Exploring Fractal Dimension Analysis as a Technique to Study the Role of Intensity of Facial Expression and Viewing Angle

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Abstract: Fractal dimension analysis of the images of facial expressions has been reported earlier by Takehara and colleagues We have performed a similar exercise for two Indian databases, the Indian dataset of basic emotions and the Indian Affective Picture Database, to examine the relationship between the geometric properties of the facial expressions vis-à-vis the intensity of expressions and the viewing angle. It is a first of its kind in the Indian context. We analyzed the geometric pattern of three regions of the face, computed pixel difference, and calculated fractal dimensions of the expressions for all the images of these two databases. Thereafter, we analyzed the obtained outcomes of the geometric analyses and the reported unbiased hit rates for these databases, respectively. Results suggest that recognition of facial expressions is independent of the viewing angle. Further, happiness and anger are recognized best irrespective of their intensity followed by more intense surprise and disgust. The Root Mean Square pixel difference shows identical pattern in the expressions of happiness and disgust. Fractal dimensions indicate self-similarity among surprise, happiness, and disgust.

1 INTRODUCTION

A substantial percentage of the information that we intend to express is conveyed through facial expressions. The analysis of feature point distance in facial expressions is the key to quantification of expression of emotions. However, most of the behavioural studies have ignored the interaction between facial morphology and facial expressions (Hess et al., 2009).

Geometric methods have the potential to map subtle changes on the face. They rely on the position of facial features and the corresponding displacement/ deformation. The higher the distance of the feature vector of a given facial expression is from the mean, the easier one finds recognizing it (Valentine, 1991). Assuming face as geometric shape implies extraction and analysis of facial components such as eye brows, eyes, nose, and lips as geometric features. The geometric feature-based methods use geometric relationships between facial feature points and extracts the features.

Fractal dimension is one of the robust but rarely used techniques for the study of facial expression. These applications also involve two-dimensional images which are produced by medical and non-medical machines. Fractal dimension has been calculated using a pixel-intensity method in several such studies (Athe et al., 2013). The same approach has been adopted to compute fractal dimension from photographs representing different facial expressions. Takehara et al. (2002) have argued that recognition of facial expressions of emotions is based in potential regularity on the basis of fractal dimension. Assuming the two-dimensional psychological space homogenous, Takehara et al. (2002) have argued that the expression prototype, and thus the geometric relationship between these prototypes, should be continuous. Fractal geometry is the best tool to analyze uneven surface with irregularities of variable sizes. They have analysed facial expressions in terms of fractal dimension and found that recognition of facial expression has fractal properties. However, the two-dimensional psychological space is not homogeneous. Some researchers have used fractal analysis to explain fractal dimension changes in facial expressions (Takehara et al., 2013). Except Takehara et al. (2007) we did not find any study examining

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facial expressions on the basis of fractals. The three studies adopting fractal analysis of facial expressions (Takehara et al., 2002, 2007, 2013) were conducted on small sample and limited images. Considering the merit of fractal mathematics, especially it being independent of how the images are obtained, we explored its application in the study of facial expression vis-à-vis the intensity and viewing angles.

Researchers have mostly used high intensity static stimuli (Lander & Butcher, 2015) and most of them have not looked at varying intensity of expression. For instance, the low, intermediate, and high intensity expressions were created by Wingenbach et al. (2016) by extracting consecutive frames. They found a linear relationship between physical intensity of expression and accuracy. Bould and Morris (2008) truncated the unfolding of facial expression of emotions from neutral to full intensity. Our day-to-day interaction involves facial expression of emotions of low to intermediate intensity (Motley & Camden, 1988) and intense expressions are exceptions (Hess et al., 2009). Thus, study of varying intensity of facial expression of emotions can help understand issues related to emotion recognition in normal as well as clinical population such as Autism Spectrum Disorder (Harms et al., 2010). Given this fact, it is important to combine the thoroughness of geometric method and the exquisiteness of behavioural method to examine what makes us decipher facial expressions and recognize the emotion as well as its intensity. Also, the angle of view and its effect on the recognition of emotions needs to be looked at. However, we did not come across any such study and decided to work on it.

