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Facial expression recognition and its application based on curvelet transform and PSO-SVM

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ABSTRACT

A novel method is proposed for facial expression recognition combined curvelet transform with improved support vector machine (SVM) based on particle swarm optimization (PSO). The whole process is as follows. Firstly, as wavelet transform in two-dimension is good at isolating the discontinuities at edge points and only captures limited directional information, the curvelet transform is applied to extract facial expression feature substitutively. However, the amount of curvelet coefficients obtained in the first stage is too huge to be classified, therefore, all of the coefficients are sorted descendantly and the former larger 5 or 10% are remained while the others abandoned to reduce the dimension. Finally, PSO algorithm is employed to search for the reasonable parameters of SVM to increase classification accuracy. Experimental results demonstrate that our proposed method can form effective and reasonable facial expression feature, and achieve good recognition accuracy and robustness, which is competent for spirit states detection of operators to decrease defect rate of production.

1. Introduction

Sensibilities are one of the intrinsic symbols of our human kind, which play great important role in perception, inference, decision, plan, and social activities. With the development of emotional intelligence, brain science and information technology, affective computing has been an intersectional discipline attracting many researchers' attention. It is widely accepted by psychologists that "affection express = 7% language + 38% voice + 55% facial expression" [1]. Therefore, emotion is an externality of affection, while facial expression embodies abundant emotion information.

Face recognition and facial expression recognition have been paid much attention in the past two to three decades, which play important role in such areas as access control, human–computer interaction, production control, e-learning, fatigue driving detection, and emotional robot. There are ordinarily seven kinds of facial expression to be classified: anger, disgust, fear, happiness, sadness, surprise and neural. In general, a facial expression recognition system includes three key steps: face detection and normalization; feature extraction and discriminant analysis; classification and verification.

Of the above three steps, facial feature extraction is most crucial to the effect of face recognition and facial expression recognition, in that only precise extraction of a representative feature set will greatly improve the performance and effect of classification algorithm. A great number of algorithms have been proposed for facial feature extraction, of which the most well-known and widely applied is wavelet transform. Wavelet transform is considered to be a significant feature extraction tool at one time for its ability of localization in both time and frequency domain. However, it can only capture the point singularities in images, while is helpless in curves and lines, which exactly are the remarkable features of human face. Studies in human visual system and image statistics show that an ideal image representation or a feature extraction method should satisfy the following five conditions: multi-resolution, localization, critical sampling, directionality and anisotropy. Therefore, a new multi-scale geometric analysis tool – curvelet transform is more suitable for facial feature extraction than wavelet transform [2–4].

Several researches have been performed in pattern recognition based on curvelet transform. Mandal and Wu proposed a face recognition algorithm combing curvelet and PCA [5]. El Aroussi et al. introduced a method combing curvelet and LDA for face recognition [6]. Kazemi et al. proposed a numeral algorithm combing curvelet and SVM for vehicle recognition [7]. Saha et al. put forward the use of curvelet entropy for classifying facial expressions [4]. However, little work has been done to reveal the potential of curvelet transform in facial expression pattern recognition situation.

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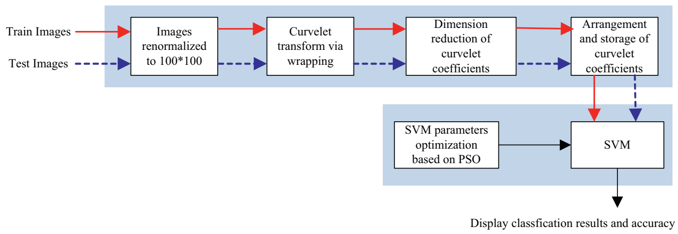

Fig. 1. The whole flow chart of our algorithm.

In this paper, a novel method is proposed for facial expression recognition based on curvelet transform and improved PSO-SVM. The rest of this paper is organized as follows. In Section 2, the whole flow chart of our proposed algorithm is described. The expression feature extraction method using curvelet transform and then dimension reduction is proposed in Section 3. In Section 4, the principle of SVM is introduced and then SVM parameters optimization is realized based on PSO algorithm. Experimental results are given out in Section 5, while discussion and conclusion are in Section 6.

2. Flow chart

The proposed method is based on facial image decomposition of curvelet transform and then uses dimension reduction of curvelet coefficients for expression recognition. Distinctive feature sets generated by curvelet transform are used to train and test a SVM classifier. The whole flow chart of our algorithm is shown in Fig. 1, which mainly includes two parts: facial expression extraction based on curvelet transform and facial expression classification based on PSO-SVM, shaded in Fig. 1, respectively.

