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A Study on Texture Analysis of Facial Expressions

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Facial texture analysis deals with the facial feature changes appeared in facial expressions. Gray Level co-occurrence Matrix (GLCM) has been taken for texture analysis. The facial expression images have been taken from DeitY-TU face database which is still under development in Biometrics Laboratory of Tripura University. The standardization of facial expression images has been discussed here. The second order statistical approaches like energy, homogeneity, contrast have been calculated over different face images containing six basic expressions. Small values of energy and homogeneity reveal the heterogeneous feature of face images. Contrast provides a considerable distinction in closed and open mouth expressions.

Keywords : DeitY-TU Face Database, Facial Expression, Statistical Approach, Texture Analysis .

1. INTRODUCTION

Facial expression analysis has a growing research area in the field of human-computer interaction. Facial emotions are fundamental form of nonverbal communication for conveying feelings. In 1872, Darwin introduced the idea of basic emotions, which are principally in born emotions derived from similar habits [1]. Emotions are basic research topics used in cognitive science [2], neuroscience [3], social psychology [4] *etc.*. According to psychology, there are two theories of emotions: categorical theory and dimensional theory. The categorical theory is all about six basic emotions: happy, anger, sadness, surprise, disgust and fear [5]. The dimensional theory proposes two fundamental dimensions that form emotional spaces. The two dimensions are known as arousal and valence. Arousal ranges from calm to excited, and valence ranges from negative to positive. Each facial expression causes facial muscle movements which indirectly associates with facial texture. The variations of facial textures signify the intensity variations from normal one. Textures can be regarded as complex visual patterns comprising brightness, color, slope, size *etc.*. one complex pattern consists of several subpatterns that describes the uniformity, density, regularity, linearity etc of the whole texture [6]. In another sense, texture can be defined as a group of mutually related pixels.

Now in case of facial texture analysis, the facial features like eye, nose, and eyebrow play a major role. They act in active area which changes along with the expression changes. In this paper, a brief illustration is carried out on DeitY-TU face database. The six basic expressions of DeitY-TU face database are being analyzed. Then facial texture analysis is investigated using Haralick statistical approach that considers textures as the arrangement of spatial distribution of gray-values in images. The discussion about similarity and dissimilarity of various expressions of different persons is reported here.

2. PREVIOUS WORKS

Many researchers have done investigations on image texture using Gray Level co-occurrence Matrix (GLCM). But very few works have been reported on facial texture analysis. M Pietikainen and A Hadid [7] consider the local binary pattern (LBP) as an instance of texture-based approach and discuss its efficiency in various aspects of facial image analysis. Face recognition has been performed in few papers based on statistical approaches. A Eleyan and H Demirel [8] propose an approach for face recognition using co-occurrence matrix and its statistical features. They conduct experiments on FERET, FRAV2D, YALE B and ORL face database. To implement GLCM technique, they propose two different situations for face recognition. In the first case, co-occurrence matrix is directly converted into column vector and in the second case, the vector of Haralick features extracted from GLCM has been taken for recognition.

Four different angles ($0^\circ, 45^\circ, 90^\circ, 135^\circ$) have been taken separately in four experiments of GLCM. Later, all four results are fused to obtain a better result. Experiment results show that direct GLCM is comparatively better than Haralick features. In the paper of A H Bishak *et al.*, [9], Co-occurrence matrix of Local Average Binary Pattern operator (CMLABP) has been applied to face recognition. An LBP histogram calculated over whole face image represents the occurrences of patterns without indicating their position. LABP replaces single pixel of original image with the average gray values of p-neighbour values of pixels. The statistical parameters like energy, entropy, contrast, variance etc have been extracted from the CMLABP and used as a feature vector for classification. Experiments have been conducted on FERET and ORL face dataset. More than 97% accuracy has been obtained in ORL face dataset.

3. CATEGORIES OF FACIAL EXPRESSIONS

Facial expression with an emotion entails the categories of human emotions into which expressions can be allotted.

1. **Sadness.** Sad expression is associated with following facial feature movements.
   - Corners of lips pulled down.
   - Raised cheeks.
   - Inner corners of eyebrows raised and brought together.
   - Upper eyelids drop.
   - Lower lip may push up in a pout.
2. **Surprise.** Following facial feature movements are associated with surprise expression.
   - The upper eyelids and brows rise.
   - The jaw drops.
   - Eyes staring straight ahead.
   - The skin below the eyebrows stretch and horizontal wrinkles can be seen around the forehead.
   - Head is tilted in 2 ways. If the head tilts forward, it specifies disbelief, and if head pulls back, it signifies fear.
3. **Happy.** Joy expression associates following facial feature movements.
   - The corners of the mouth lift.
   - Eyelids tighten.
   - Cheeks rise.
   - Outside corners of the brows pull down.
4. **Fear.** Fearful face associates following facial feature movements.
   - Eyes widen.

- Upper lids rise, but brows draw together.
- Lips stretch horizontally.

