

Comparison of Facial Emotion Recognition Using Effective Features

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ABSTRACT

In this paper, a trial has been done dependent on various classifiers to explore the abilities of various removed highlights for the acknowledgment of facial feeling. From this examination work, facial highlights, like the lips, the jaw line locale, and particularly the eyes, were removed for dimensionality decrease and an exceptional face portrayal utilizing the Principal Component Analysis (PCA) is done. The front-facing faces were standardized utilizing LBP, Gabor, and histogram of arranging slopes for the expulsion of commotion and light invariance before the application of the PCA. An examination has been made utilizing execution records, for example, normal acknowledgment precision and calculation time. Japanese Female Facial Expression (JAFFE) Database has been utilized here. It is seen that the Gabor with PCA gives a better outcome when contrasted with LBP and HOG.

Keywords: *Histogram of Oriented Gradients, Principal-Component Analysis, Local Binary Pattern, Database and Classification*

I. INTRODUCTION

Facial Emotion Recognition (FER) draws extensive in the field of man machine interface. It gives idea on communication in between peoples. Most application zones recognized with face and its demeanors incorporate one's recognizable proof and control, video telephone and remote coordination, legal application, individual-PC cooperation, mechanized system cosmetics, etc. Yet, presenting the face identification positively controls the presentation of the relative multitude of application. Numerous strategies have been stated to recognize individual countenances in images [1-5]. They grouped indifferent classifications such as information-based strategies, layout-based techniques, and appearance-based techniques. These techniques cannot tackle this problem of face

location like direction, posture, and demeanor if used independently. Henceforth it is intelligent to work with advance strategies. A large portion of the look acknowledgment strategies answered to date is centered around acknowledgment of six primary articulation classifications, for example, satisfaction, pity, dread, outrage, disdain, and pain. For a depiction of definitely looks, the Facial Action Coding System (FACS) was planned by Ekman and Friensen during the 70s. In FACS, movements of the muscles of the face are separated into 44 activity units and any looks are depicted by their mixes [1]. Growing such a Facial Expression Recognition framework (likewise alluded to as a FER framework) is not a trifling assignment, because of the great inconstancy of information. Pictures are addressed under different conditions like the goal, quality, brightening, or size. Each one of these limitations must be mulled over for choosing suitable strategies, to convey a framework that is hearty, individually free, and works in a perfect world continuously.

This paper presents the comparison of different classifiers such as Discriminant Analysis (DA), K Nearest Neighbor (KNN), Support Vector Machine (SVM), Naïve Bayes (NB), Random Forest (RF), and Decision Tree (DT) based on the parameter of recognition accuracy and computation time. Different Feature extraction and minimization techniques such as Gabor, Local Binary Pattern (LBP), Histogram of oriented Gradients (HOG), and Principal Component Analysis (PCA) are used in this paper.

The design of this article has been engineered as follows. Section-II explores the feature extraction and feature minimization techniques. Section-III briefs the decision of the information about the database. The reenactment results utilizing the classifier with the removed capabilities have been clarified in section-IV and section-V finishes up the work with the conclusion and future work.

II. THE PROPOSED FEATURE EXTRACTION TECHNIQUES

The facial picture ID displaying is appeared in Fig.1. It includes a few segments implied for picture procurement, pre-handling, highlight extraction, and characterization.

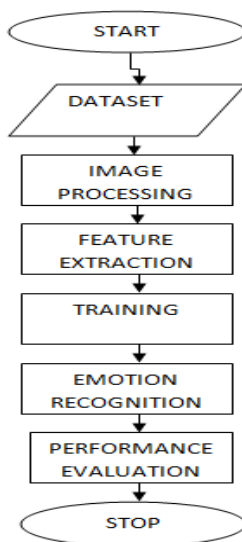


Fig.1.The facial image identification modeling

Subsequent to clicking an expressive picture utilizing a camera, it is pre-prepared to limit any variables because of the climate and different sources. The pre-preparing step includes picture scaling, change of difference and brilliance, and picture upgrade. As the facial pictures of the picked JAFEE information base data set [2] have effectively been pre-handled, it is not needed to include this progression here. This work investigates the Gabor channel, LBP, HOG, and PCA. Highlight extraction procedures to order the expressive states utilizing facial pictures. The element extraction procedures have been momentarily clarified in the accompanying subsections.

