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Design and Implementation of a Facial Character Analysis Algorithm for Humanoid Robots

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SUMMARY

Humanoid robots (HR) equipped with a sophisticated facial character analysis (FCA) algorithm can able to initiate crucial improvements in human–robot interactions. This paper, for the first time in the literature, proposes a three-stage FCA algorithm for the HR. At the initial stage of this algorithm, the HR detects the face with the Viola–Jones algorithm, and then important facial distance measurements are obtained with the geometric-based facial distance measurement technique. Finally, the measured facial distances are evaluated with the physiognomy science to reveal the characteristic properties of a person. Even though the proposed algorithm can be implemented to all HR, in this paper, it has been specifically applied to NAO HR. The reliability of the developed FCA algorithm is verified by analyzing each terminal decision about the character and its connection with the measured facial distances in the anatomy science.

KEYWORDS: Geometric-based facial distance measurement technique; Facial character analysis; Feature extraction; Human–robot interaction; NAO humanoid robot; physiognomy science; Viola–Jones algorithm.

1. Introduction

Human–robot interaction (HRI) is a challenging research field at the intersection of the psychology, cognitive, artificial intelligence, and robotics sciences. Currently, the humanoid robots (HR) have increasingly become an essential part of our society as they have been used for various purposes such as serving for elderly people, cleaning houses, and entertaining kids. Although the HR are mechanical systems, it is possible to convert them into social robots by equipping them with various properties of the human–human interaction (HHI) such as being able to extract human emotions, maintain appropriate eye contact, understand gestures, and make character analysis. Having an idea about the character of a person allows the HR to interact with them appropriately. During the HRI, for instance, an easily effected sensitive person might require bilateral warm communication, whereas a confident person with strong character might prefer staying alone for internal decision making. In this paper, as human face carries crucial information about the character of the people, it is considered for the facial character analysis (FCA). The proposed algorithm consists of three key stages: human face detection, facial distance measurements, and physiognomy-based interpretation.

Face detection is the first stage of the FCA algorithm developed for the HR. For object recognition such as human face detection, a number of promising algorithms have been proposed in the literature. To specifically detect a human face, Viola–Jones developed an algorithm which initially extracts features from the taken image, and then creates weak and strong candidates based on the summation of the features, and finally eliminates the weak candidates until detecting the frontal face.[1,2]

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The succeeding Viola–Jones algorithms are able to detect the faces from various angles and profiles. For example, rotation invariant neural network-based 3D face detection Viola–Jones algorithm has been proposed and successfully experimented on various facial images.[3] It is important to note that similar face detection algorithms such as the ones developed by Rowley–Baluja–Kanade and Schneiderman–Kanade exist in the recent literature.[3,4] However, even though they share a number of commonalities with the Viola–Jones algorithm, their face detection speed and correct detection rate are lower.[5] While the key reason for the Viola–Jones algorithm being faster is the implementation of a boosting algorithm called AdaBoost, the Cascade classifier contributes the improvement of the correct face detection rate of the Viola–Jones algorithm.[6] These are the motivation behind selecting the Viola–Jones algorithm for the face detection in this research.

After detecting the face, the second stage of the FCA is to obtain the facial distance measurements. In this paper, the geometric-based facial distance measurement technique is preferred because of its simplicity and higher accuracy in measuring the facial distances.[7] Kanade proposed a geometric-based facial distance measurement technique, where the horizontal distances are used to measure left and right boundaries of the face and nose, and the vertical ones are used to measure the top and bottom borders of the head, eyes, nose, and mouth. He examined the reliability of the algorithm on 16 facial images and reported that the distance measurement accuracy was 75%.[5] Brunelli and Paggio developed a further geometric-based facial distance measurement technique including a simple matching approach and assessed its efficiency on 35 facial images where its distance measurement accuracy was 100%.[5–18] The geometric-based technique considered in this paper has similar properties with both these techniques.

Finally, to equip the HR with the FCA capability, physiognomy-based interpretation of the measured facial distances is performed. One of the earliest physiognomic researches on the relationship between the human face distances and human characteristics was the work of Charles Bell, James Parsons, and Johann Caspar Lavater.[8] In this work, human face was divided into 32 regions and specific characteristic comments are made based on the measurements obtained from these regions. A similar physiognomic interpretation technique developed by Wells divided the face into three main regions, namely eyebrows, nose, and chin, and used width and length differences of each facial parts for facial characteristic interpretation.[9,13–16] According to the Well's approach, if the forehead zone is the widest (y-axis length) between the allocated three zones of a face, then this implies intellectuality of that person. If it is the longest (x-axis length) in all three zones, the person is rational and logical with a strong memory and can make self-decisions. If the nose region, which is the zone of cheekbones, is widest (y-axis length), the person is emotional. If it is the longest (x-axis length), the person has a good command over the feelings and emotions. If the jaw zone is widest (y-axis length), the person is one who is ready for immediate responses. If it is the longest (x-axis length), it implies common sense, wisdom, and strength of determination. In this research, Wells' approach is preferred since it incorporates the key facial measurements for the FCA.