5. **Disgust.** The disgusted face associates following facial feature movements.
   - Nose wrinkles.
   - Upper lip rises, lower lip protrudes.
   - Lower eyebrows.

6. **Anger.** The following features are changed accordingly in aggressive mode of expression.
   - Raised upper eyelids.
   - Possibly tensed lower eyelids.
   - Tighten up the area around eyes.
   - Eyebrows lowered and brought together.
   - Lower jaw can be forward.
   - If teeth exposed, mouth has rectangular shape.
   - The lips press together, and lower lip may push up a little.

4. STATISTICAL APPROACHES FOR TEXTURE ANALYSIS

There are four types of approaches for texture analysis *i.e.*, structural, statistical, model-based and transform [10]. Structural approach provides a good structural description of the image. But it is useful for image synthesis, rather than analysis. Model-based analysis considers the image texture using generative image model and stochastic model. The parameters of the model are estimated and then use for image analysis. This approach is not perfect for describing local image structure. Transform based approach of texture analysis represents the image in the form of frequency or size. Statistical methods characterize image texture based on distributions and relationships between the gray levels of an image. Image histogram calculation only measures distribution of intensities; but cannot measure the relative pixel position. The textures in gray-level images are discriminated spontaneously only if they differ in second order moments. The most popular 2^{nd} order statistical features for texture analysis are derived from the co-occurrence matrix [11]. Co-occurrence matrix helps to provide valuable information about the relative position of the neighbouring pixels in an image. Given an image I of size $N \times N$, the co-occurrence matrix P can be defined as

$$P_{i,j} = \sum_{x=1}^{N} \sum_{y=1}^{N} \begin{cases} 1, & if I(x,y) = i\, and \\ & I(x+\Delta x, y+\Delta y) = j \\ 0, & otherwise \end{cases}$$

The offset ($\Delta\ x$, $\Delta\ y$) specifies the distance between pixel of interest and its neighbour. To achieve rotational invariance, a set of offsets are used (*i.e.*, $[0\ \Delta]$ for 0°: P horizontal, $[-\Delta\ \Delta]$ for 45°: P right diagonal, $[-\Delta\ 0]$ for 90°: P vertical, $[-\Delta\ -\Delta]$ for 135°: P left diagonal). The dimension of a GLCM is determined by the maximum gray value for the pixel. More levels mean more accurate extracted information. In order to estimate the similarity between the different gray level co-occurrence matrices, Haralick proposed 14 statistical features extracted from them. Some most frequently used GLCM features are described below:

i. Contrast:

$$\sum_{i,j=0}^{N-1} P_{i,j} (i-j)^2$$

It measures the amount of local variations present in the image. Spatial frequency represents the difference between highest and lowest values of a contiguous set of pixels. If i and j differ by 1, the weight is 1 *i.e.*, low contrast. If i and j differ by 2, the weight is 4 *i.e.*, high contrast. Contrast increases as $(i-j)$ increases. Local intensity variation will favour contributions from $P_{i,j}$ away from the diagonal. *i.e.*, $i \neq j$.

ii. Homogeneity:

$$\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2}$$

This statistic is also known as Inverse Difference Moment (IDM). IDM is influenced by the homogeneity of the image. Smaller gray tone differences between two pixels produces larger values of IDM *i.e.*, higher values for homogeneous images. GLCM contrast and IDM are inversely correlated [12].

iii. Energy:

$$\sum_{i,j=0}^{N-1} {P_{i,j}}^2$$

This parameter is also termed as Angular Second Moment (ASM). It is measured by pixel pair repetitions *i.e.*, textual uniformity. It is used for disorders in textures. The term ASM comes from physics and it is a measure of rotational acceleration. High energy values occur when gray-level distribution over the window has either a constant or a periodic form [13]. The maximum value of energy is 1.

5. DeitY-TU FACE DATABASE:

The DeitY-TU face database is a visual face image database, which is still under progress. The database is being created in the Biometrics Laboratory of Computer Science and Engineering Department of Tripura University, Tripura, India, with the face images of the different tribe as well as non-tribe people of the seven North-Eastern states of India. In this database, we include total eight different types of expressions including the six basic expressions (*i.e.*, anger, happy, sad, surprise, fear, and disgust). The other two expressions are neutral and closed eye.

6. STANDARDIZATION OF DEITY-TU FACIAL EXPRESSION IMAGES:

Here, we present one individual of Nagaland face image database. Basic six facial expressions are compared with the Ekman standard database [14]. Figure 1 shows the various muscle movements of captured face expression images. While comparing with the standard given in previous section, we found most of the expressions of NEI face are matched to that of standard expressions. Some changes of muscle movement have been observed.

In Anger expression margin of the lips is not rolled in and Lips are loose. Expression may differ from person to person. So it is not possible to get complete uniqueness.

