Human Facial Aggressive Detection System Based on Facial-Width-to-Height Ratio

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Abstract. Recent researches have shown closely related evidence between the human individual social behavior and precisely measurable facial features. The Facial-width-to-height ratio (FWHR) has become quite an interesting topic concerning human aggressive behavior. Recent studies presented evidence showing that the precise measurement of FWHR can be used to predict human aggressive behavior based on facial landmark extraction. In this paper, the Facial-width-to-height ratio is extracted and analyzed among men, women, and children using the recently presented Convolutional Experts Constrained Local Model (CE-CLM). Then, extracted features are used to train the Numeral Virtual Generalizing Random Access Memory (NVG-RAM) pattern recognition technique. The results show promising clues in depending on this feature extraction method for the Facial-width-to-height ratio, and depending on SVG-RAM classifier for aggressive behavior. Moreover, the proposed method is less susceptible to facial rotation error ensuring accurate FWHR extraction.

Keywords: Facial expression; Aggression; Facial-width-to-height ratio (FWHR); facial landmark extraction; and Numeral Virtual Generalizing Random Access Memory (NVG-RAM).

1. Introduction

Social interaction depends mostly on human facial expression. Human emotions, ideas, and personality can be recognized from the face and its features. The highest informative channel for social communication is represented by nonverbal signs and it possesses 7% of the communication message (Mehrabian, 1968). While vocal voice retains 34% of communication, facial expression occupies 55% of the communication channel. Thus, the facial expression became a main subject for studying and analyzing for different sciences such as behavior, psychology, computer, and medicine for more than a century (Darwin & Darwin, 2009). Face recognition, feature extraction, and tracking...
went through intense advances in the last two decades. Such techniques become the major focus in many applications such as sleepy driver detection (Pinto et al., 2019) marketing (Spivak et al., 2019) surveillance (Ya et al., 2017) and more. Race, age, sex, and other important information can be extracted from a human face (Oladipo et al., 2019). Additionally, human personality, emotions, and behavior can be obtained by analyzing the human face. One particular characteristic that draws attention recently is the tendency to aggression. Aggressive people are people who may arise physical threats to the surrounding social community. Predicting and preventing such behavior helps to protect and survive public life before becoming higher risk to other people (Sell et al., 2009). Although anger expression provides a good signal of a serious threat, the facial structure provides valuable evidence about the tendency of aggression (Carré & McCormick, 2008). The dominant definition of aggression is “aggression is any form of behavior directed toward the goal of harming or injuring another living being who is motivated to avoid such treatment” (Fischer et al., 2013).

Aggression behavior is found in both animals and humans. Any creature might use aggression for maintaining its position, control, dominate, or compete for resources. In other words, aggression is related to the survival of individuals. It is interesting to study the mechanism behind aggression and its effect on social interaction in life, because individuals may suffer from negative influence in their social communications. Social sciences and especially psychology focused intensely on the human aggression field of study. Many studies have been done for quantifying aggression. Some evaluation depended on self-assessment questionnaires such as the Buss–Perry Aggression Questionnaire (BPAQ) (Buss & Perry, 1992). The questionnaire consists of four scales: physical aggression, verbal aggression, and hostility. Other forms of evaluation depend on facial expression such as facial-width-to-height ratio (FWHR). Although there have been many studies, to our knowledge, the work proposed in this paper is the first to explore using the NVG-RAM classifier on aggressive behavior classification. Our research attempts to find a relationship between the human facial to width ratio (FWHR) and Aggressive behavior. The FWHR landmark is used as data source to feed the classifier network for both training and testing.

2. Previous work

Previous works have been done trying to investigate the relationship between the FWHR and aggression. The studies included different social group individuals under different circumstances. Other studies distinguished the aggressive behavior between men and women with different age groups.

