

Abstract

FACIAL ASYMMETRY: A BEHAVIOMETRIC INDEX FOR ASSESSMENT DURING A FACE-TO-FACE INTERVIEW

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Choosing the right person for the right job makes the personnel interview process a cognitively demanding task. Psychometric and biometric tests have often been used to aid the process, but they have their own limitations. We propose the use of behaviourmetry as an assistive tool to facilitate an objective assessment of the interviewee without increasing the cognitive load of the interviewer. Behaviourmetry analysis thin slices of behavior and provide unbiased information about the interviewee. The current study details the methodology of the behaviourmetry tool to capture asymmetry and micro expressions of the face. Hemi-facial composites using a structural similarity index were used to develop a progressive time graph of facial asymmetry. In the pilot test, frame by frame analysis was performed on 3 youtube video samples, where Structural similarity index (SSID) scores of 75% and more showed behavioral congruence.

Keywords: *behaviourmetry, facial asymmetry, micro expressions, hemi-facial, congruence*

Introduction

The popularity of face-to-face interviews for personnel selection cannot be denied. An employment interview is often the first contact between the interviewee (seeking employment) and interviewer (employer). Many applicants recognize the importance of this initial contact and make efforts to ensure a positive outcome. The nonverbal behaviors that an applicant exhibits during this stage of the interview are often a major determinant of the kind of impression that is made. These behaviors often influence the employer's decision to hire. Between the interviewee's verbal and nonverbal behavior, it is the latter that can provide personal information without the conscious awareness of the respondent. Such information is frequently sought by interviewers, but at the same time, identifying discrepancies between content (content) and intent (nonverbal) of the interviewee's speech or facial expressions during the ongoing personnel selection interview itself is cognitively overbearing. This compromises the objectivity of assessment in a selection interview process, making the assessment vulnerable to subjectivity, behavioral and cognitive bias. To address this concern, we propose the development of behaviormetric tool based on machine learning to assist interviewers to make objective decisions about the interviewee. A proposed assistive tool is a behaviormetry tool. We present the details of this tool along with the results of a pilot study conducted with the help of this tool, to qualify the effectiveness of the tool.

Behaviormetry

Presently psychometry is popularly used to understand human behavior. Psychometry involves profiling of behavior based on the measurement of cognitive capabilities, affective predisposition, behavior orientation including personality. Alongside psychometry, biometric data is also used at times to understand human behavior. While biometry data fails to reflect the mental or emotional states of an individual, psychometric data fail to reveal objective verifiable real-time human behavior. Although psychometric tests are developed based on behavior samples and are internally validated, items do not always match a visual image or reflect a signature behavior for assessment which is good for external validity. The science of behaviormetry, which uses thin slices of nonverbal behavior as the measure of mood states, is fast evolving and appears to be a probable solution to the existing problem.

Behaviometry interfaces between psychometric and biometry by utilizing unique behavioral signatures like the facial expression of emotion, ocular motion, gait pattern and body language, vocalization, proximal behavior (use of physical space during communication), and other forms of nonverbal behaviors. This study limits the use of behaviometry to analyze facial expressions to assist objective understanding of human behavior during personnel selection. The term behaviometry is made up of two words: behavior and metric. While behavior relates to the unique identification of an individual based on behavior characteristics, metric indicates measurement. Behaviometry is an objective measurement of the unique and common behavior pattern exhibited by an individual. It helps in reinforcing, faking, substituting, or at times contradicting verbal behavior.

The reason for developing behaviometry as a tool to capture and analyze FE during an interview situation is because for many years behaviometry has stood the test of time to understand psychopathology. its application to understanding normal human behavior however has been restricted

Microexpressions of emotions and facial asymmetry

The face is a salient and powerful representation of an affective state (Matsumoto, 2001). It helps portray the importance of emotions essential for basic survival, be it physical, psychological, or social and communication (Mandal & Ambady, 2004). The face is exposed to others for the facilitation of social system interaction. The amount (especially for a brief moment) and kind (emotional, attitudinal) of information that it conveys is easy to comprehend. Ekman and Friesen (1992) noted ‘the face is a multi-signal as well as multi-message system and one of the most important messages that it renders is emotion’. It is assumed that expressions of the face have enhanced innate disposition to reflect true psychic reality through genuinely felt emotional expressions. With the advancement of technology involving computer vision and artificial intelligence, it has become possible today to detect facial behaviors. Furthermore, brief expressions in dynamic conditions such as during interviewing that easily evade our notice can also be captured using computer vision.

