

Human Facial Expression Recognition Using Fusion of DRLDP and DCT Features



M. Avanthi and P. Chandra Sekhar Reddy

Abstract Recognition of facial expressions is a major challenge in the field of computer vision. Using single-function models, the level of acknowledgment even in controlled capture conditions is considerably small. This paper proposed a method for facial emotion classification with the fusion of dimensionality reduced local directional pattern and discrete cosine transform features using SVM classifier. Local characteristics are extracted utilizing DRLDP, and global characteristics are extracted from facial expression images using DCT. SVM is used to classify the face images into six emotions (surprise, smile, sad, anger, fear and disgust). This method is experimented on JAFFE database and compared with existing approaches shows higher classification rate.

1 Introduction

Facial expression recognition plays an important role in computer vision-based applications like human–computer interaction, video interaction, cataloging, biometrics, including image recovery, with security, etc. Facial expression was its adjustments in the face in support of the inner emotional states as well as intentions of an individual person. Emotion is a familiar word used at a given moment for a person’s feelings like surprise, smile, sad, anger, fear and disgust. Generally, emotions are identified with very little attempt of the human intelligence. Facial emotions machine identification and classification are cumbersome to realize people’s feelings. An algorithmic methodology of classification is used for the labeling in one of the predefined sequences of provided input data. A classification algorithm is a template which executes the input data category.

One is the geometric methods of extraction based on features, while the other is the technique for extraction of features based on appearance. Geometric characteristic methods [1] derive the position but structure of facial components includes nose, eyes, mouth but eyebrows. The remaining part of the paper is organized as follows.

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Section 2 proposed the methodology adopted; experimental results are given in Sect. 3 and conclusion in Sect. 4.

2 Methodology

After acquisition, the next sequence is to extract the information from input data, attributes such as eyes, nose, cheek, mouth, in case of geometric feature-based technique. Two main methods are used for the production of facial expressions (Fig. 1).

2.1 Local Directional Pattern

The local directional pattern is an 8-bit code representing edge responsiveness value. Kirsch masks (M_0, \dots, M_7) shown in Fig. 2 are used to find edge response value in eight directions. LDP is computed considering only three prominent edge responses.

