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Optimal Gabor Kernel's Scale and orientation selection for face classification

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Abstract

2D Gabor-based face representation has attracted much attention. However, owing to the fact that Gabor features are redundant and too high-dimensional, appropriate feature dimension reduction appears to be much more paramount. Allowing for each individual Gabor feature constructed by a combination of scale and orientation pair, we equate feature dimension reduction problem to optimal Gabor kernels' scales and orientation selection problem. Genetic algorithms (GAs) have represented a useful tool for optimal subset selection. However, population premature and optimization stagnancy problems exist in traditional GAs. Here we present an improved algorithm: Hybrid Genetic algorithms-based (HGAsb), which introduces the concept of the simulated annealing into traditional GAs to effectively solve the problems mentioned above and to improve optimization efficiency. Experimental results on IMM face database demonstrate that in contrast to GAs, our proposed algorithm can provide 4.25 improvements. The distributions of orientations and scales of the selected features by HGAsb are also analyzed. Results indicate that the features in the larger scales have equal importance as those in the smaller scales in discriminating nuance of faces. The features in horizontal, vertical and 225° orientations have more discriminative power.

Keywords: Gabor; Genetic algorithms (GAs); Simulated annealing

1. Introduction

A good face recognition methodology should consider representation as well as classification issues. There are mainly two approaches for face representation: holistic and feature-based. In the holistic approaches, statistical methods are used to represent face images as a whole. However, feature-based methods try to extract local features from face images. Often, feature-based approaches require the localization of fiducial points. Early attempts use typical geometrical features such as the location and relative positions of facial features (i.e. eyes, nose). Recently, 2D Gabor wavelet-based methods are used [1,2] for local feature-based human face representation.

In 2D Gabor wavelet-based method, sparse sampling at the fiducial points in face images is carried out and local features are extracted using multi-scales and multi-orientation Gabor kernels. Typically, the features extracted by this method have large dimensionality. Therefore, in order to reduce Gabor features' dimension and eliminate redundant features, it is required to statistically analyze the contribution of each feature vector to the recognition task, i.e. measuring the relative importance of each fiducial point and the effect of Gabor kernels' scales and orientations used. Kruger [3] and Malsburg [4] examined the discriminative power of the nodes of a graph that is placed over face features. The aim was to learn the weight of nodes for face discrimination. The problem is formulated as an optimization problem. According to their results, the eyes are more important for discrimination of half profiles and frontals than the mouth and chin. In contrast, research on contribution of each scale and orientation to face representation has not received the amount of attention it deserves.

In this paper, in order to make clear the effect of each scale and orientation on face recognition performance and to select optimal ones among them, we assume that all

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fiducial points important to face classification are equal and reduce the scale and orientation selection problem to a feature selection problem. According to maximization of criterion function that is used to evaluate the quality of selected features subset from original features, the optimal feature vectors, i.e. optimal scales and orientations, in terms of face classification are selected. The criterion function can be inter-class distance measure or the classification rate of a classifier. The optimal solution could be found by exhaustive search. However, for higher-dimensional problem, this solution is unusable. Alternatively, several fast sub-optimal algorithms such as sequential forward selection, sequential backward selection, plus-L-minus-R and floating search methods are frequently used [5]. As it is demonstrated in [6] that sub-optimal algorithms above are inferior to Genetic algorithms (GAs) [7,8], which allows searching for solutions spaces by simultaneously considering multiple interacting attributes and can obtain optimal or near-optimal solutions on complex, large spaces of possible solutions.

Whereas, there are two potential problems existing in traditional GAs: (1) in the initialization stage, there may be a few individuals with very high values of fitness, these individuals will reproduce abundantly and become preponderant, but then the population will lose the variety and result in prematurity; (2) in the terminative stage of GAs, the fitness values of all individuals are close to each other, and the selection probability of each individual is almost equivalent. The capability of searching for the optimal solution will not be improved prominently and the optimization process will be stagnated. Here, we present our improved algorithm, Hybrid Genetic algorithms-based (HGAsb) to efficiently solve the above problems and find the scales and orientations with most discriminative power from Gabor kernels.