Even though the emotion analysis based on the facial expressions has been extensively studied in the social robotics literature, the FCA, for the best of authors' knowledge, has not been considered yet in the literature. However, an advanced HR should be able to make character analysis together with emotion analysis and combine them to make meaningful decisions during their interactions with humans. This paper presents the developed three-stage FCA algorithm and assesses the performance of the algorithm in the simulation and real environment on NAO HR.

The proposed FCA algorithm for the HR has four key stages as shown in Fig. 1. In the first stage, images are taken from HR's camera, and then at the second stage, the face is detected from the image taken by using the Viola–Jones algorithm. At the third stage, the distance measurements are taken from the detected face. Finally, at the fourth stage, these distance measurements are interpreted by using the physiognomy science. The proposed algorithm has been implemented to the NAO HR, and the corresponding results have been analyzed.

In the rest of the paper, Section 2 reviews the Viola–Jones face detection algorithm, Section 3 presents the geometric-based facial distance measurement technique to measure the each facial distances, and Section 4 specifies the corresponding clusters based on the facial measurements and the knowledge in the physiognomy science. This section also analyses the facial characteristic of five persons. Section 5 presents implementation of the facial characteristic algorithm to the NAO HR, Section 6 analyses the simulation and experimental results, and finally Section 7 summarizes the paper.

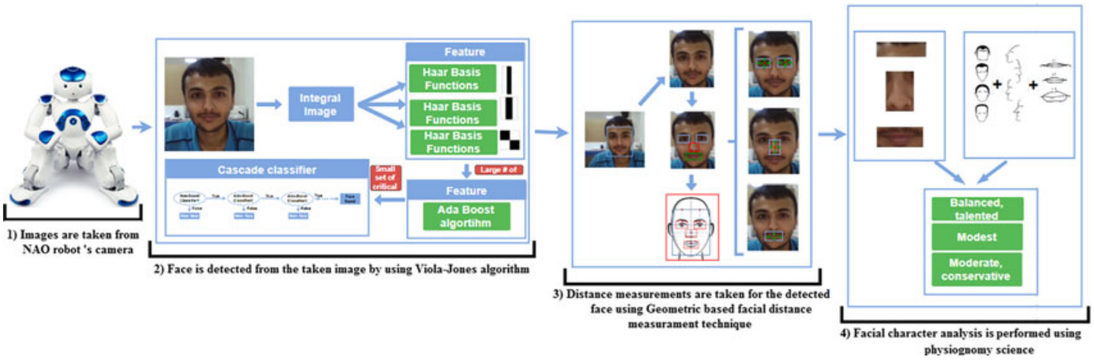

Fig. 1. Proposed FCA architecture.

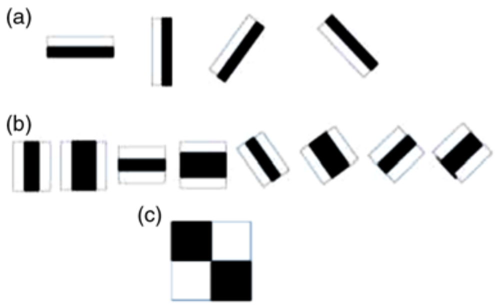

Fig. 2. Rectangle-based feature collection with (a) two rectangles, (b) three rectangles, and (c) four rectangles.

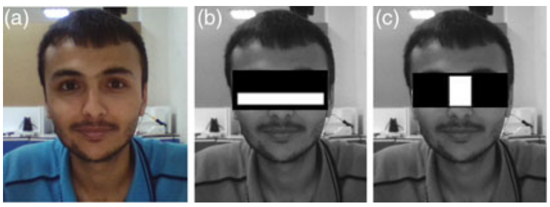

Fig. 3. (a) The original image, (b) features collected with two rectangles determined based on the intensity difference between the eyes and the upper cheeks where the eyes region is darker than the cheeks, and (c) features collected with three rectangles from the eyes and nose regions where the eyes region is darker due to intensity difference.

2. Face Detection with the Viola–Jones Algorithm

Face detection is the initial stage of the FCA algorithm after taking the images. In real-time applications, the Viola–Jones algorithm is extensively considered for detecting the objects, particularly the faces, as its recognition accuracy for the objects having unknown size is high and also requires less computational time. This algorithm consists of four steps, which are Haar-like features, integral image, Ada-Boost, and Cascade classifier.