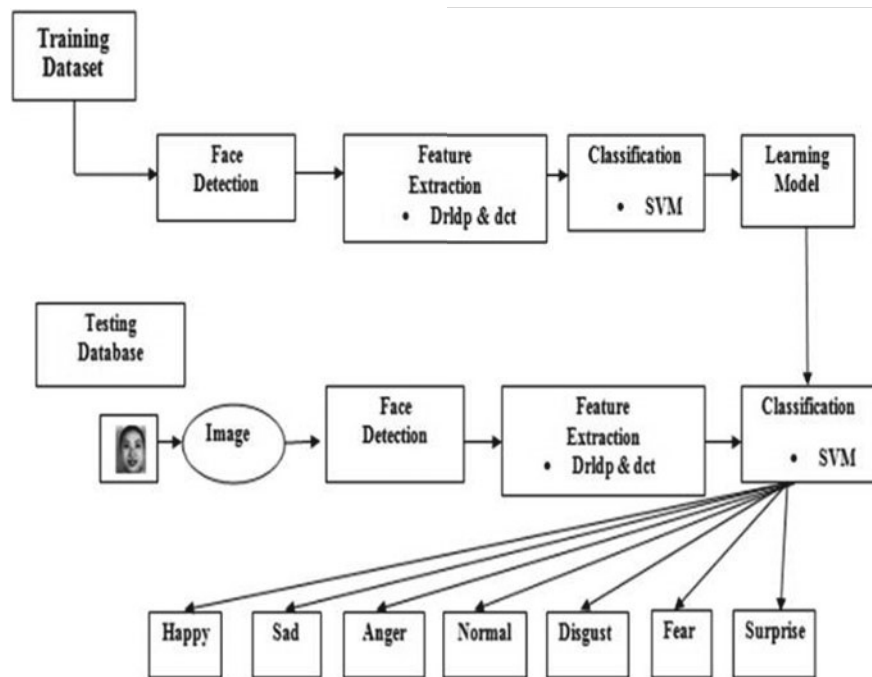


Fig. 1 Architecture of facial expression

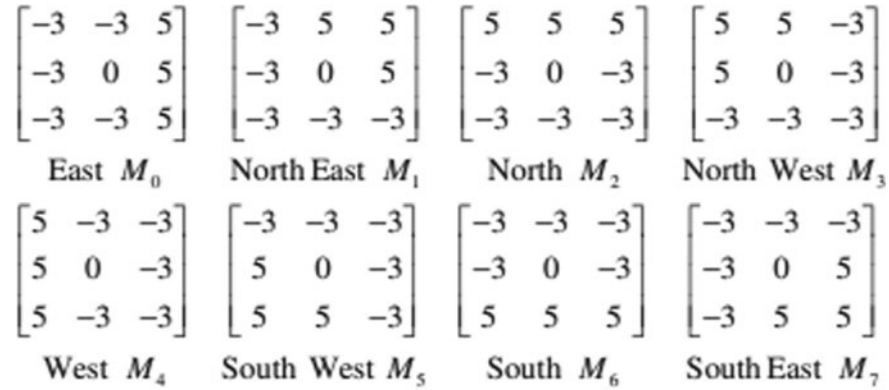


Fig. 2 Edge response masks of Kirsch in eight directions

2.2 Facial Expression Recognition Using DRLDP

In this, human face reorganization method is shown in Fig. 3. The input images are preprocessed to decrease the noise, lighting recompense plus resizing. Then DCT is utilized to extract the feature vector. DRLDP [2] is utilized to diminish the measurements of extracted features. Features be particular as input to SVM classifier pro training the model. Then knowledge information base is updated. SVM classifies the test image into six different expressions such as shock, fear, sadness, joyfulness, vexation and disgust.

2.2.1 Dimensionality Reduced Neighborhood Directional Examples

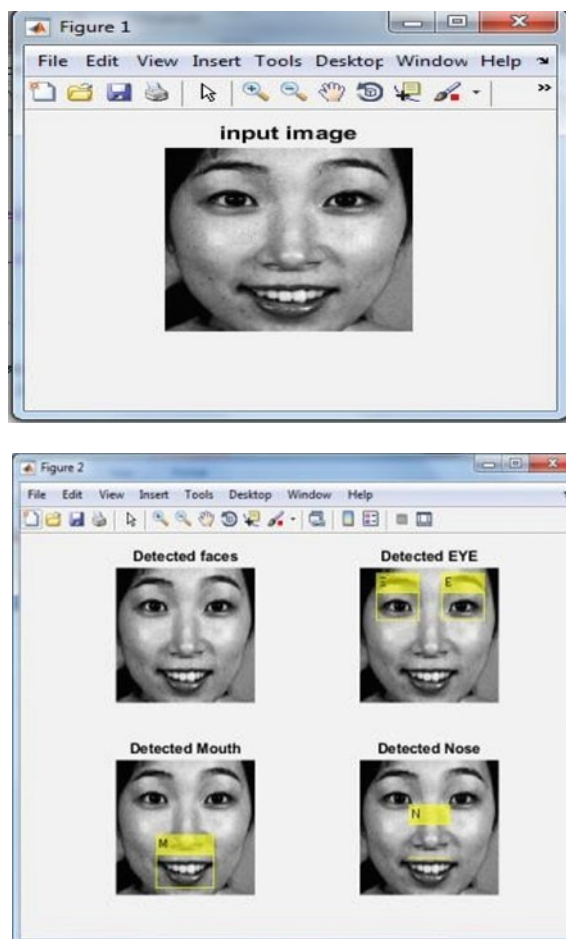
The suggested size reduced neighborhood positional example (DRLDP) is an eight-piece code assigned to each size three to three sub-districts. That software speaks to the square's textural instance. LDP is a single eight-piece code by each 18 a 3/3 square pixel. Both for square, the suggested DRLDP estimates a single eight-piece script. Models such as that of LDP are the suggested DRLDP statistics; however, differences arise in view of the fact which post handling of LDP design elements acquired for a square reduces the illustrations to a solitary eight-piece code.

For example, believe a picture I of size $A \times B$. Let $p = A/t$, and $q = B/u$.

For the picture I, the number of sub-images shaped is $= A \times B t \times u \equiv p \times q$.

The size of every sub-picture is $ai = A/p \times B/q \equiv A \times B/a$ pixels. We describe the RR as the ratio of the no. of pixels in the input picture mapped onto the no. of pixels in the reduced image.

$$\text{Redundancy Ratio(RR)} = \frac{\text{No. of pixel in the input image}}{\text{No. of pixel in reduced image}}$$

Fig. 3 Detected features

$$\text{For an image } I, \text{RR} = \frac{A \times B}{\frac{A \cdot B}{p \times q}} = p \times q = a$$

On the basis of two parameters t and u , the generalized DRLDP is supported. The general practice is to describe filters of size $n \times n$, i.e., a square mask. Therefore, it is unspecified that t plus u are equal.

2.3 Discrete Cosine Transformation

Two-dimensional DCT is used mainly to exclude the worldwide highlights from the exterior presence studies. The full face image is provided as a submission to DCT.

From the start, the image is divided into sub-image squares (8×8), and then subsequently discrete cosine transformation is used to extract the coefficients from each square. DCT produces one coefficient of DC as well as sixty-three coefficients were also dissimilar by each sub-square. Appropriately, it is registered again from above, and it left coefficients. Every sub-squares separated coefficients include ordinary vitality including recurrence information of under-square picture variety. Additionally, the upper as well as left sub-square districts speak to the information on the edge as well as directional substrate.

