Robust Face Recognition Using Multiple Self-Organized Gabor Features and Local Similarity Matching

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Abstract

Gabor-based face representation has achieved enormous success in face recognition. However, one drawback of Gabor-based face representation is the huge amount of data that must be stored. Due to the nonlinear structure of the data obtained from Gabor response, classical linear projection methods like principal component analysis fail to learn the distribution of the data. A nonlinear projection method based on a set of self-organizing maps is employed to capture this nonlinearity and to represent face in a new reduced feature space. The Multiple Self-Organized Gabor Features (MSOGF) algorithm is used to represent the input image using all winner indices from each SOM map. A new local matching algorithm based on the similarity between local features is also proposed to classify unlabeled data. Experimental results on FERET database prove that the proposed method is robust to expression variations.

1. Introduction

Important practical applications of automatic face recognition have made it a very popular research area in the last three decades. Although humans can detect and identify faces in scene with a little or no effort, building an automated system that accomplishes such objectives is, however, very challenging [10]. The challenges are even more profound when one considers the large variations in the visual stimulus due to illumination conditions, partial occlusion, viewing directions or pose, and facial expression.

Solving face recognition problem can be mainly divided into two subtasks, feature extraction and feature classification. In general, there are two feature extraction approaches, global and local methods. In global methods, a face image is represented by a high dimensional vector containing all pixel values, the dimensionality corresponds directly to the number of pixels in the image. A common way to reduce the huge dimensionality of the feature vector is to employ one of the various dimensionality reduction techniques such as Principal Component Analysis (PCA) [8], Linear Discriminant Analysis (LDA) [3]. On the other hand, local approaches describe only local region/part of the image by some transformation techniques such as Gabor filters [9] and Local Binary Pattern (LBP) [1]. Local feature methods exhibit a strong robustness against local distortions in the face due to expression, occlusion and illumination variations.

Among the varieties of local feature extraction methods, Gabor wavelets is considered as the most successful one due to its robustness against illumination, rotation, and scale variations. Algorithms employed Gabor filters can be classified into two categories, analytic [9] and global [5] methods. Analytic methods extract feature from a set of selected facial landmarks, while global methods extract features at each pixel then concatenate these features to construct one global vector for the whole face.

In this paper, a new Gabor-based face recognition system is proposed. Multiple self-organized maps are used to learn the distribution of Gabor features. In order to handle local distortion caused by shift or misalignment variations, a MAX filter is applied on the Gabor filter response. For each pixel in the face, one self-organizing map (SOM) [4] is trained using a set of Gabor features extracted from training face images. Gabor space is quantized by the SOM which has a limited number of neurons. To recognize an input image, a feature vector constructed from the set of winner neurons of each SOM map is used by the proposed Local Similarity Matching (LSM) algorithm. LSM algorithm compensates local feature changes due to different expression variations using two tricks. First, using Gaussian function helps to give large similarity values for similar
local features and small values for dissimilar ones. Second, discriminative regions like eyes take large weights while features from mouth region, which greatly affected by expression variations, take small weights.

2 Proposed Face Recognition System

The architecture of the proposed face recognition system is shown in Fig. 1. The Multiple Self-organized Gabor Features (MSOGF) algorithm first derives a Gabor feature vector using a set of Gabor wavelets at each point in the input image. MAX filter is then applied to reduce the dimension of the Gabor response and to tolerate for shift or misalignment variations. The set of Gabor features extracted from training face database at each pixel are used to create a local feature map using self-organizing map learning algorithm.

The rationale behind integrating Gabor wavelet and SOM is twofold. On the one hand, the Gabor transformed face images exhibit strong characteristics of spatial locality, scale and orientation selectivity. These images can thus produce salient local features that are most suitable for face recognition. On the other hand, SOM would further reduce the redundancy and represent Gabor features in a set of topological ordered nodes. In which the features are encoded only by the position of the best matching nodes. The feature image is represented by a set of winner neurons in which each winner represents a local facial feature.

Finally, to identify an unlabeled input face image, a classifier should be built on the top of SOM maps. We propose a new Local Similarity Matching (LSM) algorithm. LSM algorithm uses Gaussian function to calculate the local similarity between each input local feature and all corresponding features in the gallery images. The similarity values for all local features are combined to produce the final similarity score. The advantage of LSM algorithm is that the local similarities can be weighted according to its importance in discrimination. Furthermore, some features which change significantly due to expression variations can be weighted less while the most stable features can be amplified. More details about each component in the proposed face recognition system will be given in the following subsections.