Early investigations on aggression depended on stimuli such as questions. In such studies, individuals were asked to answer questions related to their personality. Then, the results were scored and analyzed to understand the relationship between human aggression behaviors. The oldest and the most known questionnaire is (Buss and Perry aggression questionnaire (Buss & Perry, 1992). They constructed a group of questions with different ascended answers. Their results yielded four scales: Verbal Aggression, Physical Aggression, Hostility, and Anger. They have found that anger is the interconnection between hostility and both verbal and physical aggression. Their experiments included both men and women. Men scored high in verbal, physical, and hostility while there was no sex difference in Anger scoring.

Piątkowska & Martyna (Piątkowska & Martyna, 2012) tried to extract aggression from facial expressions by analyzing spontaneous facial expression. They depended on tracking specific points on face trajectories calculated by following human face movement. Then, they used Local Binary Patterns (LBP) and Gabor filter for extracting and analyzing facial features. Finally, they used the support vector machine (SVM) classifier for classifying spontaneous face features and obtained 85% accuracy.

Other studies tried to link between the aggressive questionnaire scaling and FWHR such as in (Özener, 2012). This study depended on studying both questionnaire aggression and FWHR on Turkish people only. They depended on a sample of 470 Turkish students from both male and female. The study concluded that there is no relationship between self-reported aggressive questionnaire and facial width to height ratio for either sex.

Carré et al. (Carré et al., 2009) exposed photographs of both neutral and aggressive men into a group
of observers. The observers had a limited time for estimating the propensity of the photographs. The study suggested that the facial width to height ratio contains evidence that can be used in predicting the aggression of others.

Another research conducted by Taylor and Jose (Taylor & Jose, 2014) explored the influence of physical aggression on the identification of facial expression among healthy participants. The expressions of different faces are evaluated by the participants in addition to the measure of self-report aggression. The mistake decision ratio was high among high physically aggressive participants in identifying non-angry facial expressions. The differences explanations did not depend on response time or gender. The results extremely supported the idea that aggressive people express confrontational biases when identifying facial expressions.

Arriga and Aguiar (Arriga & Aguiar, 2019) focused on studying the gender difference of aggression depending on facial expression signs. The aggression is induced by a fictional opponent. Their results presented that men are more aggressive than women when they receive emotional cues of anger and sadness from the sender. On the other hand, both genders evaluated equally when neutral expressions were showed. Moreover, men expressed the same stage of aggression in all conditions, whereas women expressed higher aggressive behavior in no feedback and neutral conditions than in the anger or sad conditions. This research confirms the gender difference in aggression between men and women without studying FWHR.

Both Krenn and Meier (Krenn & Meier, 2018) studied the FWHR and aggression in football players in sports only. The aggression is a fair part of the game and most players depend on aggressive behavior while playing the game. The complete details and terms of the investigation are included in their paper. The study ensured that there is no relationship between sport and the FWHR researches with aggressive behavior. In other words, the investigation of aggression on football players and normal individuals yielded close results with social position effects.

Goetz et al. (Goetz et al., 2013) tried to find an association between FWHR aggressive study and both subjective and objective social status. The study reported that there is a positive correlation between FWHR and aggression among men students with low social status. Additionally, there was a positive correlation among hockey players who received low salaries. So, the study provided convincing evidence for the role of social status in controlling the relationship between aggression and facial structure.

Haselhuhn et al. (Haselhuhn et al., 2015) focused on the argument of depending on the facial width-to-height ratio (FWHR) on men for predicting aggressive behavior. The research investigated the success and failure of researchers on finding a reliable cue between aggression and FWHR. Their results showed that there is enough evidence to ensure that a connection does exist between men’s aggression and FWHR.

Lefèvre and Lewis (Lefèvre & Lewis, 2014) studied the robustness of the FWHR connection with the aggressive behavior in both men and women. Moreover, the study compared the results with self-reported aggressive behavior. Their results showed that the faces of both females and males with higher facial masculinity and higher FWHR masculinity were observed as more aggressive. However, they did not find any systematic clues for the effects of self-assessed control on the perception of other individuals’ aggression. Furthermore, their results supported the robustness of FWHR and facial expression as evidence of aggressive behavior.

