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Fragrance Generation based on Facial Mood Recognition

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***Abstract*— Facial expressions and gestures play a consequential role in human communication. These expressions can be used to study and detect the mood and use this information to elevate the mood. This paper aims to compare the techniques used for mood and gender detection such as Viola Jones, back propagation using neural networks, Local Gabor directional pattern and predicts the most efficient technique. The generation of fragrance is then done to elevate the mood based on the detected mood and gender.**

***Keywords*— Image processing; Face detection; Gender classification; Mood detection; Viola Jones.**

I. INTRODUCTION

Image processing is one of the developing fields in Computer Science. As the use of human-machine interactions is on the rise, it is essential for machines to be able to interpret facial expressions so that the authenticity can be improved. If machines could be trained to determine mood in a better way than humans can, then this could be helpful in fields like counselling. This could also be useful for capturing reactions of large audiences in various contexts, such as political talks.

Moreover, face recognition and gender classification has various applications in Security. Face recognition has already been proven to be a trusted login credential but it has certain problems such as illumination problem where a slight change in lighting, causes the system to deny the request. These problems have been tackled in the algorithms discussed. The ability to identify various facial expressions could also improve technology that recognizes to whom specific faces belong. This feature can be used to auto tag people in pictures on social media. The future scope of mood recognition involves detecting the correct mood even if the user is faking it. The fragrance generation based on mood detection can be used in aroma therapies to elevate moods of psychologically disturbed people.

II. LITERATURE REVIEW

The ability to identify various facial expressions could also result in better technology that identifies the sources of those faces. This could then be used to search an extremely large number of pictures for a particular photo, which is now becoming increasingly complex, as storing images digitally has been extremely mundane in the past decade [1].

Gender classification can be represented as a two class problem (Male or Female), where the given face image is assigned to either one of the classes. It is actually a simple task for humans to classify gender but challenging for machines. A large number of potential application areas are identified where gender recognition is very much involved [2].

2.2 Comparison of alternative methodologies

2.2.1 Gender Classification of Facial Images Based on Multiple Facial Regions [8]

This algorithm is based on seven different facial regions for gender classification. These regions are the whole face (including hairline), the internal face, and the upper region of face, the lower region of face, the left eye, the nose, and the mouth.

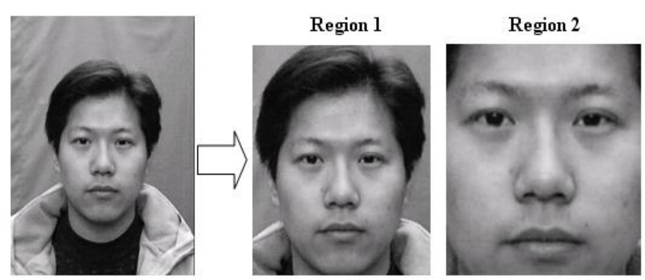

Figure 1: The whole face region and the internal face region are obtained from the original image. Left: an original image; Middle: the whole face region; Right: the internal face region

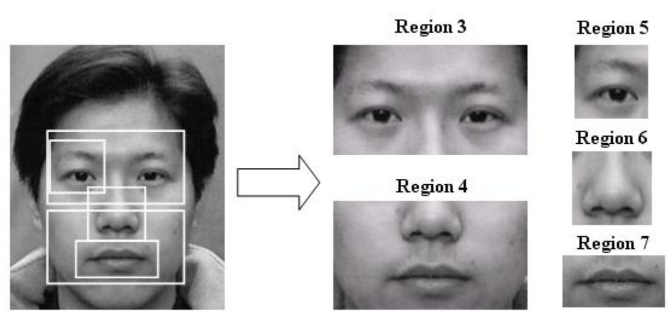

Figure 2: Five facial regions are obtained from the whole face image

The facial regions are labeled from Region 1 to 7 as illustrated in Figure 1 and Figure 2. Given a face image, the images of the seven facial regions are obtained.

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The gray scale image is then transformed to a normalized face image and a normalized internal face image (see Figure1). Five facial regions are obtained from the whole face image (see Figure 2). Considering the efficiency and effectiveness of Support vector machines (SVMs) based on pixel-based face information for gender classification, we apply SVMs on these seven facial regions to evaluate the significance of different facial regions.

2.2.2 Local Gabor Directional Pattern for Facial Expression Recognition [3]

First from an image with a face we detect the face and normalize it. After the normalization process is carried out we apply the Gabor filters at 8 orientations namely 0, 22.5, 45, 67.5, 90,112.5, 135 and 157.5 degrees and 5 scales. That gives us total 40 resultant images.

Table 1
Average Gender Classification Rate Of Each Facial Region

Facial Region	Classification Rate
Whole Face	92.50
Internal Face	91.67
Upper Region	92.90
Lower Region	80.50
Left Eye	91.17
Nose	88.00
Mouth	82.00

Each consist the magnitude value after applying a particular Gabor filter. Each of the 40 images emphasizes edges of a particular direction and width. For each scale we detect the three top most edge responses. After that, in an LDP fashion we generate our code. This code representation only emphasizes the major edge responses and suppresses the weak edges. So, this method more accurately detects micro patterns present in a face. As we are selecting the top three responses the possible number of patterns we can have is c3=56. Now, we divide each of the images in non-overlapping blocks and compute the histogram for each block separately. Then we concatenate all the histograms. The same process is carried out for all the 5 scales and finally we concatenate the five histograms.