2.1 Histograms of Oriented Gradients (HOG) Technique:

HOG procedure has been picked in this work as it gives due significance to both neighborhoods and worldwide look credits in changed directions and scales. The HOG highlights are delicate to varieties looking like an item except if the shape is steady [3][4]. This work uses nine container histograms addressing the bearings and strength of an edge utilizing 4×4 cells comparing to each fixture. These HOG highlights of every dynamic facial fix are affixed to remove the ideal component vector. In the HOG technique, the gradient for the pixel $f(a, b)$ is determined by

$$T_p = f(a - 1, b) - f(a + 1, b) \quad (1)$$

$$T_q = f(a, b - 1) - f(a, b + 1) \quad (2)$$

The gradient magnitude is given by

$$T = \sqrt{T_p^2 + T_q^2} \quad (3)$$

The orientation of the bin is given by

$$\theta = \arctan(T_q/T_p) \quad (4)$$

Where θ signifies the container point. Both the size and the canister point are utilized to shape the HOG include vector. Along these lines, it is feasible to focuson the variety of the state of the mouth, eyes, and eyebrow which moves all the more in an upward direction during an enthusiastic expressive state. To pick the cell size, we start with 2×2 pixels to 64×64 pixels utilizing every one of the potential varieties in both vertical and flat measurements and taking note of the RFE precision. The cell size 8×16 has given the most elevated precision, consequently saved for additional preparation. It has been seen that with an increment in cell size, there is a deficiency of picture subtleties and the calculation time increments. Despite what might be expected, the component vector measurement stays little, and the calculation time turns out to be quicker with a more modest estimated cell.

2.2 Local Binary Pattern (LBP) Technique

LBP is a well-known, straightforward, and productive surface descriptor which is utilized for some PC vision applications. It can catch the spatial example alongside the dark scale contrast. It utilizes a straightforward thresholding strategy, where the forces of the adjoining pixels are contrasted and that of the middle pixel bringing about a paired example known as LBP [5][6]. The essential LBP activity with a 3×3 window is communicated and exhibited as beneath:

$$LBP(j_c, k_c) = \sum_{n=0}^7 h(i_n - i_c) 2^n \quad (5)$$

Where i_c conveys to the intensity of the centre pixel (j_c, k_c) , i_n conveys to the grey values of the eight nearer pixel and if $i_n - i_c > 0$, then $h(i_n - i_c) = 1$, else $h(i_n - i_c) = 0$. Fig. 2. Show basic LBP operation.

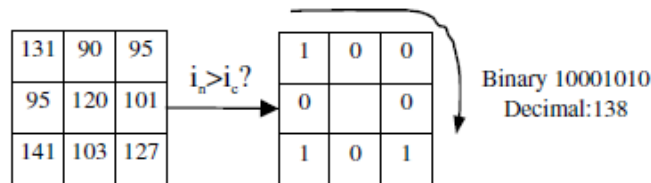


Fig.2. An example of a basic LBP operator

2.3 Gabor Filters

Gabor channel is a straight channel and is portrayed by the spatial and recurrence area portrayal of the sign. It can give critical data on feelings as the channel can inexact the human's insight satisfactorily [7]-[11]. It tends to be communicated as a blend of the perplexing outstanding capacity and the 2D Gaussian capacity as follows

$$s(r, s) = \exp\left(-\frac{r_1^2 + \gamma^2 s_1^2}{2\sigma^2}\right) \exp\left(j\left(2\pi \frac{r_1}{\lambda} + \varphi\right)\right) \quad (6)$$