3. Facial Width-to-Height Ratio and Aggression

Facial width to height ratio is a face feature determined by calculating the ratio between the distance from the mid-brow to the upper lip and bizygomatic width. The latter is calculated by measuring the maximum horizontal distance between the right facial boundary to the left facial boundary (Hehman et al., 2015; Weston et al., 2007). An example of facial width to height calculation is shown in Figure 1. (Ma et al., 2015b). The calculated FWHR for the shown neutral face is 1.9521 and for the aggressive face 2.0594. The FWHR can be calculated either from face images directly or from landmarks that have been extracted from the face image. Longer faces have smaller FWHR and wider faces have higher FWHR (Haselhuhn & Wong, 2012).
4. Methodology

This work depends on different hardware and software resources connected as shown in Figure 2. Most libraries become open source and can be implemented using different platforms or programming languages. Moreover, a slight modification of the currently available sources makes them possible to operate with different programming languages. This work consists of three phases: Landmark extraction phase, training phase, and classification phase which are executed and analyzed by Matlab R2020a software.

4.1 Landmark Extraction

The OpenFace library is used for the extraction of face landmarks. The OpenFace tool is designed by developers for researchers who are interested in building applications for face recognition and analysis of facial behavior (Baltrusaitis et al., 2016). The OpenFace tool can extract landmarks from live video cameras, recorded videos, or captured images. During the first step, Matlab calls the OpenFace library and hands the source of media and the extraction method. The most accurate and robust landmark extraction approach is Convolutional Experts Constrained Local Model (CE-CLM) that depends on Convolutional Experts Network (CEN) as a local detector. This ensures a precise calculation of the facial width to height ratio FWHR from the input sources. The exact face features are fetched by Matlab for calculations and analysis. Since face tilt has a high effect on miscalculation of the FWHR, our code ensures to correct the tilt of every captured face. Finally, the FWHR is calculated as shown in Figure 3. The source image used for this example is from the public Chicago face database (Ma et al., 2015b).

Figure 1. Facial Width to Height ratio calculation and face source conducted from (Ma et al., 2015a)

Figure 2. Proposed FWHR and Aggressive behavior estimation

Figure 3. FWHR extraction from face landmarks
4.2 NVG-RAM

The NVG-RAM is a high efficient weightless neural network classifier that requires a onetime training only. Moreover, the classifier functions with decimal numbers instead of binary numbers as in VG-RAM. The training process is equivalent to storing the pairs of inputs and outputs in the virtually created RAM. Later, these pairs are called for classification. A high number of pairs results in improved accuracy for classification because of the higher efficiency training process (Hasan et al., 2018).

The classifier becomes ready after the training of the NVG-RAM is completed. The classification operation depends on the calculation of minimum Manhattan Distance (MD) between the entire recorded pairs and the unidentified input according to Equation (1). The class of the closest Manhattan distance is fetched as the output for classifier depending on its class number.

\[ d(p,q) = \sum_{i=1}^{n} |p_i - q_i| \]  

where \( n \) is the number of elements in each vector, and \( d(p,q) \) is the Manhattan distance between two vectors \( q \) and \( p \) (Hashim & Sadah, 2015). The NVG-RAM operation is explained in the next sections.

4.2.1 Databases

The group of datasets consists of 82 images with minimum resolution 250x300 pixels (40 normal faces, 42 aggressive faces) which are collected from online medical sources identifying as aggressive or normal (Inc, n.d.; Malaga, 2020; Wilber, 2015). Then, each group of the database is divided into two halves. Examples from the used database are shown in Figure 4 below. The first half of each collection is used for training the NVG classifier and the other half is used for classification. The dataset images include different ages of men and women as well as images of children. However, the data is applied to classifier without taking into consideration the gender issue.

![Figure 4. Aggressive man face samples from used database](image)

4.2.2 Training Phase

The training phase uses the Numeral Virtual Generalizing Random Access Memory (NVG-RAM) classifier for preparation and classification Dataset images serves as a source for both operations as explained below.

