Haar Wavelet Transform Based Facial Emotion Recognition

Siyuan Lu^{1, a} and Fidel Evans^{2 3, b}

¹School of Computer Science & Technology, Nanjing Normal University, Nanjing, 210023, China

²Herbert Wertheim College of Engineering, University of Florida, Gainesville, FL 32611, USA

³School of Information, Florida State University, Tallahassee, FL 32304, USA

^a269125022@qq.com, ^bf.evans.uf@gmail.com

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Abstract. In order to propose an effective emotion recognition system, this paper proposed a novel Haar wavelet transform based emotion recognition system. This system is based on facial expression images obtained by digital camera. Our method used principal component analysis as the dimensionality reduction approach. The support vector machine (SVM) was used as the classifier. The results showed that our method achieved an accuracy of $78.37 \pm 1.50\%$. In all, our method is effective in emotion recognition.

Background

Emotion recognition (ER) identifies the motion of humans. The typical methods are based on facial expression images obtained by digital camera. Traditional ER methods are usually developed a three-stage algorithm: feature extraction, feature reduction, and classification. Besides, ER can be applied to detect neurological and psychiatric diseases.

In the last decade, many new methods were proposed. Drume (2012) [1] proposed a multi-level classifier (MLC). Lu (2016) [2] used biorthogonal wavelet entropy (BWE). In the classification stage, they used fuzzy support vector machine. Yogesh (2017) [3] used a hybrid particle swarm optimization assisted biogeography-based optimization.

In this study, we proposed a novel method based on Haar wavelet transform (HWT), principal component analysis (PCA), and support vector machine (SVM). These three traditional components help the success of our system.

Materials and Methods

The 42 volunteers were enrolled by advertisements. These volunteers lay seven facial expressions (happy, sadness, surprise, anger, disgust, fear, and neutral). Each volunteer showed five different pictures for each emotion, and thus generated in total 35 pictures. For the 42 volunteers, we generated 1470 images. Then, we extract the face region by Photoshop.

The Haar wavelet is a square-shaped functions, which generate a wavelet family. Haar wavelet is the most famous wavelet in the field of discrete wavelet transform [4-9]. Its mother wavelet $\delta(a)$ is defined as:

$$\delta(a) = \begin{cases} +1 & 0 \leq a \leq 1/2 \\ -1 & 1/2 \leq a \leq 1 \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Here a denotes the time domain. The scaling function $\sigma(a)$ is defined as:

$$\sigma(a) = \begin{cases} 1 & 0 \leq a < 1 \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

In this study, we chose to use a three-level Haar wavelet transform.

Afterwards, the principal component analysis (PCA) was used to extract reduced features of at least 98% of the whole variance of original wavelet subband coefficients. The PCA can be regarded as a transformation that the first PC has largest variance, and the following PCs has largest variance and should be orthogonal to preceding PCs [10-15].

In the final stage, we used support vector machine (SVM) as the classifier. The SVM can analyze and classify data into two categories [16-21]. The SVM can generate a pair of hyperplanes, which separate the data of two different classes. Compared to feed-forward neural network [22-27] and multilayer perceptron [28-30], SVM is easy to train and its results are stable. Finally, 10 times of 10-fold cross validation was used to measure the classifier.

Experiments, Results, and Discussions

The sensitivity results of the seven classes by our HWT + PCA + SVM are shown below in Table 1. The overall accuracy result is listed in Table 2. In all, our method achieves an overall accuracy (OA) of $78.37 \pm 1.50\%$.

Table 1 Sensitivity result over 10 runs of 10-fold cross validation

Run	Anger	Disgust	Fear	Happy	Neutral	Sadness	Surprise
R1	76.19	72.86	77.62	81.43	78.57	78.10	79.52
R2	78.10	79.52	80.48	81.43	79.05	77.62	78.57
R3	83.33	81.43	80.00	79.05	77.62	78.10	77.14
R4	82.86	78.10	77.14	77.14	79.05	80.00	77.14
R5	76.19	77.62	77.62	73.81	75.24	77.62	76.19
R6	73.33	72.38	73.81	77.14	75.24	81.43	75.71
R7	81.90	81.43	78.57	80.00	82.86	74.76	80.48
R8	79.05	84.76	79.05	80.48	79.05	77.14	80.95
R9	76.19	76.19	80.00	78.57	79.05	80.00	79.05
R10	75.24	80.48	80.00	74.76	77.14	80.48	78.10
Avr	78.24 ± 3.45	78.48 ± 3.90	78.43 ± 2.01	78.38 ± 2.65	78.29 ± 2.20	78.52 ± 1.96	78.29 ± 1.76

Table 2 Accuracy result over 10 runs of 10-fold cross validation

Run	Accuracy	Run	Accuracy
R1	77.76	R6	75.58
R2	79.25	R7	80.00
R3	79.52	R8	80.07
R4	78.78	R9	78.44
R5	76.33	R10	78.03
Avr	78.37 ± 1.50		

The shortcoming of this method is lack of comparison with state-of-the-art approaches. Besides, we shall try to test kernel SVM [31-33]. Besides, the extreme learning machine (ELM) [34, 35] shall be used as an alternative to our system. Furthermore, the meta-parameters in our system are assigned by experience. In the future, we shall try to use bioinspired algorithms (such as pattern search [36], ant colony algorithm [37], particle swarm optimization [38-40], biogeography-based optimization [41-43], firefly algorithm, artificial bee colony [44-46], artificial immune system, etc.) to seek their optimal values.

Conclusion and Future Research

In this paper, we proposed a novel ER method. Its accuracy achieved $78.37 \pm 1.50\%$. In the future studies, we shall try to increase its identification performance. Besides, the seven emotions may not

cover all the human emotions. Hence, we may try to develop new human emotions based on the slight motions of facial muscles.

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