A second reason for the paucity of attempts to quantify facial behavior is the sheer volume of expressions that mimetic muscles of the face can elicit. These muscles are activated by facial nerves, which cause contractions resulting in observable movements. Visible facial actions are blocks of skin motions or wrinkles, the configuration of which changes with the change in mood state. Since mood state is rarely reflected in pure form, the face reveals compound emotion (blended with another emotion like happiness, sadness, fear, anger, surprise, disgust, (see Du et al., 2014), the nature and variety of which depends on cultural display rules (like intensification, de-intensification, neutralization, masking (see Matsumoto et al., 2005), personality disposition, clinical state, demographic characteristics (like gender, ethnicity, age), and other factors. Thus, it is challenging to calibrate each expression for objective assessment.

Unlike Psychometry which is a behavioral assessment of the subject by asking relevant questions, behaviometry is the analysis of thin slices of human behavior by recording nonverbal cues of micro-expression of the face or body and analyzing them with the help of machine learning

Lateralization of facial expression: Quantifying facial asymmetry

Quantifying facial asymmetry is a challenging task. Available measures are either scanty or lack the exactitude which would help measure subtle changes across the face. No doubt, facial expression recognition systems have tried to address these issues, but they perform well when the intensity of expressions is high (Pantic & Rothkrantz, 2000).

It was Darwin's (1890) classical work that suggested that the two halves of the face differ in terms of facial expression. Wolff (1933) further suggested that the right side is the social face that expresses desirable emotions unlike the left side of the face that expresses personal emotions. The left side of the face is governed by the right hemisphere, specialized to process emotions.

Asymmetry is a structural description that cannot be captured by a local measure. We propose the development of a split-face composite method. It is a process wherein a full face is reconstructed by combining the lateral half of one side of the face to its mirror opposite (Mandal, Bulman-Fleming, & Tiwari, 2000). The right hemisphere of the brain, which exerts contralateral motor control on the left side of the face, is also considered dominant in the processing of emotion (Borod et al., 1997). Empirical evidence suggests that the left side of the face is more affect-laden as opposite to its counterpart (see Asthana & Mandal, 1997; Sackeim, Gur, & Saucy, 1978). The right side of the face is more under the voluntary control of the expresser and displays socially desirable emotion expressions in healthy adults (for a detailed review on the subject, see Murray et al., 2015). Compelling evidence for this proposition has come from a series of experiments conducted by this author on normal subjects (Mandal et al., 1995) and brain-damaged patients (Mandal et al., 1999).

Based on the available literature, we hypothesize that a composite of the left-left (L-L) side of the face developed using the split-face composite method would be indicative of personal emotions while a composite of the right-right (R-R) face would be indicative of social expression. A discrepancy in the expression of an L-L and R-R facial composite would suggest faking while synchrony or enhancement of L-L and R-R facial composite would suggest the authenticity of emotion. By using a computer-based program that utilizes open-source codes, we have demonstrated an example of how we can generate the L-L and R-R facial composites dynamically from a video, analyze how similar they are, and predict whether the emotion expressed is genuine.

The purpose of the present study is to demonstrate the utility of examining the facial asymmetry of the candidate during the interview, develop an artificial intelligence-based program to decipher the mental state or emotion, and utilize the hemifacial asymmetry index to supplement the judgment of the interviewer.

Methodology

Sample

The sample of the study comprised of three video snippets available on the internet as open source. These videos were comprised of structured interview sessions and chosen randomly from a set of such sessions. The face of the interviewee was discernible in each session. Theoretically, a video is a combination of continuous image frames put together in motion. To detect the presence of a face in the video clips, and henceforth its asymmetry, each video clip was run through the software, and analysis was done frame by frame using algorithms that operate only on a single image.

Flow of logic

The sequence of activities followed the selection of videos is outlined below

1. Dlib face detector was used to detect faces from a video file. After detecting the faces, Dlib identified 68 facial landmark points. The added advantage of the algorithm is that it also takes care of the alignment of an image (a very little tilted image). This is one of the primary reasons for choosing Dlib from other state-of-the-art face detector algorithm such as Viola-Jones.

2. The algorithm measures the left side of the face and then makes a copy of all pixel values from the left side of the face to create a Left-Left combination of the face and follows the same for creating the Right - Right composition of the face. Then the Structural similarity index (SSID) technique was used to verify the similarity between two consecutive faces i.e the LL and RR face from a frame. SSID technique returns a value whose range is between 0 and 1. 1 or close to 1 indicates that the faces are more similar whether 0 or close to 0 reveals the dissimilarity between faces.