A careful screening of the datasets revealed that three datasets (Bhushan, 2007; Bould & Morris, 2008; Wingenbach et al., 2016) contains variable intensity of emotions based on extraction of consecutive frames. However, all of them have only front view of the expresser. Two other databases, the Karolinska Directed Emotional Faces (Lundqvist et al.,1998) and the Indian Affective Picture Database (IAPD: Sharma & Bhushan, 2019), contains facial expressions of the basic emotions taken from five different angles. We looked at the three existing Indian datasets reviewed by Sharma and Bhushan (2019) and taking care of the cultural and ethnic concerns selected two of the existing Indian datasets. The choice of the database was based on three criteria, the database should have facial expressions of the basic emotions, it should have expressions of variable intensity and/or facial expressions captured from different viewing angles, and both of them should have expressers and respondents from the same culture. This was done to take care of issues pertaining to cultural variations in recognition patterns.

The objective of the study was to examine— (i) the interplay of physical properties of facial expression of emotions and their recognition, and (ii) the relationship between physical intensity of expression and response accuracy for front and angular view of expressions. Accordingly, we hypothesized that (i) the geometric properties of the face would significantly affect the recognition of facial expression of emotions, and (ii) the geometric properties of the face for front view will differ from the angular view of the facial expression and this will affect recognition accuracy.

2 MATERIAL AND METHOD

2.1 Stimuli

As stated above, facial expressions of two datasets, the Indian dataset of basic emotions (Bhushan, 2007) and IAPD (Sharma & Bhushan, 2019), were used in this study. The Indian dataset of basic emotions comprise of 36 coloured images (6 emotions x 6 intensity) of a male expresser (see figure 1). They are static frames of sequential changes derived from videos. Depending upon their sequence of occurrence, these static images are numbered from 1-6 wherein the numbers also refer to the increasing order of intensity of the expression (1= lowest intensity – 6= highest intensity). All the images show the front view of facial expression. This dataset has been used to identify the areas of the face scanned during emotion recognition (Bhushan, 2015).

IAPD contains 140 coloured pictures (7 emotions X 5 angles X 4 expressers) of four expressers (two males and two females) from five different angles— -90 (full left profile), -45 (half left profile), 0 (straight), +45 (half right profile), and +90 (full right profile) degrees (see figure 1).

The pictures of both the database were of same size (562x762 pixels). Although, both the databases have adopted Likert scale for rating the intensity they are bit different. While the first dataset requires the participants to recognize the emotion (happy, sad, fear, anger, surprise, disgust, or neutral) and then rate its intensity on a 5-point Likert scale (1= minimum, 5= maximum), IAPD has adopted 9-point scale ranging from 1 (not at all intense) to 9 (completely intense) for rating the intensity of the emotion.

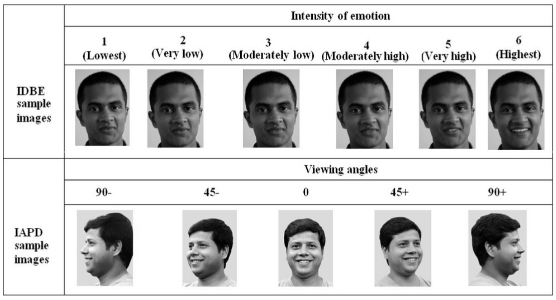

Figure 1: Sample images of facial expressions of both, the Indian dataset of basic emotions and the Indian Affective Picture Database.

2.2 Procedure

Behavioural studies have relied on subjective response of human participants by quantifying them in terms of accuracy and/or response time. However, we did not collect behavioural data; rather we conducted three tier analyses of the images of both the databases— analyzing geometric pattern in the area attended on the face, computing root mean square (RMS) pixel difference, and fractal dimensions to examine the geometrical deviation among images depicting facial expression of emotions. Thereafter, we compared these outcomes with the behavioural outcomes reported by the respective authors of these two databases. RMS is root-mean-square which is bread-and-butter term for engineers. Scattered data points can be fit into a straight line and root-mean-square (RMS) is the standard techniques for making such a fit. Most engineering application adopt this strategy to represent seemingly large collection of individual points by a straight line. The major advantage of such a representation is that a straight line can be quantified by only two parameters, the slope and the intersect. This two-parameter system now represents the set of several individual points and the RMS value of zero (goodness-of-fit value of 1) represents a perfect fit.