2.1 Multiple Self-Organized Gabor Features (MSOGF)

Gabor filters are used for image analysis because of their biological relevance and computational properties such as spatial locality and orientation selectivity. In this paper, the following form of a 2D Gabor filter function in the continuous spatial domain has been employed:

\[
\psi(x, y, \theta, \lambda, \gamma) = e^{-\frac{x'^2 + y'^2}{2\sigma^2}} \cos\left(2\pi \frac{x'}{\lambda}\right) \tag{1}
\]

\[
x' = x \cos \theta + y \sin \theta, \quad y' = -x \sin \theta + y \cos \theta \tag{2}
\]

The Gabor wavelet representation of an image is the convolution of the image with a family of Gabor kernels as defined by Eq. (1). Let \(I(x, y)\) be the gray level distribution of an image, the convolution output of image \(I\) and a Gabor kernel \(\psi(x, y, \theta, \lambda, \gamma)\) is normalized to unit length in order to reduce the effect of lighting variations, the following equation define a normalized Gabor feature vector:

\[
O(x, y, \theta, \lambda, \gamma) = \frac{I(x, y) \ast \psi(x, y, \theta, \lambda, \gamma)}{\|I(x, y) \ast \psi(x, y, \theta, \lambda, \gamma)\|} \tag{3}
\]

We previously examined the distribution of Gabor filter response around center of eyes using principal component analysis algorithm [2]. The results reveal that the distribution exhibits a nonlinear manifold in the Gabor space, in this sense linear projection methods may fail to model these variations. Therefore, we utilize self-organizing map to learn this curved distribution for each point in the face.

SOM network [4] is a biologically motivated neural network, which emulate the ability of the brain to map the outside world into cortex, where nearby stimuli are coded on nearby cortical areas. A pattern is projected from an input space to a position in the map where the information is coded as the location of the activated neuron. The SOM codebook has the following two characteristics. First, the probability distribution function (PDF) of the codebook is a good approximation for the PDF of the training data. Second, the
topographic order of the training data is preserved in the codebook even if the dimensionality of the SOM is smaller than that of training data. The second characteristic means that similar features are mapped to nearby positions in the feature map. These characteristics make SOM an appropriate choice to learn the distribution of Gabor features.

The Multiple Self-Organizing Map (MSOM) network shown in the top part of Fig. 1 consists of one SOM map for each feature point in the input Gabor response. The number of SOMs in X and Y directions are decided by the width and height of the input Gabor response image respectively. SOM map receives its input from the response of all Gabor filters at different scale and orientation at specific point in the input image. The MSOGF training algorithm uses the batch learning algorithm of SOM to construct its feature maps. The learning process is applied separately for each map where the normal learning algorithm of SOM is used to update each unit in the map. All SOMs in the MSOM network can be trained in parallel. After presenting the input pattern to the SOM network, the training algorithm find the best matching winner from its corresponding feature map and update the weights of this winner and its neighbors. This process is repeated for each SOM in the MSOM network. In the recognition phase, the competition is also applied for each map separately. The network uses the same competition algorithm used by the SOM to find the winner. Then the winner position indices of all SOMs are integrated to construct the feature image.

### 2.2 Local Similarity Matching

In order to identify unlabeled faces based on the features extracted from MSOGF algorithm, a new local matching algorithm is proposed. Recently, Soft-KNN [7] algorithm which is a modified version of KNN algorithm is proposed. In Soft-KNN algorithm, an ensemble of local KNN is employed to output a confidence vector contains the similarity between the local feature of the input and all corresponding features in the training data. Although the algorithm exhibit a robustness against expression and occlusion variations, selecting appropriate K parameter is a difficult task.

The proposed algorithm is an extension for the Soft-KNN algorithm by replacing each local KNN with a Gaussian function. The Gaussian function measures the similarity between each corresponding local features. Therefore, the contribution of similar local features will increase while the contribution of dissimilar features will significantly decreased. The width of the Gaussian function (\(\alpha\)) controls the contribution of the similarity values in the total similarity value.