3. Our algorithm takes care of the non-detected and non-aligned faces from image sequences using SSID. It returns a negative value (-0.1) if a rotated or non-detected face is found. The methodology generates a graph after analyzing each video based on SSID (as a percentage) and time (duration of the clip). It does not consider the negative SSID value while creating the graph.

4. The algorithm creates a baseline asymmetry (which is an SSID) from a static image during a neutral emotional state. The baseline varies from person to person. Where the SSID is significantly less than the baseline, it indicates the facial asymmetry which further suggests the incongruity. After analyzing the video file of a subject, the incongruity has been found in the graph where the SSID is less than the baseline in a particular time instance. [See Fig. 2]

By using the python opensource software, the composite of left-left faces and right-right faces were developed from the recorded video file to analyze the possible incongruencies across time domains.

Result

To identify facial asymmetry the randomly selected videos were analyzed using Dlib. The SSID values of the videos were then calculated. For frames having a well-aligned face, the SSID generated is shown in fig 4 [See Fig 4 for details]. The graph suggests that 45% of the time SSID values were below 60%, whereas at other times it was 70% and above. Instances where the SSID values are below 45% it is indicative of facial asymmetry.

Furthermore, if a 'baseline' asymmetry value is pre-generated as explained above, and for instance, it is found to be 70 units, then such instances where the SSID is substantially less than 70 units would represent incongruity. The baseline asymmetry SSID could be calculated by analyzing the facial features of the subject in a neutral state of emotion. For this, the subject may be asked to share beforehand the picture of his face without any emotional expression.

For this particular study, the SSIDs have been calculated from the video feeding. Once the algorithm detects a face at a particular time instant, it creates SSID. A two-dimensional (time(x-axis) and SSID(y-axis)) graph is generated automatically after the analysis of a video file. In Fig 4, SSID is above 70 units throughout the video where at the 45th time unit, it is below 60 units. This sudden fall of the SSID may represent an incongruity of the subject at that time and may be used as complementary evidence.

Results also suggest that a longitudinal analysis of facial expression would give reliable results rather than a cross-sectional analysis.

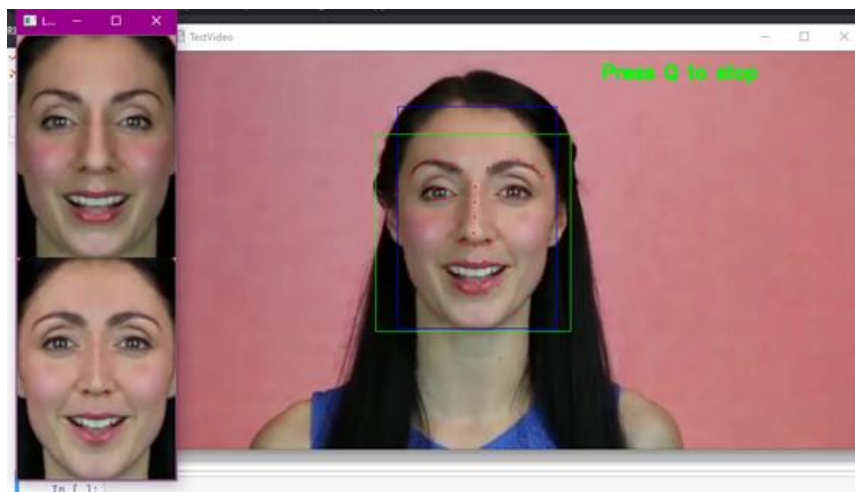


Fig 1: A sample frame of a video snippet, where both the LL(upper left corner), RR(lower left corner) along with original (middle of the window) faces are being displayed on the image (ref: [Welcome to Anna's British English: Elocution Online](#))



Fig 2 demonstrates the implementation of aligning the face first and then constructing the LL(upper left corner), RR(lower left corner) along with original (middle of the window), and aligned (extreme right) faces. A small tilt of the face is allowable. Using geometrical transformation, the face is rotated and aligned, and then the same process is followed