2.1. Haar-like features

Since the Viola–Jones algorithm detects the objects by essentially classifying the features of the images, initially features from the images must be extracted. Generally, the features are collected within a rectangle covering two, three, or four rectangles in itself as shown in Fig. 2.

It is important to note that each rectangle is determined based on the intensity of the corresponding regions. Figure 3 illustrates the intensity specification of the rectangles for the eyes and cheeks regions of the face.

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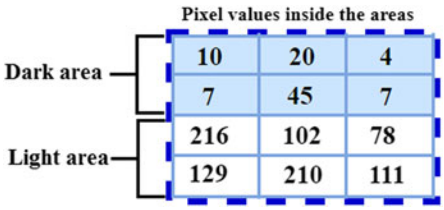

Fig. 4. Total sum of the features for the four rectangles having different intensities.

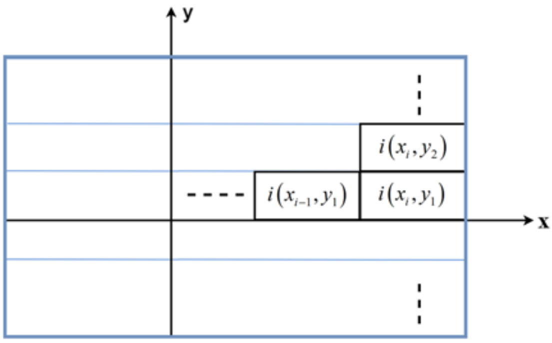

Fig. 5. Integral sum of the features within rectangles.

2.2. Integral images

The second stage of the Viola–Jones algorithm is to transfer the extracted features with the Haar-like into the numerical sum values by using integration. In this stage, translation or rotation of the rectangles does not affect the final integral sum.

To perform integral sum, initially each rectangle with different intensity is partitioned into fractions and each fraction inside the rectangle is summed up iteratively (every rectangle in an integral image is the summation of the pixels above and to the left of it), so that the sum of the features for a rectangle is obtained. Later, to get the total sum of all the rectangles, a sign is assigned to the sum of each rectangle based on the intensity of the rectangles. This is illustrated in Fig. 4 for two dark and two light rectangles.

$$\begin{aligned} I_{\mathrm{t}} &= \sum I_{\mathrm{d}} - \sum I_{\mathrm{l}} \\ I_{\mathrm{t}} &= (216 + 102 + 78 + 129 + 210 + 111) - (10 + 20 + 4 + 7 + 45 + 7) = 753 \end{aligned} \tag{1}$$

where I_{t} is the total amount of the features, I_{d} is the sum of the features in the dark rectangles, and I_{l} is the sum of the features in the light rectangles.

This summation can be generalized as in Fig. 5.

Sum of the features in each rectangle can be represented as:

$$s(x_i, y_j) = s(x_{i-1}, y_j) + i(x_i, y_j) \tag{2}$$

where i is the indices of the partitioned rectangle in x direction, y is the indices of the partitioned rectangle in y direction, $s(x_i, y_j)$ is the current area of the one rectangle, $s(x_{i-1}, y_j)$ is the previous total area of the one rectangle, where $s(x_0, y_j) = 0$, and $i(x_i, y_j)$ is the each partitioned area of the rectangle where y_j is constant.

In order to obtain the total integral sum of all the rectangles, representation (3) can be formed.

$$ii(x_f, y_j) = ii(x_f, y_{j-1}) + s(x_f, y_j) \tag{3}$$

where $ii(x_f, y_j)$ is the iterative sum of the areas of the rectangles with the final (terminal) value x_f and y_j is the *jth* rectangle, $ii(x_f, y_{j-1})$ is the previous iterative sum of the areas of the rectangle, and $s(x_f, y_j)$ is the total area of the each rectangle.

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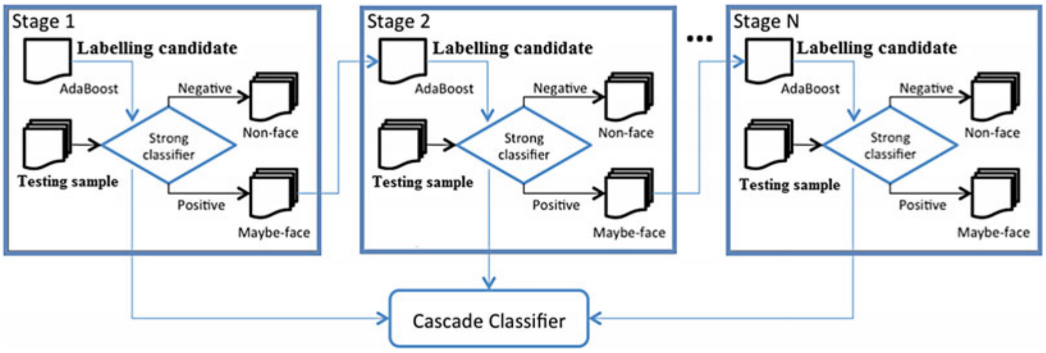

Fig. 6. Cascade classifier configuration.

