FACE FEATURES-BASED PERSONALITY ASSESSMENT

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ABSTRACT
Personality assessment has been widely used in the professional psychology and signal processing fields. Recently, it has been a great interest from the computer vision research community in assessing personality from visual data. Many state-of-the-art models are assigned the Big-Five personality indicators using either external judges or personal interviews. We propose Face Features-based Personality Assessment (FFPA) that assesses the personality of a person based on one's facial features. It maps facial appearance into the Big-Five personality indicators, namely Extraversion, Agreeableness Conscientiousness, Neuroticism and Openness. The geometry-based and appearance-based approaches are used to extract features from the face and mapped to the personality indicators using Partial Least Square Regression (PLSR). The corresponding personality indicator values are collected by filling the online form of the Big-Five personality assessor. The computational experiments are performed on a synthetic dataset, consisting of the face images of 200 students. The experimental results show that the proposed model predicts the personality indicators with 0.95 coefficient of determination (approx.) and Mean Squared Error (MSE) is 0.001 (approx.).

KEYWORDS
Personality Assessment, Face/Facial Features, Big-Five Personality Indicators

1. INTRODUCTION
Personality is the combination of one’s emotion, motivation, behavior and characteristics of their thought patterns. It has a great impact in representing one’s life, well-being, health along with desires and preferences. Thus, the ability to detect one’s personality traits has numerous applications in the fields of psychology, neuropsychology and signal processing.

Face appearance has a high influence on social interactions, which in turn could potentially influence personality (Rublee et al., 2011). Face or facial features may speak a lot about a person. There is a popular saying; Face is the index of mind (John & Srivastava, 1999). These have various applications in the field of computer vision. Its applications include face recognition, security, crime investigation and healthcare. However, facial features change when emotion changes.

Personality assessment is widely used in professional psychology for the administration and interpretation of experimentally supported personality traits. Physiognomy (Aparna & Ravi Kumar, 2014) deals with inferring the person using the facial features. It assesses the personality of a person based on outer appearance, especially the face. That is, it extracts the facial features and enables one for judging the personality of a person based on extracted facial features. The experiments were done on a small dataset, consisting of 25 people and the results show that their personality matched the output obtained by approximately 72%. Numerous computer vision approaches are proposed to analyze body postures, faces, and behaviors and infer apparent personality traits (Rammstedt & O. John, 2007; Sharat Chandra et al., 2015; Shu Liao et al., 2006; Noura Al Moubayed et al., 2014; Julio C. S. Jacques Junior, et al., 2019).

1.1 Big-Five Indicators
The Big-Five personality indicators are derived from examinations of the natural language terms, individuals use to portray themselves as well as other people. Its taxonomy serves an integrative function and provides a starting place for various researches in the descriptive taxonomy. The Big-Five dimensions Facet (John & Srivastava, 1999; Rammstedt & O. John, 2007) are enlisted in Table 1.
Table 1. Big Five Dimensions Facet

<table>
<thead>
<tr>
<th>1. Extraversion vs. introversion</th>
<th>Gregariousness (sociable)</th>
</tr>
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<tbody>
<tr>
<td>Assertiveness (forceful)</td>
<td></td>
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<tr>
<td>Activity (energetic)</td>
<td></td>
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<tr>
<td>Excitement-seeking (adventurous)</td>
<td></td>
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<tr>
<td>Positive emotions (enthusiastic)</td>
<td></td>
</tr>
<tr>
<td>Warmth (outgoing)</td>
<td></td>
</tr>
<tr>
<td>2. Agreeableness vs. antagonism</td>
<td>Trust (forgiving)</td>
</tr>
<tr>
<td>Straightforwardness (not demanding)</td>
<td></td>
</tr>
<tr>
<td>Compliance (not stubborn)</td>
<td></td>
</tr>
<tr>
<td>Modesty (not show-off)</td>
<td></td>
</tr>
<tr>
<td>Tender-mindedness (sympathetic)</td>
<td></td>
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<tr>
<td>3. Conscientiousness vs. lack of direction</td>
<td>Competence (efficient)</td>
</tr>
<tr>
<td>Order (organized)</td>
<td></td>
</tr>
<tr>
<td>Dutifulness (not careless)</td>
<td></td>
</tr>
<tr>
<td>Achievement striving (thorough)</td>
<td></td>
</tr>
<tr>
<td>Self-discipline (not lazy)</td>
<td></td>
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<tr>
<td>4. Neuroticism vs. emotional stability</td>
<td>Anxiety (tense)</td>
</tr>
<tr>
<td>Angry hostility (irritable)</td>
<td></td>
</tr>
<tr>
<td>Depression (not contented)</td>
<td></td>
</tr>
<tr>
<td>Self-consciousness (shy)</td>
<td></td>
</tr>
<tr>
<td>Impulsiveness (moody)</td>
<td></td>
</tr>
<tr>
<td>Vulnerability (not self-confident)</td>
<td></td>
</tr>
<tr>
<td>5. Openness vs. closeness’ to experience</td>
<td>Ideas (curious)</td>
</tr>
<tr>
<td>Fantasy (imaginative)</td>
<td></td>
</tr>
<tr>
<td>Aesthetics (artistic)</td>
<td></td>
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<tr>
<td>Actions (wide interests)</td>
<td></td>
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</tbody>
</table>