7. EXPERIMENTAL DISCUSSIONS:

Total experiment is carried out on 15 DeitY-TU face images. The face images are resized into 256x256. The distance between a pixel of interest and its neighbour is 2. In the offset, angle has been considered as 90°. Before calculating the properties of GLCM, each element of the GLCM has been normalized. Each element of the normalized GLCM is considered as $P_{i,j}$. The size of the GLCM is 32. The experiment results show that the values of energy is very low *i.e.*, less than 1. It reveals that elements of normalized GLCM are too small that after squaring those, the values still remain small. The reason behind the small values of energy is non-uniformity or heterogeneous feature of face images. Facial expression creates more textual changes in face surface. Some values of energy for different persons with different expressions have been listed in Table 1. In case of contrast, it can be said that as the number of gray-level increases, values of contrast increase. When the difference between i and j increases, the value of the contrast increases. A graphical representation of the contrast values with respect to six expressions is given in Figure 2. The expression numbers 1, 2, 3, 4, 5 and 6 represent sad, anger, disgust, happy, fear and sur-

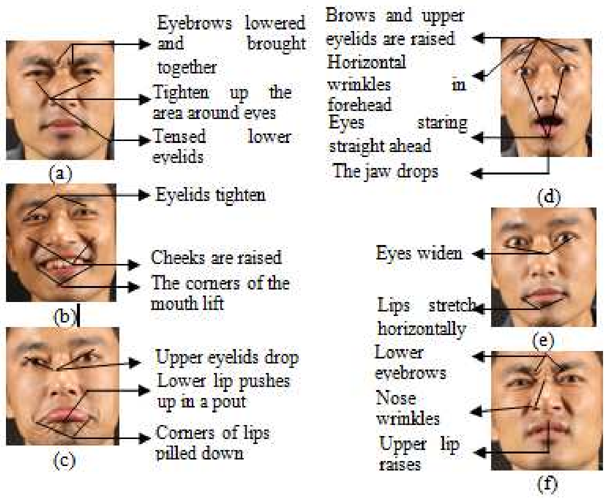

Figure 1. Changes of Facial Features During Expressions

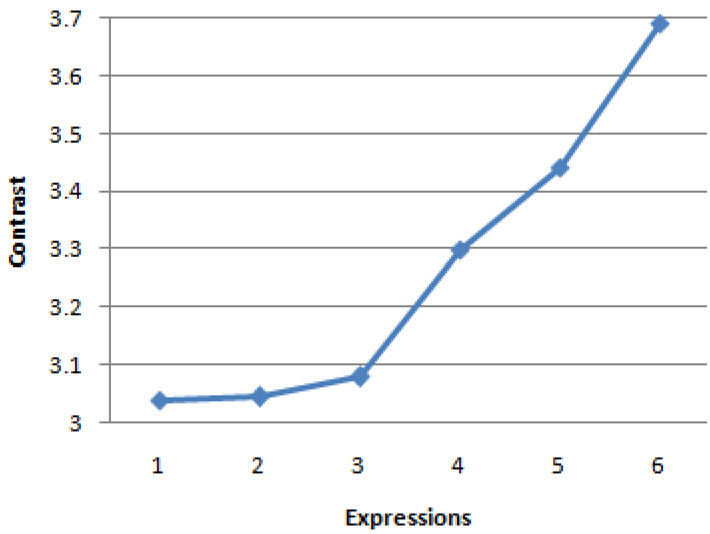

Figure 2. Average Values of Contrast for 15 Persons for Different Expressions

prised respectively. The graph indicates that sad has the lowest contrast and surprised has the highest contrast.

The expression numbers 1, 2, 3, 4, 5 and 6 represent sad, anger, disgust, happy, fear and surprised respectively. The graph indicates that sad has the lowest contrast and surprised has the highest contrast. As contrast measures local variations, it is noticed that the closed mouth expressions have low contrast and open mouth expressions have high contrast. The Table 2 lists out the values of homogeneity during different expressions for different persons. The different persons have different values for same expression. But, the values are very near to each other. Homogeneity is inversely proportional to the contrast.

Table 1
Values of Energy for Different Persons and Expressions

Expression	Person	Energy
Anger	1	0.0291
	2	0.0187
	3	0.0158
	4	0.0263
	5	0.0389
Happy	1	0.0268
	2	0.0226
	3	0.0139
	4	0.0261
	5	0.0364
Disgust	1	0.0245
	2	0.0234
	3	0.0161
	4	0.0301
	5	0.0423

Table 2
Values of Homogeneity for Different Persons and Expressions

Expression	Person	Homogeneity
Anger	1	0.7070
	2	0.6586
	3	0.6081
	4	0.6945
	5	0.7125
Happy	1	0.6980
	2	0.6825
	3	0.5976
	4	0.6903
	5	0.7116
Disgust	1	0.7062
	2	0.6744
	3	0.6093
	4	0.7120
	5	0.7191

8. CONCLUSIONS

This paper only analyzes the second order statistical properties of the facial expression images. Three different properties of co-occurrence matrix have been computed over different facial expression images. After experimentation, it is observed that no such significant differences have been noticed in the values of energy for different expressions. The same statement can be made for homogeneity also. In case of contrast, some differences have been observed in expressions. This analysis will be extended in future by measuring statistical properties only for particular facial features like eye, lip, nose which are changed during expressions.

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