2.3. *Ada-Boost algorithm*

After summing up the features within the rectangles having different intensities, the Ada-Boost algorithm labels them as a weak or strong candidate for being the part of the desired facial object. The Ada-Boost algorithm requires a threshold value to distinguish weak and strong l candidates allocated for the face.

For $i = 1 \ldots l$:

1) *Normalization*: Normalize the summed features to lessen the overall effects of unexpected (noisy) features.

$$\frac{s(x_f, y_j)}{\sum_{j=1}^{l} s(x_f, y_j)} = s_N(x_f, y_j) \tag{4}$$

where $s_N(x_f, y_j)$ is the normalized sum of the features of each rectangle.

2) *Labelling error*: Introduce a variable h_j, which is initially randomly chosen for each rectangle and needs to be trained and classified as a weak or strong candidate for the recognized object.

$$E_j = s_N(x_f, y_j)\left|h_j - y_j\right| \tag{5}$$

For each rectangle $y_j = \{0, 1\}$ represents intensity of each rectangle where 0 corresponds to light rectangle or negative sum and 1 corresponds to dark rectangle or positive sum.

3) *Weighting parameter*: Based on the error obtained from labelling of each rectangle, a weighting parameter α_j is determined.

$$\alpha_j = \log \frac{1}{E_j} \tag{6}$$

This α_j and the threshold σ are used to update the candidates h_j. The log operation is only considered to expand the numerical value of the labelled error.

4) *Selecting strong classifiers*: Determine the terminal strong classifiers from the candidates.

$$h_j = \begin{cases} 1, & \left|\alpha_j\right| \geq \sigma \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

where the threshold for the weak and strong candidates is $\sigma = \log(1/s_N(x_f, y_j))$.

2.4. *Cascade classifier*

In this part of the Viola–Jones algorithm, the Cascade classifier evaluates the strong and weak candidates specified with the Ada-Boost algorithm in terms of the possibility of being part of the face. The Cascade classifier considers each candidate separately and compares them with the test sample at each stage. If one candidate manages to pass from the first stage, then it is transferred to the next stage as shown in Fig. 6. For example, the labelled candidates for the nose are compared with the test sample, and if they fall into the same category, then these labelled candidates are assessed in stage 2. This process continuous until the face is detected.

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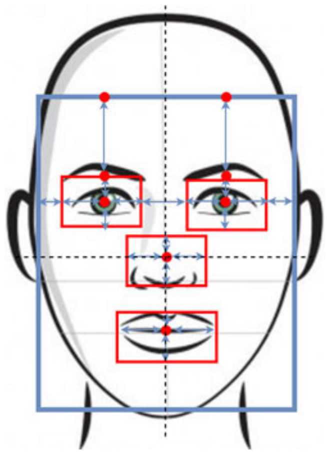

Fig. 7. Geometric-based facial parts specification.

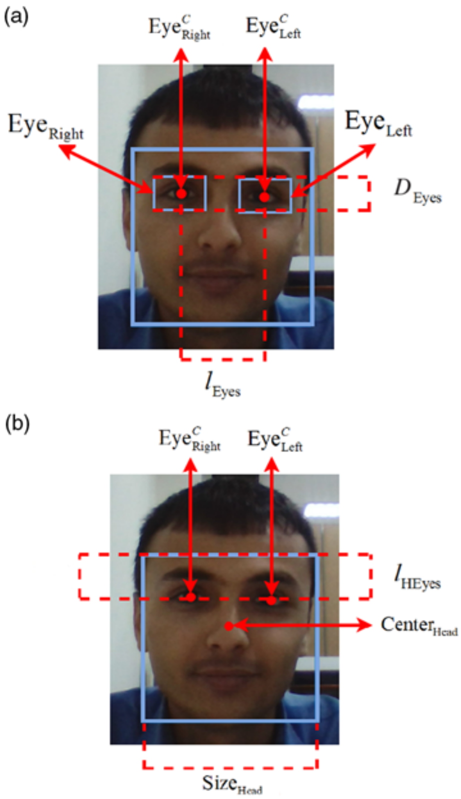

Fig. 8. Configuration of eyes-related and eyes-centered facial measurements.