4.2.3 Classification Phase

Two types of facial expressions (aggressive, nonaggressive) are required to be classified by the NVG-RAM for two different FWHR factors. There is not an exact number to quantify the relationship between the FWHR and aggressive behavior. Therefore, training the NVG-RAM with the collected face dataset helps to predict the closest form of behavior. After the training process, the NVG-RAM is tested on the training data to determine the 100% accuracy of the classification. The evaluation of the classification method is calculated in terms of specificity, sensitivity, accuracy, and testing time.

The sensitivity reflects the correctly identified proportion of the actual positives. It identifies humans with aggressive behavior positively depending on facial expression. The sensitivity can be calculated
as in Equation (2) (Kuruvilla & Gunavathi, 2014).

\[
\text{Sensitivity} = \frac{T_P}{T_P + F_N} \quad (2)
\]

Where \( T_P \) (True Positive) is the number of samples that have aggressive behavior and identified properly, \( F_N \) (False Negative) is the number of samples that were aggressive but incorrectly identified as normal. Equation (3) measured the proportion of people who are correctly identified as normal, i.e. a condition where a set of normal humans is correctly identified as not having aggressive behavior (Panday & Godara, 2012).

\[
\text{Specificity} = \frac{T_N}{T_N + F_P} \quad (3)
\]

Where \( F_P \) (False Positive) is the number of samples that are normal but identified aggressive incorrectly. \( T_N \) (True Negative) is the number of samples that are normal and properly identified. In addition to sensitivity and specificity, the success rate can also be evaluated with Positive Prediction Value (PPV) which calculates how accurate a positive test result determines that the aggressive behavior is present as illustrated in Equation (4).

\[
PPV = \frac{T_P}{T_P + F_P} \times 100 \quad (4)
\]

Equation (5) measures the Negative Prediction Value (NPV), which calculates how well a negative test result determines that the aggressive behavior is absent (Olaniyi et al., 2015).

\[
NPV = \frac{T_N}{T_N + F_P} \times 100 \quad (5)
\]

The statistical evaluation of a classifier is called accuracy and it measures the precision of identification or exclusion of a condition. It is the proportion of true results (both true positive and true negative) in the population, it can obtained as in Equation (6) (Kuruvilla & Gunavathi, 2015).

\[
\text{Accuracy} = \frac{(T_P + T_N)}{(T_P + T_N + F_N + F_P)} \quad (6)
\]

5. Results and Analysis

The NVG-RAM performance results for the classification phase of the provided image database are shown in Table 1. These results were obtained from the second half of dataset which was selected for classification. The analyzed results showed that aggressive faces have FWHR ration mostly greater than 2.0. The maximum accuracy reached 87.8% with a sensitivity of 86.3% and classification time 0.026 seconds. The acquired number exceeds the maximum previously recorded number 85% which depended on facial expressions analysis and used the Support Vector Machine (SVM) classifier (Piątkowska & Martyna, 2012). The increased accuracy resulted from the correction of the face tilt and the usage of the NVG-RAM as classifier. None of the previous studies mentioned correcting the tilt error and its effect on the miscalculations of FWHR. Moreover, all previous studies deepened on other humans assessed or SVM classifier for the organization process.
Table 1. NVG-RAM Performance Results

| Testing Data samples | TN | FN | FP | TP | Test time Sec | Specificity | Sensitivity | NPV% | PPV% | Accuracy% |
|----------------------|----|----|----|----|---------------|-------------|-------------|------|------|-----------|
| 41                   | 17 | 3  | 2  | 19 | 0.0268        | 0.8947      | 0.863       | 85   | 90.4762| 87.8049   |

6. Conclusions

The conducted research successfully confirmed that the human aggressive behavior can be predicted by relying on the facial expression as previous studies. However, this is the first reported study to show that the NVG-RAM can be used as facial landmark classifier for facial aggressive detection. Facial landmarks are extracted from aggressive and normal individuals and are used for calculating facial width to height ratio FWHR. The output results were obtained from the NVG-RAM classifier after training the classifier on a previously prepared dataset. The reported outcomes showed better accuracy from previously recorded result. The FWHR estimation accuracy is increased by correcting the tilting error produced from the incorrect angle of the human face. In the future, the proposed method will be tested on live video cameras for aggressive behavior prediction.

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