3 RESULT

3.1 Identifying Geometric Pattern

To see the interplay of physical properties of facial expression of emotions and their recognition it was important to extract embedded geometric pattern in the photographs depicting facial expressions and see the interplay of these physical properties and their recognition accuracy. Based on eye-tracking Bhushan (2007) has reported that the observers look at only three regions while trying to understand human facial expressions— the eyes (eyebrows, eyes, and eyelash), nose (without the bridge) and lip regions (centre and two diagonals). Thus, we investigated the geometric pattern in all the 36 images of the Indian dataset of basic emotions. The initial parameters were shortest vertical and horizontal distance among the three facial regions. Figure 2 illustrates the three regions. The shortest distance between point *'P'* and line *'L'* is the minimum vertical length and is denoted by '*d'*. Distance '*d'* can then be defined as the length of the line segment that has $P\ (x_0, y_0)$ as an endpoint and is perpendicular to $L\ (ax+by+c=0)$. It was calculated using the formula—

$$d = \frac{|ax0 + by0 + c|}{\sqrt{a^2 + b^2}} \qquad (1)$$

The resultant horizontal distance is estimated by

$$W_{ij} = W_i - W_j, \qquad (2)$$

where W_i is the width of ith line and W_j is the width of jth line.

These equations (1 and 2) were worked out for all six intensity levels of all the six basic emotions using MATLAB© 2014 software. Significant changes were observed in all the three regions for surprise and disgust. For surprise the eyebrows, lips centre and diagonal changes play important role (higher value of vertical distance) at higher intensity. For disgust the eyebrows, eyelash, and nose play important role at low intensity. Expansion (horizontal distance) of lips centre is more expressive at lower intensity level, whereas vertical distance of lips centre section is more sensitive at higher intensity levels of disgust. Fear had a distinct pattern. Each region of fear expression becomes more prominent as the intensity increases. For the remaining three emotions, happiness, sadness, and anger, the horizontal-vertical changes were not exhibited in all the three regions. In happy expressions the expansion of lips centre increases at higher intensity of happy expression. In sadness the expansion of both nose and lips centre become more prominent at higher intensity of expression. The nose region plays important role at low intensity of anger, whereas lips centre and diagonal changes are more prominent (high values of vertical distance) at high intensity of anger.

The overall comparison of the facial expressions with respect to changes in the vertical and horizontal distance points out that as far as horizontal distances are concerned the findings suggest that the eyebrow, eyelash, lips centre and diagonal sections of happy emotion indicated distinguished pattern compared to other emotions. Disgust facial expression show variance in the eyelash, nose and lips centre section compared to other emotions. Analysis of the vertical distance indicated that the eyebrow section is the most expressive part in surprise compared to the remaining facial expressions of emotions. Eyelash, lips centre and diagonal sections of happy emotion indicate distinguished pattern compared to others emotions. Disgust facial expression show anomaly in nose and lips centre section compared to other emotions.

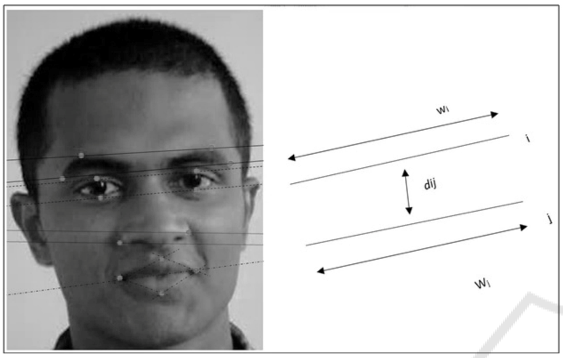

Figure 2: The three regions of the face.

3.2 Root Mean Square and Average Value

The root mean square (RMS) pixel difference was estimated for facial expressions of all six intensities of all the six emotions. RMS was compute using following formula—

$$Root\ mean\ square(e) = \sqrt{\sum_{i,=1}^{M^2} (f_i)_j - (f_i)_k)^2}$$

where the image size is M x M implying a total of M^2 pixels and f_i is the value of the gray-level for i^{th} pixel. The six emotions are represented by the index j which takes on integer values between 1 and 6. The index k also takes on integer values between 1 and 6. Whenever j=k we have RMS value as zero since the image is compared by itself. The observer sees the whole face and identifies the person concerned.