3. Facial Distance Measurements

After the face detection with the Viola–Jones algorithm, the next step is the determination of the distance measurements of the face, carrying crucial information about the character of the people. This part of the paper presents a geometric-based approach for measuring the distances between the specified points on the face.

3.1. Geometric-based facial distance measurements

In this approach, the detected face is assigned to a coordinate system where the center of the face and its parts such as eye, nose, and mouth can be specified by using boxes as shown in Fig. 7.

3.1.1. Distance measurements for the eyes. To determine the measurements of the eyes, one box for each detected eyes is placed as shown in Fig. 8.

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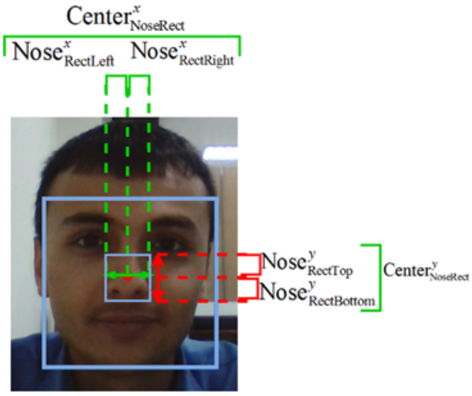

Fig. 9. Configuration of the nose-related measurements.

The terms $\text{Eye}^C_{\text{Left}}$ and $\text{Eye}^C_{\text{Right}}$ are center of the left and right eyes, Eye_{Left} and $\text{Eye}_{\text{Right}}$ are x and y coordinates of the eyes, D_{Eyes} is the distance between eyes' centers, l_{Eyes} is the distance between the eye centers, l_{HEyes} is the distance between the upper border of the face and center of the left and right eyes, $\text{Size}_{\text{Head}}$ is the size of the face in the rectangle, and $\text{Center}_{\text{Head}}$ is the selected center for the detected face.

Eyes-related two distances are as follows:

1. $D1$ – Average ratio of the distance between the top border of the face and center of the eyes.
2. $D2$ – Average ratio of the distance between the eyes.

These two ratios are determined according to the size of the face in the rectangle ($\text{Size}_{\text{Head}}$), and the exact eyes locations are:

$$D1 = \frac{1}{N}\sum_{i=1}^{N}\frac{l^i_{\text{HEyes}}}{\text{Size}^i_{\text{Head}}}, \quad D2 = \frac{1}{N}\sum_{i=1}^{N}\frac{l^i_{\text{Eyes}}}{\text{Size}^i_{\text{Head}}} \tag{8}$$

where l^i_{HEyes}, l^i_{Eyes}, and $\text{Size}^i_{\text{Head}}$ are the measurement samples taken from the same person for N times. This basically eliminates the bias stemmed from the variable size of the rectangles around the face, due to distance between the robot and person and also because of the rotation of the taken image. The coordinates of the eyes can be obtained as:

$$\begin{aligned} \text{Eye}^y_{\text{Right}} &= \text{Eye}^y_{\text{Left}} = \text{Center}^y_{\text{Head}} + \text{Size}_{\text{Head}}\left(D1 - \frac{1}{2}\right) \\ \text{Eye}^x_{\text{Right}} &= \text{Center}^x_{\text{Head}} - \text{Size}_{\text{Head}}\left(\frac{1}{2}D2\right) \\ \text{Eye}^x_{\text{Left}} &= \text{Center}^x_{\text{Head}} + \text{Size}_{\text{Head}}\left(\frac{1}{2}D2\right). \end{aligned} \tag{9}$$

These coordinates represent the two-dimensional approximate position of the eyes.

3.1.2. Distance measurements of the nose, mouth, and forehead. In addition to the distances for the eyes, distance measurements for the nose, mouth, and forehead needs to be performed for the FCA. The coordinates for the center of the nose are as follows:

$$\text{Center}^x_{\text{NoseRect}} = \frac{\left(\text{Nose}^x_{\text{RectLeft}} + \text{Nose}^x_{\text{RectRight}}\right)}{2} \tag{10}$$

$$\text{Center}^y_{\text{NoseRect}} = \frac{\left(\text{Nose}^y_{\text{RectBottom}} + \text{Nose}^y_{\text{RectTop}}\right)}{2} \tag{11}$$

Figure 9 illustrates the parameters used for determining the nose coordinates.

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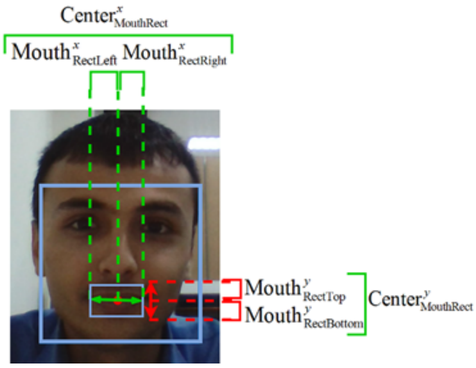

Fig. 10. Configuration of the mouth-related measurements.