We propose FFPA to assess the personality of a person based on facial features. There are basically three parts of the work; first extracting facial features from the face images, second is to get the values of the corresponding Big-Five personality indicators, and the third is to map the extracted features to the corresponding personality indicators. Although facial features change on emotion, we have captured static features of the faces with the normal state in order to capture static personality aspects.

2. RELATED WORKS

In this section, the major category of approaches, which have been proposed to extract the facial features from the images and to assess one’s personality are discussed. In a nutshell, as follows:
2.1 Face Features Extraction

2.1.1 Geometric-based Approaches
To extract facial features, these approaches use the size and the relative position of important components of the face. First, edges of important components of the face and the direction are detected. Then, feature vectors are built from the detected edges and direction (Urvashi Bakshi & Rohit Singhal, 2014). Gradient analysis and Canny filter are usually used for this purpose. In order to avoid lighting effects, Local Binary Patterns (LBP) (Sharat Chandra et al., 2015) is applied. LBP builds a histogram to create a feature vector for the face image.

2.1.2 Appearance-based Approaches
In these approaches, the image is processed as two-dimensional patterns (Urvashi Bakshi & Rohit Singhal, 2014). These achieved the best performance to extract face features because these maintain the important information of the image and reject the less important information. The Independent Component Analysis (ICA) and Principal Component Analysis (PCA) are widely used approaches to extract the feature vector (Sharat Chandra et al., 2015). It is observed that the ICA achieved better performance than PCA in the presence of noise such as expressions of face and variations in lighting.

2.1.3 Color-based Approaches
To detect the skin region, these approaches use different color models such as RGB (Urvashi Bakshi & Rohit Singhal, 2014). First, the gray-scale image is transformed into the Hue Saturation Value (HSV). The color and saturation values are eliminated to consider only the luminance part. The luminance part is transformed into a binary image by using a certain threshold. After thresholding, certain opening and closing operations are applied to remove noise. Then facial features are extracted from the binary image.

2.2 Personality Assessment
The Vedic Personality Inventory (Dasa, D.G., 1999) is based on the Vedic concept of the three gunas, or modes of nature. It is an instrument that assesses the validity of the three guna constructs. A sample of 619 persons of varying ages and occupations from the Southeastern United States is studied. In (Beatrice Rammstedt, & Oliver P. John b, 2007), the authors proposed Automatic Personality Perception (APP) that automatically predicts the personality indicators of the people that they attribute to others. They mapped facial appearance into the Big-Five personality indicators to assess the personality of individuals. The experiments are performed on the Facial Recognition Technology (FERET) corpus, consisting of a total of 829 face images. The results show that it predicts with an accuracy of around 65%. In (Rublee et al., 2011), the authors give more importance to the first impression of the faces generated artificially and visualize the characteristics having an effect on first impressions for several personality traits. The shape variations and texture of the faces are extracted by Principal Component Analysis (PCA). They established the relationship between first impressions, facial characteristics and self-reported personality traits. The experimental results reveal that the model fails to reliably infer personality indicators from either first impressions or facial features.