The findings suggest that RMS pixel difference value of happy and disgust emotions are in increasing order. Thus, these emotions show identical behaviour. Similarly, fear and sad emotions show identical pattern. The diagonal matrix shows all possible RMS difference for all intensity levels. It is observed from the matrix that fear facial shows maximum RMS difference values with all combinations, whereas happy and sad emotions show comparatively lower values.

RMS pixel difference shows identical patterns in the expressions of happiness-disgust and fear-sadness. It suggests that changes in eyebrows (region 1) affect expression of surprise whereas changes in nasal area (region 2) and lips (region 3) affect expression of disgust. Happiness is affected by changes in eye-lash (region 1) and lips (region 3).

We neither analyzed geometric pattern (of the area attended on the face) nor computed root mean square (RMS) pixel difference for IAPD images for two reasons— (i) all expressions of any given emotion in IAPD show only one static pose and therefore doesn't have variance, and (ii) except one (straight), all other images of IAPD are from varying degree which limitsgeometric comparison of select regions.

3.3 Fractal Dimension

The mathematical formulation of fractal involves analysis of distribution of these gray-levels and it is independent of the source that makes the image/photograph. This study is an attempt to quantify emotions with the help of photographs taken of the subject. These photographs have been taken from different angles since observer in real life situations may not be present exactly in front of the subject. The effect of viewing angle thus becomes important in this work. The geometric property considered in the fractal theory is the change in pixel-value (gray-level) from one pixel to another. This notion of "self-similarity" exists in nature and we see that facial photographs also exhibit this behaviour. The facial muscles expand/contract in an interesting way to produce facial expressions unique to the basic emotions. This aspect has been captured by fractal dimension computation. Fractal theory illustrates the characteristics of images/photographs based on the similarities of neighboring regions from the gray-level perspective. The "measurement" aspects is embedded in the fractal variable normalized-range-scale (NSR) parameter which incorporates physical distances in the formulations. These distances are in pixel units since an image is composed of square pixels. Each pixel in this study is 0.26 mm x0.26 mm square shape and it is used in image processing steps for computing fractal dimension.

3.3.1 The Indian Dataset of Basic Emotions

We analyzed fractal dimensions for all expressions of the Indian dataset of basic emotions across all six intensity levels. Table 1 summarizes the obtained fractal dimensions whereas figure 3 illustrates the change in fractal dimensions with increase in the intensity of expression.

Table 1: Fractal dimensions for IDBE (all six intensity levels) and IAPD (all five viewing angles) facial expressions of all six basic emotions and respective unbiased hit rates (Hu).

IDBE							
Emotions	**Intensity**						**Reported Hu**
	1	**2**	**3**	**4**	**5**	**6**	
Happy	2.58	2.59	2.59	2.59	2.59	2.61	0.64
Sad	2.61	2.64	2.64	2.65	2.62	2.63	.13
Fear	2.61	2.61	2.64	2.64	2.64	2.64	0.11
Anger	2.56	2.57	2.58	2.59	2.57	2.56	0.44
Surprise	2.58	2.58	2.58	2.59	2.59	2.60	0.25
Disgust	2.57	2.58	2.58	2.58	2.59	2.61	0.15

IAPD						
Emotions	**Viewing Angles**					**Reported Hu**
	90-	**45-**	**0**	**45+**	**90+**	
Happy	2.29	2.23	2.42	2.34	2.37	0.88
Sad	2.33	2.16	2.39	2.29	2.37	0.8
Fear	2.3	2.18	2.33	2.35	2.44	0.86
Anger	2.38	2.17	2.42	2.41	2.31	0.92
Surprise	2.3	2.27	2.4	2.22	2.38	0.89
Disgust	2.26	2.2	2.35	2.34	2.41	0.9
Neutral	2.33	2.21	2.46	2.32	2.37	0.74

*Hu for IDBE has been reported separately for all intensity levels across six emotions. Here average Hu for the given emotions have been reported.