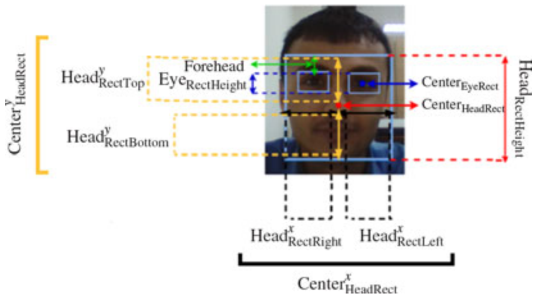

Fig. 11. Configuration of the forehead-related measurements.

The terms $\text{Nose}^x_{\text{RectLeft}}$ and $\text{Nose}^x_{\text{RectRight}}$ are the nose distance measurements in x direction from the center of the nose to the left and right corner of the nose rectangle, respectively. Herein, $\text{Nose}^y_{\text{RectTop}}$ and $\text{Nose}^y_{\text{RecBottom}}$ represent the nose distance measurements from upper and lower corners to the center of the nose in y direction.

In order to determine the coordinates of the mouth, same procedure for the nose is followed where Fig. 10 shows its respective variables.

Finally, to determine the forehead measurements with respect to the specified eyes coordinates and center of the head in x and y directions, the following equations are applied.

$$\text{Center}^x_{\text{HeadRect}} = \left(\frac{\text{Head}^x_{\text{RectLeft}} + \text{Head}^x_{RectRight}}{2}\right) \tag{12}$$

$$\text{Center}^y_{\text{HeadRect}} = \left(\frac{\text{Head}^y_{\text{RectBottom}} + \ \text{Head}^y_{\text{RectTop}}}{2}\right) \tag{13}$$

$$F = \left(\text{Centre}^y_{\text{EyeRect}} - \left(\frac{\text{Eye}_{\text{RectHeight}}}{2}\right)\right) - \left(\text{Center}^y_{\text{HeadRect}} - \left(\frac{\text{Head}_{\text{RectHeight}}}{2}\right)\right) \tag{14}$$

$$F_r \ = \ \frac{F}{\text{Head}_{\text{RectHeight}}} \tag{15}$$

where F is the forehead distance measurement and F_r is used to find the forehead ratio. Figure 11 shows the related parameters for the forehead distance calculation.

After obtaining these necessary distance measurements of the detected face, the next step is to comment on them by using the physiognomy science, briefly discussed next, to make a decision about the character of the people.

4. Physiognomy-based FCA

In the last part of this paper, the physiognomy science is used to perform the FCA based on the facial measurements obtained in the previous section.

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Table I. Facial parts and their labels.

Facial feature measurements	
Label	**Facial parts**
d1	Distance between center of left eye and left border of left eye
d2	Distance between center of left eye and right border of left eye
d3	Distance between center of left eye and top border of left eye
d4	Distance between center of left eye and bottom border of left eye
d5	Distance between center of right eye and left border of right eye
d6	Distance between center of right eye and right border of right eye
d7	Distance between center of right eye and top border of right eye
d8	Distance between center of right eye and bottom border of right eye
d9	Distance between center of nose and left border of nose
d10	Distance between center of nose and right border of nose
d11	Distance between center of mouth and left border of mouth
d12	Distance between center of mouth and right border of mouth
d13	Distance between center of mouth and top border of mouth
d14	Distance between center of mouth and bottom border of mouth
d15	Distance between eye_rectHeight, center of head, and head_rectHeight

4.1. Physiognomy science

The physiognomy science deals with interpretation of the characters by evaluating the measurements of the face. It is basically an assessment of the characters or personality of the people based on their outer/physical appearance, particularly the face.

In physiognomy, human face has been divided into three primary or primitive regions for the character analysis. The first one is the forehead, which is the region between hairlines to just above the eyebrows, revealing information about the mathematical skills and reasoning ability of the people. The second one is the nose region or middle zone lying from the eyebrows to the tip of the nose, leading to information about the mechanical and practical skills, executive qualities, and literary abilities of the people. The last region extends from the tip of the nose to the chin and states information about domestic, moral, and social properties of the people.

4.2. Labelling the facial parts

Selecting the appropriate facial parts and having their corresponding distance measurements are essential to reveal the correct character of the people. Table I lists the facial parts used for the physiognomic-based character analysis.