where $r_1 = r \cos \theta + s \sin \theta$ and $s_1 = -r \sin \theta + s \cos \theta$. Here, θ , λ , φ and γ indicate the direction in degrees, frequency, stage balances, and the spatial angle proportion compared to the state of the Gabor channel separately. The term σ addresses the standard deviation of the Gaussian expression. Utilizing the genuine part of the condition, the articulation for the Gabor channel becomes

$$f(a, b) = \exp\left(-\frac{a_1^2 + \gamma^2 b_1^2}{2\sigma^2}\right) \cos\left(2\pi \frac{a_1}{\lambda} + \varphi\right) \quad (7)$$

2.4 Principal Component-Analysis (PCA)

Principal Component-Analysis (PCA) is used for dimensionality reduction, creates an ideal direct least square decay of preparatory group of set. It has been successfully explored to recognize a human face and facial expressions [12][13]. In applications, for example, picture pressure and face acknowledgment, a supportive measurable method called PCA is frequently used. PCA is a far-reaching procedure for deciding examples in the information of enormous measurements and it is regularly alluded to as the utilization of Eigenfaces [13]. The PCA approach is then further applied to lessen the element of information through information pressure and uncovers the best minimum dimensional construction of face examples. The benefit of decreasing in measurements is that it eliminates nonvaluable data. It explicitly disintegrates the design of a face into segments that are not correlated and is known as Eigenfaces [14]. Each pixel of the face might be put away in 1D cluster, it is the portrayal of the weight total (include vector) of Eigen faces. The event of this methodology a total frontal perspective on the facial is required; or, more than likely the yield of acknowledgment shall not be exact. Significant advantage of strategy is that it manages down information needed to perceive the substance to $1/1000^{\text{th}}$ of an information existing [15]. The given steps sum up the process of PCA. Let a face image A (a.b) is a $2-d \text{ m} \times n$ array of pixel values. An image vector of dimension $m \times n$ so that an image of size 112×92 becomes a dimension 10304. For, a training set images $\{A_1, A_2, A_3 \dots A_N\}$.

The average face is denoted by:

$$\bar{H} = \frac{1}{N} \sum_{i=1}^N H_i \quad (8)$$

Calculate for estimated covariance matrix to present the scatter degree of total feature vectors related to average vector. The C(covariance matrix) is given by:

$$C = \frac{1}{N} \sum_{i=1}^N (\bar{H} - H_i)(\bar{H} - H_i)^T \quad (9)$$

The Eigen-vectors and corresponds to Eigen values are calculated by using

$$CV = \lambda V \quad (V \neq 0) \quad (10)$$

Where V gives the set of eigenvectors, matrix C gives its Eigenvalue λ . Project all the training images of i^{th} individual to the corresponding Eigen subspace:

$$y_k^i = G^T(x_i) \quad (i = 1, 2, 3, 4, \dots, N) \quad (11)$$

Where the y_k = projections of x and is called as the principal components also known as Eigen faces. The dimensionality can further be reduced by selecting the first N eigen-vectors that have greater variances and discarding the remaining one that have smaller variances.

III. THE CHOSEN DATABASE

This work picks the Japanese Female Facial Expression (JAFPE) dataset [2] for the facial feeling acknowledgment task. The data set is effectively available and has been picked by a few outskirts specialists in this field, which makes the examination stage uniform for this piece of work. The pictures are put away on a dark scale with a goal of 256×256 . The glad, disdain, dread, furious, nonpartisan, pitiful, and amazing passionate articulation tests from the JAFPE data set have been given in Fig. 4. We have considered 188 pictures comprising 6 feelings in this paper.