2.4 Support Vector Machine

Support vector machine—similarly, it is a convincing AI technique or data characterization process; it introduces knowledge visualization into an elevated directional element space, as well as later finds a straight separation of the hyperplane some of the most extreme edges to differentiate data in the specified higher-dimensional space. SVM makes parallel choices, because of that multi-class grouping is capable, and this method teaches double classifiers to split one articulation as a whole, but also produces the largest yield of dual scheme class.

2.5 Classification

For instance, upbeat, shock, outrage, tragic, dread, appall and unbiased will be used for intonation orders, and so on, and multi-class SVM is obtained. Seven categories are used for characterizing knowledge here. SVM is used for the conversion of Gabor highlights into vector structure. At the stage where the photo is provided as details again for test, Gabor is rendered on the direction of such an image, but instead transformed into a vector afterward. The information is isolated in two sections in SVM—training set and testing set, each involving the outline of the property. Each model is containing one objective method class name and a few traits.

2.6 Fusion

By suggesting a detailed design clustering technique, the component vectors disentangled from either the input images are entangled. Straight, presently, permutation combination strategy is 20 used to intertwine the component vectors through using DCT as well as DRLDP, which have been removed again from data images. A mixture is used to enhance precision, increase efficiency and extend the power of the frame. Currently, combination schemes for summation as well as PCA are being used to

intertwine the neighborhood as well as the worldwide illustrates extracted from facial images.

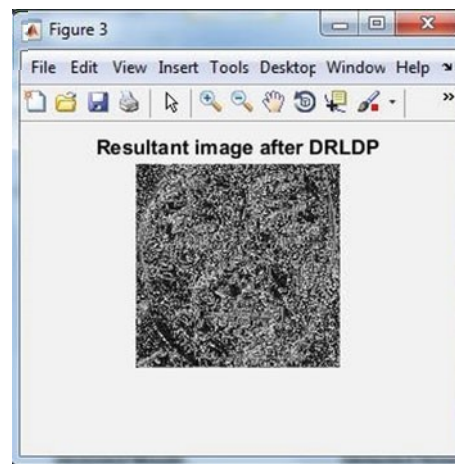
3 Experiments and Results

See Figs. 3 and 4.

See Figs. 5 and 6.

See Fig. 7.

Fig. 4 Result of the DRLDP



Facial expression recognition results with LDP

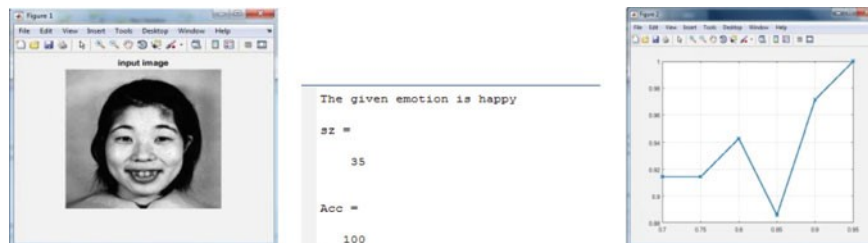


Fig. 5 Accuracy of the input image

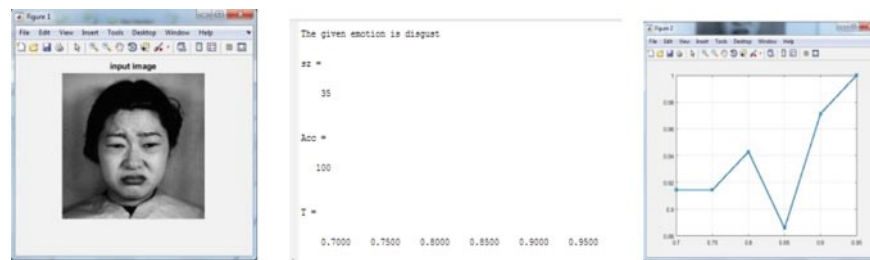


Fig. 6 Accuracy of the Input Image

Facial expression recognition results with DRLDP

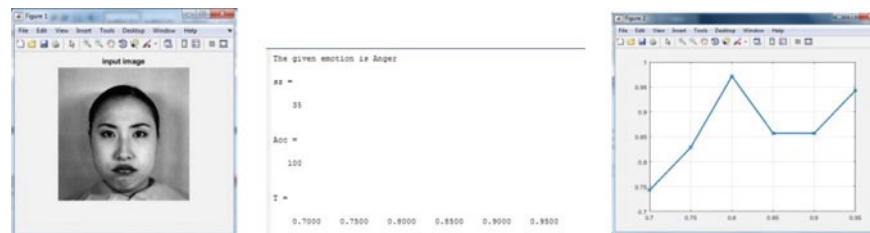


Fig. 7 Accuracy of the input image

4 Conclusion and Future Scope

The need for identification of facial expressions is rising rapidly. This approach is based on the combination of local and global significant features. This paper proposed a method for facial emotion classification with the fusion of dimensionality reduced local directional pattern and discrete cosine transform features using SVM classifier. Local characteristics are extracted utilizing DRLDP, and global characteristics are extracted from facial expression images using DCT. These features with SVM have classified considered database images for emotions with higher classification rate.

Reference

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