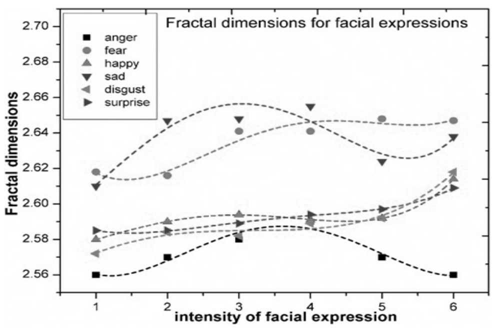

Figure 3: Fractal dimensions for the facial expressions of the Indian dataset of basic emotions across six dimensions.

For clear understanding of the results, it is presented in form of apolynomial fit. This apart can further be used for detailed mathematical analysis of emotions. The findings suggest very-very strong (say 3) self-similarity between surprise-happiness and very strong (say 2) self-similarity between surprise-disgust. Happiness and disgust also had strong (say 2.5) self-similarity. It indicates self-similarity which is one aspect of complexity of a two-dimensional function/image. Other mathematical functions can be used also but fractal dimension has become very popular in medical and industrial imaging, hence we have tried it for understanding facial expressions also. The surprise-happiness-disgust trio had self-similarity across all six intensity levels, lowest to highest. The self-similarity between surprise and anger reached a non-distinguishable level as the surprise-happiness-disgust trio between moderately low (3) and moderately high (4) intensity levels. Fear and sadness had a weak self-similarity. Sadness and anger showed a distinct characteristic. They had different base but shared same pattern (showing a bump).

3.3.2 The Indian Affective Picture Database

We computed fractal dimensions for all the images of this database. Table 1 summarizes the obtained fractal dimensions.

The result suggests that the facial expressions of IAPD images fall within a band ranging between 2.1 and -2.5 and this band is independent of the type of emotion. The uncertainty band marginally changes (Δ .4) depending upon the angle of observation. The manifestation of happy facial expression is isotropic, i.e., they are angle independent. Further, there is no sex difference as far as expression of happiness is concerned. For neutral expressions the facial expressions of the males do not change as much as the females. Although IAPD has two male and two female expressers, one of the male expressers does not show much change in the expression, especially neutral, surprise expressions.

4 COMBINING IMAGE ANALYSIS OUTCOMES AND REPORTED BEHAVIOURAL OUTCOMES

Both the databases have reported the proportion of correctly identified stimuli (hit rate), unbiased hit rate (Hu), and rating of intensity. Having quantified the geometric properties of the facial expressions we tried mapping them together with the reported behavioural response for the two respective databases to derive some meaningful conclusion. The behavioural data outcome of the Indian dataset of basic emotions

(Bhushan, 2007) clearly indicates high recognition accuracy (hit rate) for happiness and disgust across intensity levels. With increasing intensity recognition accuracy of surprise and anger also increases. The unbiased hit rate (Table 1) also suggests better recognition of happy, anger, surprise, and disgust expressions. RMS pixel difference show identical pattern in the expressions of happiness and disgust. On the other hand, fractal dimensions indicate self-similarity among surprise, happiness, and disgust. It also indicates self-similarity between surprise and anger between moderately low and moderately high intensity levels. It seems that human beings have a natural inclination to search appropriate geometric cues while deciphering facial expressions of emotions.

The outcome of behavioural data for IAPD (Sharma & Bhushan, 2019) suggests high recognition rate (mean hit rate) for happiness (99.91). The other emotions were also close (anger (96.21), disgust (95.66), surprise (95.15), sadness (94.18), and fear (92.91). They found that neutral expression (77.14) was most difficult to recognize.

A comparison of both the databases on the basis of hit rates indicates that happiness, disgust, anger, and surprise are recognized better. When the Huof the two databases were compared slight variation was observed. For IAPD anger (0.92), disgust (0.90), surprise (0.89), and happiness (0.88) had higher Hu. The Hu for the Indian dataset of basic emotions have been reported for all six intensity levels of the respective emotions. Hence, we took the overall value for each of the basic emotion. Here the Hu of happiness (0.641) is far higher followed by anger (0.443) and surprise (0.251). For remaining emotions, the reported values are low.