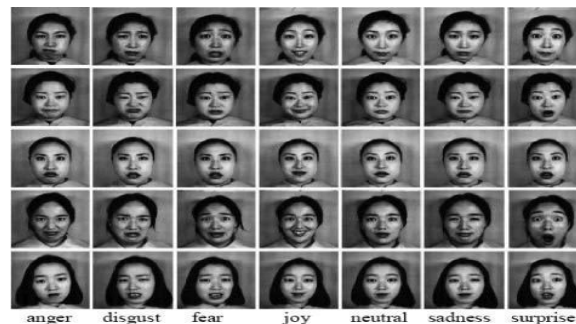


Fig.4. JAFPE Emotional Expressive States sample images

IV. RESULTS AND DISCUSSION

In this stage, we performed mining procedures to the information made in the past stage to order and anticipate the feeling discovery characteristic of extraversion. We run, the information on the JAFFE information mining apparatus. We chose a few calculations from various classifiers to analyze the presentation of every calculation. The chosen classifiers are Decision Tree (DT), K-nearest Neighbor (KNN), Random Forest (RF), Discriminant Analyzer (DA), Naive Bayes' (NB), and Support Vector Machine (SVM). The chosen parameters of these classifiers are listed in Table 1.

Table 1: The Classification Parameters Chosen

Classifier	Cross-Validation (k-fold)	Chosen Parameters
RF	ten	50 number of bags
SVM	ten	Radial Basis Kernel
NB	ten	Normal Distribution
DT	ten	50 number of splits
KNN	ten	KNN (K =3)
DA	ten	Linear

4.1 Contrast between chosen Classifiers

Table 2 provides the classification accuracy of the chosen classifiers using HOG-PCA based feature set. It shows, the RF classifier has outperformed all the chosen classifiers with the highest average FER accuracy. However, the classifier shows the slowest response among all. The reason being, the RF is based on the bagging algorithm that follows the ensemble learning approach. Unlike DT, it comprises several trees to subgroup the extracted feature set while developing the classification model. This helps in the elimination of overfitting issues generally associated with the DT algorithm. This way, the variance is reduced, which improved the classification accuracy. Nevertheless, the complexity involved in the formation of several trees makes the classifier sluggish as compared to the DT which shows the fastest response.

Table 2: Comparison of the Chosen Classifiers with the HOG-PCA Proposed Feature Set		
Classifiers	% Accuracy	Computation Time
KNN	23.19	3.40s
DA	10.07	2.31s
NB	16.72	2.15s
DT	29.26	1.11s

SVM	23.75	5.23s
RF	23.86	8.94s

Table 3 provides the FER accuracy of the chosen classifiers using LBP-PCA based feature set. In this case, the DT has shown to outperform all the chosen classifiers in modeling the desired emotional states. The classifier is simple due to the involvement of a single tree, computationally inexpensive, and does not need to take any prior assumptions on the probability distribution types, classes or attributes, etc. The robustness to noise and redundant attributes makes the classifier versatile in this case.

Table 3: Comparison of the Chosen Classifiers with the LBP-PCA Proposed Feature Set		
Classifiers	Accuracy in %	Elapsed Time
KNN	66.58	5.27s
DA	56.61	5.31s
NB	43.01	1.51s
DT	68.97	0.91s
SVM	64.26	4.09s
RF	80.33	9.51s

Table 4 provides the FER accuracy of the chosen classifiers using Gabor-PCA based feature set. In this case, the DA has shown to outperform all the chosen classifiers in modeling the desired emotional states. The classifier is unsupervised and does not need the annotated training data while learning the patterns. It generates the desired models based on the discriminant variables which are combined linearly to categorize the patterns. The categorization of the independent variables to discriminate the dependent variable in a perfect manner makes the classifier suitable in this case.