As can be seen from I, to make physiognomic interpretation for the FCA, 15 facial distance measurements are obtained, and for each facial measurement a classification criteria is determined as shown in Fig. 12.

Finally, the terminal physiognomic character analysis leads to the overall evaluation of these facial parts. In Fig. 13, character analysis of the person whose images are used in this research is presented.

5. Implementation of the FCA Algorithm to NAO HR

This section briefly introduces the implementation of the proposed FCA algorithm to NAO HR.

5.1. Dialogue model for NAO HR

In this work, NAO HR manages the FCA at two stages. In the first stage (initiation stage), the NAO HR initiates a dialogue with the person within the range of its camera and tries to engage with that person. If the detected person agrees to continue, then the actual FCA session is conducted in the second stage.

5.1.1. Initial stage of the FCA. As shown in Fig. 14, the dialogue of this stage consists of four steps. Once the initialization is finished, the dialogue enters the "Awaiting user" stage, in which the NAO HR starts the face-tracking module. The Viola–Jones face detection algorithm is used to detect faces in the scene as discussed in Section 2.1. When a face is detected, the face-tracking module enables NAO HR to track the user's face.

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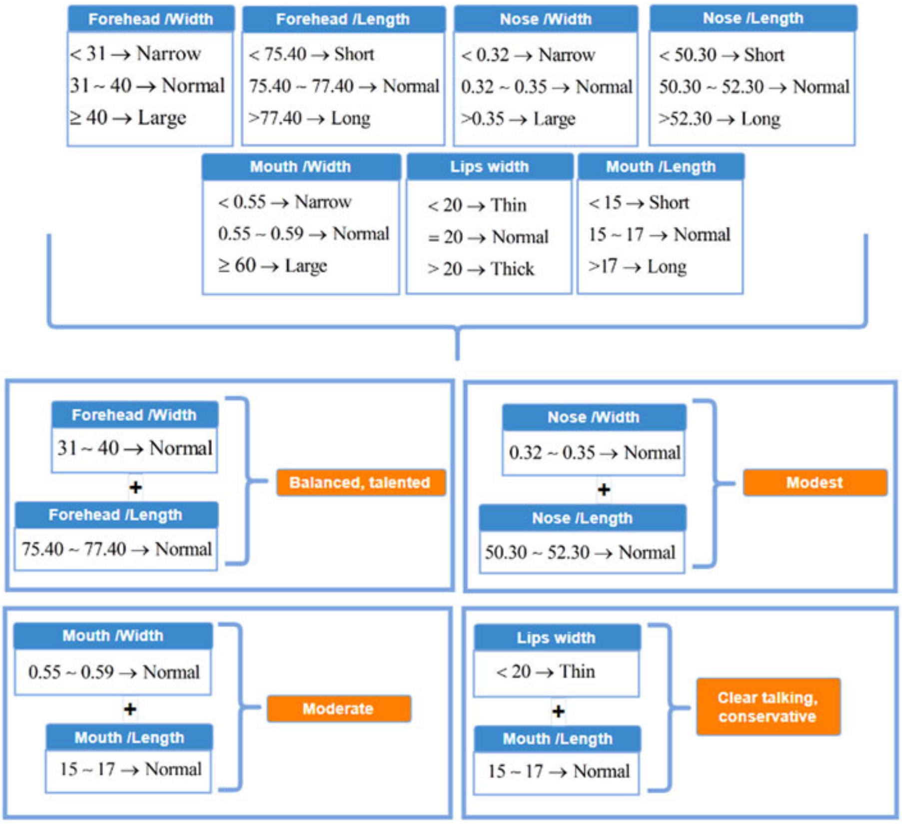

Fig. 12. Classification criteria to generate physiognomic information.

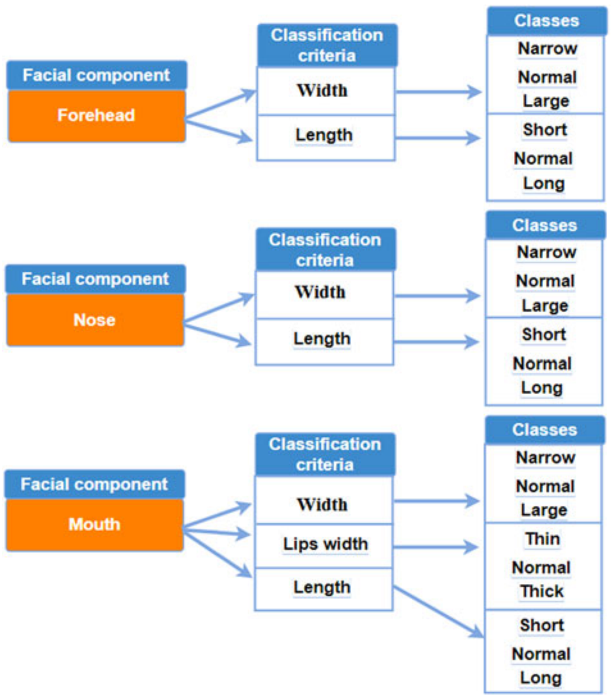

Fig. 13. Physiognomic interpretation using the facial distance measurements.