An approach is proposed based on physiognomy in (Aparna & Ravi Kumar, 2014). It first extracts facial features and enables one for assessing the personality of a person based on the extracted facial features. The authors also considered various measurements of facial features such as ear length, nose length, forehead length, lip axis, eye axis, the distance between the eyes and forehead width. A personal interview with the individual is conducted to get the Big-Five personal indicators. The experiment is conducted on a small dataset, consisting of 25 individuals. It is found that their personalities are matched with the output obtained by approximately 72%.

A new approach is proposed to automatic personality recognition based on Facebook profile pictures in (Cristina Segalin et al., 2017). The authors extracted visual features such as hue, valence and saturation and also content features from the Instagram profile pictures to predict the personality in (Bruce Ferwerda & Marko Tkalcic, 2018). In (Guntuku et al., 2019), the authors extracted interpretable features of profile and posted...
pictures to uncover the associations with users’ depression and anxiety. A Deep Neural Networks based is proposed for estimating the personality traits from portrait pictures in (Moreno-Armendáriz et al., 2020).

The proposed FFPA is different from the state-of-the-art approaches in terms of region of face features and the way of assigning Big-Five indicators. The state-of-the-art approaches are mainly assigned the Big-Five indicators either with the help of external judges or personal interviews. In our method, the Big-Five indicators are collected from the participants by filling the online standard questionnaire. Further, many existing approaches have considered the rectangular face image that includes ears and neck also. Whereas, the proposed approach considers the face features that reside inside the convex hull of the first 27-facial landmarks (V. Kazemi & J. Sullivan, 2014). Then, PLSR (Ng, K.S., 2013) used for mapping the extracted facial features with the personality indicators.

3. THE PROPOSED WORK

The steps involved in the proposed FFPA are as follows:

1. The face is cropped from the face image. Haar Cascade (P Viola and M J. Jones, 2001) method is used to detect the faces.
2. The facial features are extracted using Oriented FAST and Rotated BRIEF (ORB) method (Rublee et al., 2011).
3. The landmark points of the face are identified using the dlib\(^1\) python library.
4. A convex hull considering the first 27 landmarks of the step-3 is drawn.
5. The face features falling inside the convex hull are considered as facial features for mapping. These features are the response part of the ORB features.
6. Finally, the extracted face features are mapped to personality indicators using PLSR.

![Figure 1. The 68 Facial Landmark Points extracted based on (V. Kazemi & J. Sullivan, 2014)\(^1\)](http://dlib.net/)

\(^1\) http://dlib.net/
Given a face image, the face is detected using Haar Cascade method (P Viola and M J. Jones, 2001). Once the face is detected, one thousand facial features are extracted using ORB (Rublee et al., 2011). It is an efficient and better alternative to the state-of-the-art methods for detecting the facial features. Given a pixel \( P \) in an array, it compares the brightness of \( P \) to surrounding 16 pixels that are in a small circle around \( P \). Pixels in the circle are then sorted into three classes (lighter than \( P \), darker than \( P \) or similar to \( P \)). If more than 8 pixels are darker or brighter than \( P \) than it is selected as a keypoint. It uses a multiscale image pyramid at different scales. After locating key points at different scales, it assigns an orientation to each keypoint like left or right facing depending on how the levels of intensity change around that keypoint. Next, we use the method (V. Kazemi & J. Sullivan, 2014) to detect the facial landmarks as shown in Figure 1. A convex hull covering the first 27 facial landmarks is considered for confining the facial features. That is, the facial features that fall within the convex hull are used further for mapping with the Big-Five personality indicators. Although the face contains around one thousand features, there are facial features range in 500-600 are falling within the convex hull. We consider only 500 facial features for mapping in order to collect a uniform number of features from each face as shown in Figure 2. The extra facial features if any are ignored from dense regions (e.g., eyes).

### 3.2 Mapping Face Features to Personality Indicators

The face features are mapped to personality indicators using PLSR (Ng, K.S., 2013). PLSR reduces the predictors to a smaller set of uncorrelated components and performs least squares regression on these components, instead of on the original data. It is especially useful when your predictors are highly collinear, or when having more predictors than observations and where ordinary least-squares regression either produces large standard errors. The ORB features are composed of the coordinate point, size, response, and orientation of the feature point. In our model, the response value of each feature point is considered as a facial feature.