The whole procedure is explained as follows in more details. Firstly, the original facial images 256×256 are renormalized to 100×100 uniformly. All the images are randomly divided into training images (solid red line) and testing images (dotted blue line). Then the curvelet transform via wrapping is performed to generate facial images' features at different angles and scales since it offers superior performance in presence of singularities in higher dimension, and enhances localization of higher frequency components with minimized aliasing effects. The number of the obtained curvelet coefficients for each image is enormous, therefore, the dimension reduction is carried out by the method that all the coefficients are sorted descendantly and only the former larger 5% or 10% are remained to convert to a vector to minimize computational complexity of our framework. Lastly, SVM parameters are optimized by PSO algorithm and then applied to facial expression recognition, with the classification and accuracy results displayed.

3. Curvelet transform

3.1. The principle of curvelet transform

Curvelet transform is one kind of multi-resolution analysis tools, firstly proposed by Candes and Donoho in 1999 [8]. The obvious disadvantage of the first generation of curvelet transform is its rather slow performance. The second generation of curvelet transform is proposed by Candes and Donoho in 2006 [9]. Compared to the first generation curvelet transform, the second generation has simpler concept, faster speed and lower degree of redundance, therefore, it is used widely and adopt to extract curvelet coefficients in this paper.

Wavelet transform has been profusely employed in many occasions of pattern recognition and image processing for its capability of detecting singularities. It is good at representing points singularities in both one-dimensional and two-dimensional signals, however, it often fails to detect curves singularities efficiently, in that the standard wavelet transform only has wavelets in primary vertical, horizontal and diagonal orientations. In general, images do not always exhibit isotropic scaling and thus the above limitations of wavelets require the other kinds of multi-scale representation tools. The curvelet transform is suitable in that it has been developed specially to represent objects with "curve-punctuated smoothness", namely the objects which display smoothness except for discontinuity along a general curve.

The different capability of edge representation between wavelet transform and curvelet transform is that for the square shape of wavelets at each scale, more wavelets are needed for an edge representation than that of required curvelets, which are of elongated needle shape. The essential novelty of curvelet transform is that it is based on anisotropic scaling principle, while wavelets rely on isotropic scaling [10].

To summarize, wavelet transform suffers from the following three limitations: (1) though wavelets perform better edge representation than fast Fourier transform (FFT), it is not optimal and inferior to curvelet transform. (2) Wavelets only represent crude directional elements independent of scale. (3) Wavelets are based on isotropic scaling while without highly anisotropic element. In contrast, curvelet transform is capable of solving the above problems, which is fit for extracting facial expression features.

3.2. Implementation of curvelet transform

There are two implementation methods of curvelet transform: the first is based on unequally spaced fast Fourier transforms (USFFT), while the second is based on the wrapping of specially selected Fourier samples. These two implementations essentially differ by the choice of spatial grid used to translate curvelets at each scale and angle, while they both return a table of digital curvelet coefficients indexed by a scale parameter, an orientation parameter, and a spatial location parameter. Curvelet transform via wrapping is chosen for this paper as it is the fastest curvelet transform currently available, and the implementation steps are described as follows [9]:

Step 1: Apply the 2D FFT and obtain Fourier samples $\hat{f}[n_1, n_2]$, $-n/2 \le n_1, n_2 < n/2$.

Step 2: For each scale j and angle ℓ, form the product $\tilde{U}_{j,\ell}[n_1, n_2]\hat{f}[n_1, n_2]$.

Step 3: Wrap this product around the origin and obtain $\tilde{f}_{j,\ell}[n_1, n_2] = W(\tilde{U}_{j,\ell}\hat{f})[n_1, n_2]$, where the range for n_1 and n_2 is now $0 \le n_1 < L_{1,j}$ and $0 \le n_2 < L_{2,j}$, for $-\pi/4 < \theta < \pi/4$.

Step 4: Apply the inverse 2D FFT to each $\tilde{f}_{j,\ell}$, hence collect the discrete coefficients $c^D(j, \ell, k)$.

3.3. Dimension reduction of curvelet coefficients

The amount of curvelet coefficient obtained in 3.2 is extremely large. For example, for the original image with size of 256×256, the amount of scale in curvelet transform set by $\log_2(\min(M, N)) - 3$ (here M and N are the length and width of the image, respectively), and the amount angle in the second subband set 16, then the number of curvelet transform coefficients comes up to 184,985 correspondingly. If all these coefficients are used for facial expression recognition, the computational load of classification algorithm is too complex and the requirement of computer configuration is high-level. Therefore, the original images are renormalized from 256×256 to 100×100 uniformly, with the amount of curvelet coefficients of each image reduced to 28,097 accordingly if the parameters set as above.