Table 4: Comparison of the Chosen Classifiers with the Gabor-PCA Proposed Feature Set		
Classifiers	Accuracy in %	Elapsed Time
KNN	98.86	20.15
DA	100	20.67
NB	99.37	3.74
DT	95.29	3.77
SVM	98.82	9.76
RF	99.41	11.69

4.2 Comparison of the Proposed Feature Extraction Techniques

Between all the proposed feature-extraction techniques, the Gabor-PCA-based features have been providing the highest average recognition-accuracy. The HOG is geometric-based technique that provided limited structural information. Thus, the technique fails to model the desired emotion accurately as observed from the results. The lower accuracy is expected as the technique ignores the difference in the extracted pixel, hence cannot represent the magnitude information of the emotions adequately. The LBP-PCA-based features has shown good FER accuracy as contrasted to the HOG-PCA. The technique applies binary images representing the emotions, hence enhances the images to the desired level. Thus, the technique founds to have better emotional descriptions of the facial images as compared to the HOG method. The Gabor-PCA-based features also use binary images for enhancement like LBP. This is a linear filter and can represent the signal both spatially and in the spectral domain. These characteristics of HOG allow it to extract significant emotional attributes from a signal to represent the human affective states perceptually. Tables 5 to table 10 provide the recognition accuracy of individual emotions with different classifiers using Gabor-PCA-based features for a better understanding of the proposed work.

Table 5: The DA Testing Accuracy of Individual Emotion using the Gabor Coefficients						
Emotions	Number of Testing Samples					
Angry	28	0	0	0	0	0
Disgust	0	27	0	1	0	0
Sad	0	0	27	0	0	1
Fear	0	0	1	25	1	1
Happy	0	0	0	2	26	0
Surprise	0	0	1	0	0	27

Table 6: The DT Testing Accuracy of Individual Emotion using the Gabor Coefficients						
Emotions	Number of Testing Samples					
Angry	27	0	0	1	0	0
Disgust	0	28	0	0	0	0
Sad	0	0	28	0	0	0
Fear	0	0	0	27	1	0
Happy	0	0	0	0	26	0
Surprise	0	0	0	0	0	28

Table 7: The KNN Testing Accuracy of Individual Emotion using the Gabor Coefficients						
Emotions	Number of Testing Samples					
Angry	28	0	0	1	0	0
Disgust	0	28	0	0	0	0
Sad	0	0	28	0	0	0
Fear	0	0	0	27	1	0
Happy	0	0	0	0	26	0
Surprise	0	0	0	0	0	28

Table 8: The NB Testing Accuracy of Individual Emotion using the Gabor Coefficients						
Emotions	Number of Testing Samples					
Angry	28	0	0	0	0	0
Disgust	0	28	0	0	0	0
Sad	0	0	27	0	1	0
Fear	0	0	0	27	0	0
Happy	0	0	0	0	28	0
Surprise	0	0	0	0	0	28

Table 9: The SVM Testing Accuracy of Individual Emotion using the Gabor Coefficients						
Emotions	Number of Testing Samples					
Angry	28	0	0	0	0	0
Disgust	0	26	0	0	0	0
Sad	0	0	28	0	0	0
Fear	0	0	1	27	0	0
Happy	0	0	0	0	28	0
Surprise	0	0	0	0	0	28

Table 10: The RF Testing Accuracy of Individual Emotion using the Gabor Coefficients						
Emotions	Number of Testing Samples					
Angry	27	1	0	1	0	0
Disgust	0	28	0	0	0	0
Sad	0	0	28	0	0	0
Fear	0	0	0	28	0	0
Happy	0	0	0	0	28	0
Surprise	0	0	0	0	0	28

V. CONCLUSION

This paper is a result of an overview led to unmistakable component extraction procedures utilized

in PC vision and picture preparing applications for the errand of feeling acknowledgment from look picture datasets. In this work, an endeavor is made to perceive the human facial expressive states utilizing viable highlights. The separated capabilities from the JAFFE datasets have been utilized to mimic different classifiers. The use of the Gabor channel to double pictures improves the picture to the ideal norm, accordingly making the passionate models dependable and straightforward. Despite what might be expected, the multi-goal Gabor channels remain computationally costly when contrasted with basic channels like HOG and LBP. The outcome can be stretched out later on to other proficient element extraction strategies that can depict facial expressive states sufficiently.

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