2. Gabor feature extraction

As main local facial features, eyes, nose and mouth often contain the most distinguishable information of a given individual. However, it is very hard for computers to form a stable geometrical representation as we describe a face in our daily life. In our work, 2D Gabor wavelet is applied to create a representation of local facial features. The Gabor kernels can be defined as follows:

$$\varphi_{u,v}(z) = ||k_{u,v}||^2 \exp(-||k_{u,v}||^2||z||^2/2\sigma^2) \times(\exp(\mathrm{i}k_{u,v}z) - \exp(-\sigma^2/2))/\sigma^2, \quad (1)$$

where u and v define the orientation and scale of the Gabor kernels. $z = (x, y)$, $\|\bullet\|$ denotes the norm operator, and the wave vector $k_{u,\,v}$ is defined as

$$k_{u,v} = k_v \exp(\mathrm{i}\phi_u), \quad (2)$$

where $k_v = k_{\max}/f^v$ and $\Phi_u = \pi u/8$. $k_{\max}$ is the maximum frequency and f is the spacing factor between kernels in the frequency domain. Here we would use Gabor wavelets of five different scales, $v\in\{0, 1,\ldots,4\}$, and eight orientations, $u\in\{0, 1,\ldots,7\}$. Other parameters are taken as $\sigma = 2\pi$, $k_{\max} = \pi/2$ and $f = 1.414$.

The Gabor wavelet representation of an image is the convolution of the image with a family of Gabor kernels. Let $I\,(x, y)$ be the gray-level distribution of an image. The convolution of image I and Gabor kernel $\phi_{u,v}$ is defined as follows:

$$O_{u,v}(z) = I(z) * \varphi_{u,v}(z), \quad (3)$$

where* denotes the convolution operator, and $O_{u,v}(z)$ is the convolution result corresponding to the Gabor kernel in orientation u and scale v. Now we form a set $Q = \{O_{u,v}\,(z)$: $v\in\{0, 1,\ldots,4\}$, $u\in\{0, 1,\ldots,7\}\}$, where z refers to all pixels in the image.

We define a set Θ to denote all fiducial points coordinates. That is to say, if a pixel $z = (x, y)$ in the image is a fiducial point, $(x, y)\in\Theta$. We construct a vector $O_{u,v}$ by concatenating all fiducial points' Gabor response in orientation u, and scale v:

$$O_{u,v} = [O_{u,v}(z_1), O_{u,v}(z_2), O_{u,v}(z_3), \ldots, O_{u,v}(z_P)]^{\mathrm{T}} \quad z_i = (x_i, y_i) \in \Theta, \quad (4)$$

where P is the number of fiducial points. If we encompass $O_{u,v}$ in all orientations and scales, an augmented matrix Ω is formed:

$$\Omega = (O_{0,0}\ O_{1,0}\ \cdots O_{7,4}). \quad (5)$$

Each element in Ω is a vector that encompasses all fiducial points' Gabor feature in current orientation and scale, and the size of Ω is $P\times 40$. Feature vector Ω is referred to as facial local Gabor features.

3. The hybrid GAs-based feature selection (HGAsb)

In GAs, the search space of a problem is represented as a collection of individuals. The individuals are represented by character strings, which are referred to as chromosomes. A collection of such strings is called the population. The purpose is to find the individual from search space with the best 'genetic material'. The quality of an individual is measured with an objective function or the fitness function. Based on the principle of survival of the fittest, a few of the strings are selected and each is assigned a number of copies that go into the mating pool. Biologically inspired operators like crossover and mutation are applied on these strings to yield a new generation of strings. The process of selection, crossover and mutation continues for a fixed number of generations or till a termination condition is satisfied. Our schema of HGAsb that takes advantage of the simulated annealing is given as follows.

3.1. String representation (feature subset encoding)

An individual is a binary bit string whose length is determined by the number of elements in Ω, namely the length L is equal to 40. Each element in Ω is associated with one bit in the string as shown in Fig. 1. If the ith bit is equal