For expression recognition we used direct matching for two histograms and then applied KNN classification method. We used the histogram intersection as the similarity measurement of two histograms.

2.2.3 Viola Jones Algorithm [2]

Viola Jones algorithm and principal component analysis that tries to match an image with respect to expression of the face. Proposed method considers an image to be resized to N x N (Original image I having N value of pixel). The image considered is then changed into grayscale with two dimensions for 2-D image.

2.2.4 Facial Expression Recognition Using Support Vector Machines [4]

The facial expression database used is the JAFFE and MUFE database. The images were divided into training and testing sets. PCA and LBP were used as feature extraction algorithms. A uniform LBP of radius 1 and 8 samples (8, 1) was used in two scenarios: LBP1 and LBP2 in which the image was divided into 16 and 64 regions, respectively.

Steps for the proposed approach:

1. Facial Expression Database
2. Feature Extraction (PCA / LBP)
3. Classification Decision (KNN/SVM)
4. Decision

For the classification stage, Euclidean distance (L2) and a Support Vector Machine (SVM) were used as 2 different classifiers.137 images were used as training while 76 images were used as testing images for JAFFE database and 315 images were used both as training and testing images for MUFE database.

2.2.5 Other techniques [5]

2.2.5.1 Principal Component Analysis (PCA)

Principal Component Analysis (PCA), also known as the Eigen face approach and is one of the popular methods for facial expression detection. Face can be reconstructed easily by considering only small quantity of information that can be obtained using Eigen faces.

2.2.5.2 Hidden Markov model

This statistical model has been used for face detection. The challenge is to build an accurate HMM, so that we can trust the output probability. The states of the model would include the facial features, which are usually defined as pixel strips. The probabilistic transition between states is generally the boundaries that exist between these pixel strips. For example, in the case of Bayesians, HMMs are generally used along with other methods to develop detection algorithms. HMM needs a series of experimental 1D and 2D images such that the images should be transformed to either a chronological sequence of 1D or spatial.

2.2.5.3 Geometrical feature matching

This technique attempts to calculate the set of geometrical features from the visual display of a face. It is based on computation of a group of photos from the face geometry. It probably identifies a face even in the improper resolution as low as 8*6 pixels.

2.2.5.4 Neural network

Here all the subnets are trained for their own images. The subnets are trained on decision basis with different samples. The main advantage of neural network in face detection is the feasibility of training a system to determine the complex class of face patterns. A number of pattern recognition problems such as character recognition and object recognition have been tackled successfully by neural networks. These systems can be used in different ways to detect face. Few previous researches used neural networks to learn the face and non-face patterns. They defined the face detection problem as a two-class problem. The primary challenge was to represent the "pictures not containing faces" class. Another approach is to use neural networks to discover a discriminant function to classify patterns using measures of distance.

A few approaches have tried to find an optimal boundary between face and non-face pictures using a constrained generative model.

2.2.5.5 Template Matching

This approach can exploit other face templates from different datasets in order to characterize a single face. The complexity arises only during the extraction of template. Template matching methods aim to define the face as a function. It tries to find a standard template for all the faces. Various features can be defined independently. For example, a face can be fragmented into eyes, nose, face contour and mouth. Also, a face model can be built by edges. But these methods have certain limitations and can be applied only to faces that are frontal and unconcluded. Certain other templates use the relation between different regions of face in terms of darkness and brightness.

III. Comparative Study

Various experiments have been conducted for the same. A brief comparison of these experiments is given in Table1.

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Table 1:
Comparative study of various experiments conducted to produce reference range

Techniques Used	Datasets	Number of images used for training	Number of Images used for testing	Accuracy	Processing Time	Memory Space Required
Local Gabor Directional Pattern for Facial Expression Recognition[3]	Cohn-Kanade Facial Expression Database	900-1100	150-350	94.2%	Intensive Processing time is required for convolving image with filter	A lot of memory space is required as several convolved images with different Gabor filters need to be kept
Facial Expression Recognition Using Support Vector Machines [4]	MUFE,JAFEE	137(MUFE) 315(JAFEE)	76(MUFE) 315(JAFEE)	87% (MUFE) 77% (JAFEE)	Moderate Processing	Less
Gender Classification of Facial Images Based on Multiple Facial Regions[8]	CAS-PEAL	640	160	92.55%	Less	Less
Back Propagation Neural Networks[2]	CIPM institute	100 images of male and 100 images of Females.	100	98.40%	Less	Moderate

IV. Conclusion

Based on the comparative study, Back propagation using neural networks algorithm offers the best efficiency for mood detection using facial expressions and Viola Jones offers the best efficiency for gender classification. The problems such as illumination problem and pose problems can be better tackled using the above mentioned algorithms.

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