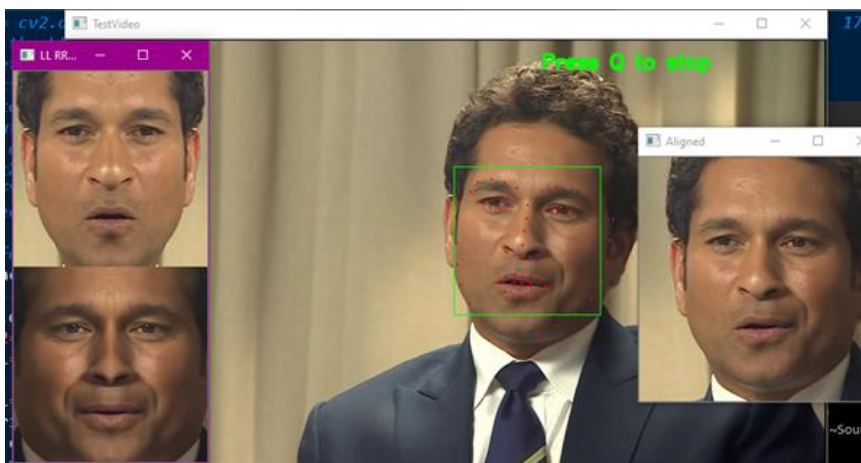


Fig 3 demonstration of the more tilted face: if the tilt of the face is too much, then the generated composite faces are very different and hence the error increases for such cases, generated LL ((upper left corner)), RR ((lower left corner) along with original (middle of the window) and aligned (extreme right) faces.

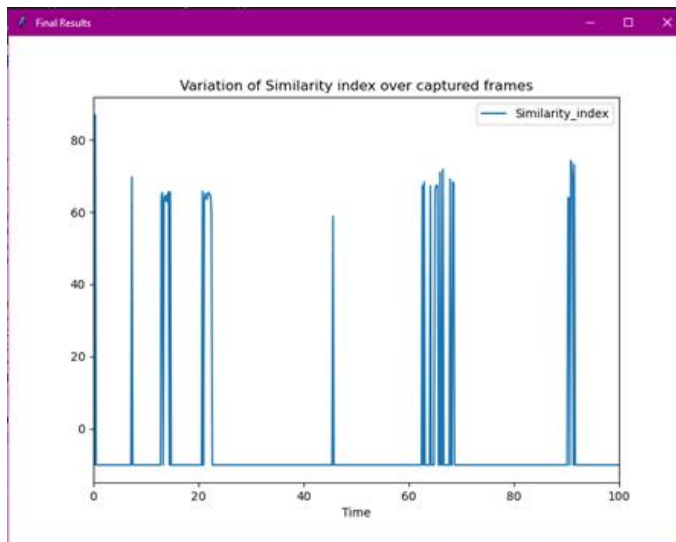


Fig 4 shows the generated graph for a small duration of a video clip. The X-axis represents time (clip duration) and the y axis shows the SSIDs in each frame (both values converted to 100 units). Values of SSID < zero means that the face was either not detected or was not well aligned.

Discussion

The facial expression of emotions lasts between 0.5 to 4 seconds (Ekman, 2003) and sometimes as fast as 1/30 th of a second. But they are an important source of information as they reflect concealed emotions. In a blink of an eye, the interviewer may miss perceiving these expressions. Quantitative analysis of such facial emotional expressions is also challenging. Unfortunately, measures that exist to capture this facial expression of emotion, are either too sparse or lack specificity to capture minute changes that happen on the face. We advocate the use of the behaviometry tool- developed on the principles of machine learning to be used as an assistive tool. Behaviometry would help reduce the cognitive demand of the interviewer during the selection process and providing supporting evidence by analyzing facial asymmetry as a function of the expression of different emotions. The effectiveness of this tool has also been presented by sharing the results of the pilot study that was conducted.

For case I (see fig,1) there is not much difference between the emotional expression of the subject in its normal picture in comparison to its L-L and R-R facial composite. But when we compare it with case II (see fig 2) and case III (see fig 3) we find that the facial composite reflects a distinct change or asymmetry in the L-L and R-R composite in comparison to the normal face. Such changes are often difficult to detect in an ongoing interaction however behaviometry helps to capture these changes and act as an aid to help decision making. Research suggests that the left side of the face is the social face while the right side of the face reflects true emotion.

It is assumed that during an ongoing interview an interviewee would try to control the expression of emotion based on certain display rules. At times the interviewees try to impress upon the interviewer by creating a particular image (Roulin, et al., 2014; Bourdage, et al., 2018). This could be in the form of neutralizing, masking, etc. The use of this behaviometry tool would assist recruiters in the interview selection by identifying facial leakage of the ongoing affective state of an interviewee. However, the advantage of the developed tool may necessarily not be restricted to the personnel selection process, it may well prove to be effective

in other situations such as scrutiny, detection of mental health issues, detecting deception, establishing trust, or interacting more humanely.

Limitation

The present study limits its understanding to the identification and analysis of facial expression. However, this method could be extended to the understanding of other nonverbal cues such as vocalics, gestures, posture, gait, etc. Secondly, the literature suggests that culture specificity influences the facial expression of emotion. This was not considered in the present study. A future study addressing this concern may be conducted.

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