Table 2 shows the sample dataset. The columns F1, F2 ...F500 represent the facial features obtained from ORB. The values in the corresponding columns represent the response values of facial features. The last five columns of the dataset are the personality indicators data which are target (or dependent) variables for PLSR. These are values obtained by getting the participants to fill the online form for the Big-Five personality indicators.
Table 2. Sample Dataset

<table>
<thead>
<tr>
<th>Face ID</th>
<th>F1</th>
<th>F2</th>
<th>F3</th>
<th>...</th>
<th>F500</th>
<th>O</th>
<th>C</th>
<th>E</th>
<th>A</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>15</td>
<td>11</td>
<td>13</td>
<td>...</td>
<td>11</td>
<td>0.31</td>
<td>0.51</td>
<td>0.26</td>
<td>0.14</td>
<td>0.17</td>
</tr>
<tr>
<td>2</td>
<td>15</td>
<td>11</td>
<td>13</td>
<td>...</td>
<td>11</td>
<td>0.64</td>
<td>0.8</td>
<td>0.96</td>
<td>0.73</td>
<td>0.26</td>
</tr>
<tr>
<td>3</td>
<td>9</td>
<td>23</td>
<td>21</td>
<td>...</td>
<td>7</td>
<td>0.51</td>
<td>0.57</td>
<td>0.85</td>
<td>0.73</td>
<td>0.71</td>
</tr>
</tbody>
</table>

F1 to F500 = Facial Features, Big-Five Personality indicators: O = Openness, C = Conscientiousness, E = Extraversion, A = Agreeableness, N = Neuroticism.

As the data set contains more features than the number of observations (or records) which is likely to contain multicollinearity problem, the Ordinary Least Square (OLS) regression is not preferred. Further, to extract latent features or reduce the dimensions of the ORB facial features obtained, it is observed that PCA is not suitable because it does not consider the correlation of features with the Personality indicators and shows random behavior as shown in Figure 3. Therefore, we use PLSR for mapping the facial features with the values of the personality indicators.

![Figure 3. Correlation between the first 50 Principal Components (PCs) (on X-axis) and Personality Indicators (Y-axis)](image)

4. EXPERIMENTS

The experiments are done on a synthetic dataset, containing the face images of 200 students. The corresponding Big-Five personality indicators of all students are collected based on their responses to the online standard questionnaire. The performance of the proposed model is evaluated based on two main metrics: coefficient of determination (R² goodness of fit) and MSE. The values of these two metrics of the proposed model are collected on a varied number of principal components. The result of MSE and R² corresponding to the Big-Five personality indicators on varying numbers of the principal components is shown in Figure 4.

![Figure 4. Plots of MSE and coefficients of determination corresponding to varied numbers of PCs](image)
Figure 4 shows that the goodness of fit (>0.95) and MSE (<0.03) are satisfactory at the number of principal components greater or equal to 25. The 95% confidence interval of the score estimate of MSE is given by 0.001 (+/- 0.0028). The convergence of MSE, R-square, and R-square adjusted (RSquare_adj) with the increasing number of components in PLSR considering ORB face features as input show the significance of regression coefficients and so we can say that it is not an intercept-only model (Null Hypothesis).

Figure 5. MSE corresponds to each iteration of the k-fold cross-validation corresponding to a varying number of PCs

The proposed model is further evaluated in terms of the variation of MSE by applying the 10-fold cross-validation. The variation of MSE corresponding to each iteration of the cross-validation is captured and is shown in Figure 5. It is observed that there is not much variation in MSE on a varying number of PCs across the 10-iterations.

5. DISCUSSION AND CONCLUSION

This work proposes FFPA for mapping facial appearance into the Big-Five personality indicators. A combination of both geometric-based and appearance-based approaches is used to extract facial features. The extracted facial features are mapped into the Big-Five personality indicators using PLSR. The performance of the proposed FFPA is demonstrated on a synthetic dataset, consisting of 200 face images. The results show that the proposed FFPA predicts the personality indicators with 0.95 coefficient of determination and MSE is 0.001. The convergence of MSE, R-square, and R-square adjusted with an increasing number of PCs in PLSR shows the significance and acceptance of the model.

However, a huge dataset and deep learning based face features extraction may provide better performance. Therefore, as an extension of this work, the proposed approach will be investigated with more data and deep learning based feature extractions to improve the performance in future.

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