Given \(C\) classes, to decide which class the test face \(x\) belongs to, a set of \(M\) local features are extracted using the MSOGF algorithm. Then a similarity matrix, describing the similarity between the test face and every training face in the new feature space is calculated. The matrix can be described as follows:

\[
S(x) = \begin{bmatrix}
  s_{11} & s_{12} & \ldots & s_{1C} \\
  s_{21} & s_{22} & \ldots & s_{2C} \\
  \vdots & \vdots & \ddots & \vdots \\
  s_{M1} & s_{M2} & \ldots & s_{MC}
\end{bmatrix}
\]

where \(s_{ij}\) is the local similarity vector, whose element \(s_{jk}\) is the similarity between the \(j^{th}\) neuron of the test face and the corresponding neuron of the \(k^{th}\) class in the same SOM feature map. Since each SOM represents features from local region of the face, it can be expected that some of the regions contain more discriminative information than others. For example, eyes seem to be an important feature in human face recognition compared with features from nose and mouth. To take this advantage, a weight \(w_j\) can be set for each region based on the importance of the information it contains. In the experiment, face image is divided into three horizontal regions which contains eyes, nose, and mouth features. The weights for each region are selected as follows: \(8\) for eyes features, \(4\) for nose features, and \(1\) for mouth features. Finally, the label of the test image can be obtained through a linearly weighted voting scheme, as follows:

\[
Label = \arg\max_k \left( \sum_{j=1}^{M} w_j s_{jk} \right), \quad k = 1, \ldots, C.
\]

### 3 Experimental Results

The FERET database [6] contains now 13539 facial images corresponding to 1565 subjects, which diverse across gender, ethnicity, and age. Several standardized subsets of FERET images have been defined, including a common set of gallery images \(fa\) and four different probe sets. In this study, the common gallery images \(fa\) are used for training, which consists of 1196 subjects with one image per person, while \(fb\) probe set is selected for testing, which contains 1195 images. Only
facial expression variation is involved between the corresponding images in $fa$ and $fb$. Before the recognition process, the raw images were cropped to contain face region only and scaled to $48 \times 48$ pixels. The cropped face region is normalized using histogram equalization and zero-mean unit-variance. The parameters for MSOGF algorithm are set as follows: size of MAX filter is $3 \times 3$, number of SOMs is $16 \times 16$ and the number of neurons in each SOM vary according to the number of training patterns.

Local features are extracted from training images using a set of Gabor filters at one size ($9 \times 9$ pixels) and 4 orientations $\theta \in \{0, \frac{\pi}{4}, \frac{\pi}{2}, \frac{3\pi}{4}\}$. Then a MAX filter of size $3 \times 3$ is employed to reduce the dimensionality of Gabor response and to tolerate for shift and distortion variations, and hence the number of SOMs is $16 \times 16$. For each pixel in the face, one SOM map was trained in batch mode using the obtained Gabor features. The initial weights of all neurons were set to the greatest eigenvectors of the training data, and the neighborhood widths of the neurons converged exponentially to 1 with the increase of training time, and only 100 updates were performed. Both classical KNN classifier (K=1) and the proposed Local Similarity Matching (LSM) algorithm were compared to perform the final classification decision. The $\alpha$ parameter of the Gaussian function for the LSM algorithm is set to 1.

The recognition accuracy are calculated with changing the number of gallery size from 100 to 1196. All features extracted by MSOGF are fed into KNN classifier and LSM algorithm for comparison. The weights for each region in the face is set to give high values to the eye features and small values for mouth feature which extremely change with varying expressions. The results shown in Fig. 2 reveal that LSM algorithm outperform KNN as the number of gallery images increase. Moreover, local features based on Gabor filters are more robust to expression variations than global features extracted by principal component analysis algorithm.

4 Conclusion and Future Works

In this paper, we addressed the problem of learning Gabor feature distribution using multiple SOMs. Employing MAX filter on the Gabor response tolerates for shift and distortion variations and helps to significantly reduce the computational cost as well. SOM can be used successfully to learn the nonlinear distribution of Gabor features. Furthermore, local similarity matching algorithm seems to be more efficient than KNN algorithm to handle expression variations. In the future, we will investigate the capability of the proposed method to tackle both expression and occlusion variations.

Figure 2. Recognition accuracy of MSOGF and Eigenfaces algorithms on FERET database as a function of gallery size.

References