramid Gabor feature and encouraging experimental results were achieved. We provide an insight onto the performances of the two kinds of features: regular and irregular in facial expression recognition. From the experiments results, it has been seen that the irregular information is more dicriminant for facial expression recognition.

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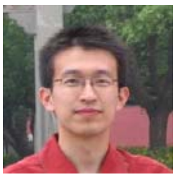

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