The fractal dimension of IAPD suggests that accuracy of recognition of emotion is not affected by the viewing angle of the facial expression. The findings confirm that geometric properties of the face significantly affect the recognition of facial expression of emotions. Further, these properties do not affect recognition of facial expressions when viewed from different angles.

5 DISCUSSION

This study examined the geometric changes in the select regions of the face during expression of emotions vis-à-vis increase in the intensity of expression and the viewing angle. IAPD study has reported happiness as 'easily identifiable emotion' and neutral to be difficult. Difficulty in distinguishing fear-surprise and anger-disgust has also been reported attributing it to similarity in'configuration of the facial muscles'. Further, recognition of emotion on the face is not affected by the viewing angle. The findings of IDBE study has also endorsed that the accuracy of recognition depends on the intensity of surprise, happiness, and disgust. Other studies have also reported that happiness is very distinct compared to other basic emotions and hence is distinctly recognized. They show that happy and surprise expressions are easily recognized (Calvo et al., 2014). Recognition of happiness has also been found to be faster compared to negative emotions (Leppanen & Hietanen, 2004). Du and Martinez (2011) have reported higher recognition of happiness and surprise, poor recognition of anger and sadness and worst recognition of fear and disgust. If we look at these expressions in terms of larger face transformations, surprise involves largest deformation followed by disgust and fear. However, both disgust and fear are very poorly recognized. (Calvo & Lundqvist, 2008) found that fear is difficult to be recognized.

Another significant finding of the study was the relationship between geometric changes and recognition of facial expression. We found high recognition accuracy as well as self-similarity between surprise, happiness, and disgust. Neth and Martinez (2009, 2010) have reported distance changes between facial features in specific emotion expression. Happiness involves change in the curvature of mouth and surprise involves opening of the eyes. These expressions share additional sclera. The distance between eyebrows and eyes is large and the face is thinner for surprise. The distance between eyebrows, eyes, nose, and mouth is shorter for disgust. Our findings are in consonance with these results. The distance between eyebrows and mouth and the width of the face are distinct to sad and anger expressions. Larger distance has been reported between eyebrows and mouth (Neth & Martinez, 2009) and a thinner face than usual (Neth & Martinez, 2010) for sadness. The distance between eyebrows and mouth is much shorter and the face is wide for anger. Further, the distinction between these two expressions blurs with reduction in the computational space between them.

Fearful expression had a distinct pattern but we did not find self-similarity across intensity levels. The evolutionary viewpoint has endorsed fair degree of recognition of fear due to its survival significance but later researchers have reported poor recognition of fear in healthy population (Du & Martinez, 2011). Susskind et al. (2008) have argued that the sensory channels open in fear and closes in disgust.

These findings have several applications. The understanding of facial expressions has application in mental health setting where it can help identify mental state, intensity of pain, deception of symptoms, subjective experience of treatment/ interventions, automated counselling, and many more areas. Such findings are also likely to affect human computer interaction (HCI), interactive video, and other related areas. Calder et al. (2001) have classified emotion expression into three categories and the take away for HCI research. Happiness and surprise can be detected easily irrespective of the distance between the expressor and the person perceiving it. Anger and sadness are reasonably detected from proximity. Fear and disgust constitute the third group of emotions for which people are not very good at recognizing. Although, we also found the relationship between happiness and surprise, our findings show little deviation from the findings of Calder et al. (2001). These findings might be useful for HCI researchers looking for systems that can at least reasonably imitate human perceptual ability. Some researchers suggest variability in the perception of dynamic expressions in the clinical population such as Pervasive Developmental Disorder (Uono, Sato, & Toichi, 2010) and Asperger Syndrome (Kätsyri et al., 2008). The stimulus used in the present study has graded intensity level adding to the dynamic nature of facial expression and thus might be useful for study of the clinical population as well.

The advantage of the two databases analyzed in this work is that they contain static stimuli extracted from dynamic source that represents real life condition. Thus, together they consist of facial expression of emotions of all the six basic emotions of six varying intensities and five different viewing angles. However, there is an inherent limitation as well. While IDBE consists of facial expressions of only one male expresser, IAPD comprise of expressions from five different viewing angles but not of variable intensity. Although, the absence of larger database limits the generalizability of specific findings but it does establish that RMS and fractal dimension can be very well applied in behavioural science studies as well.

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