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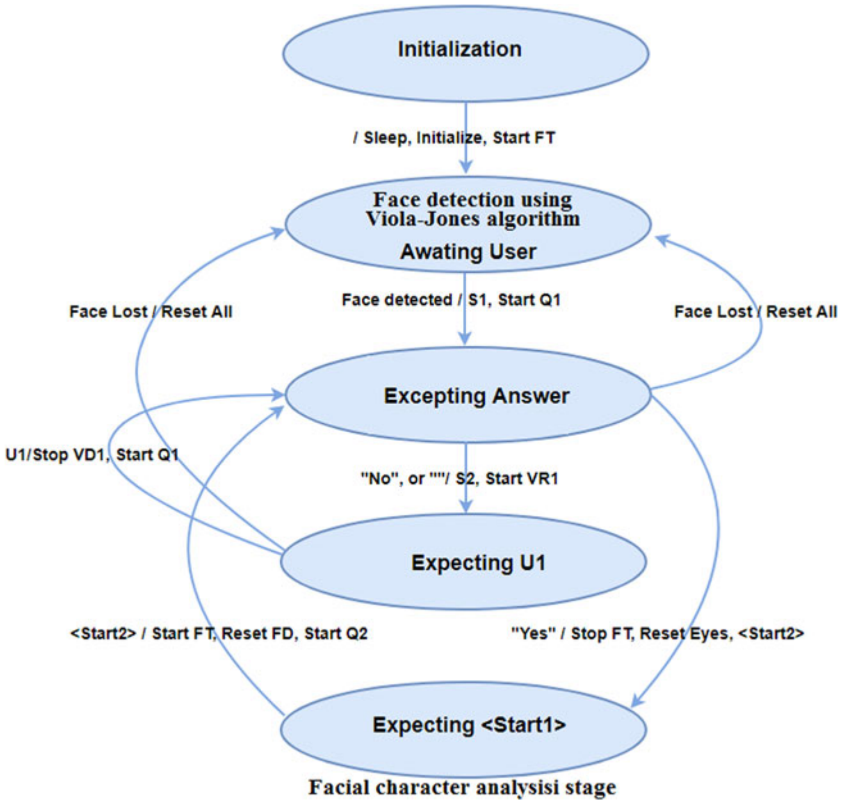

Fig. 14. Dialogue model of the initialization and face detection with the Viola–Jones algorithm.

Within the figure: 'FT' stands for 'Face Tracking', 'FD' stands for 'Face Detection', 'S1' stands for the statement 'Hello my name is NAO! Nice to meet you!', 'S2'stands for the statement 'Ok, please just call me when you are interested', 'S3' stands for the statement 'Hello again! I am still here.', 'Q1' stands for the question 'Do you want me to do your FCA?', 'VD1' stands for the voice detection session used to detect 'U1', and 'U1' stands for user utterance of 'Yes', 'No', or 'Okay'.

After detecting the face of a person, NAO HR first introduces itself (S1), then asks the person whether he/she wants to have FCA (Q1), and the dialogue enters the 'Expecting Answer' state. The NAO HR's on-board voice detection engine is used to detect 'Yes', 'Okay', or 'No' uttered by the user. A positive answer from the user marks the completion of the FCA-initiation stage and triggers the start of the FCA stage. Upon receiving a negative answer 'No', NAO HR prompts the person to call it when the person is interested in FCA (S2) and the dialogue enters the 'Expecting U1' state. In this state, the voice detection engine is configured to detect 'Yes', 'Okay', or 'No' with an identified timeout. If any word is detected, NAO HR asks again whether the person wants to make FCA application and the dialogue re-enters the 'Expecting Answer' state. If the answer is positive, the dialogue manager moves to the FCA stage which is 'Accepting <Start1>'. The face tracker runs continuously in all stages. If the tracked face is lost, the dialogue manager assumes that the detected person has left the scene and triggers the dialogue to move back to the 'Awaiting User' state.

5.1.2. FCA stage. The dialogue of this stage (as illustrated in Fig. 15) contains four stages. After the initialization, the dialogue enters the 'Expecting <Start2>' state to wait for the completion of the FCA-initiation stage. Once the response is received, the dialogue manager instructs the user to display facial characteristics (S3) and activates the 'Awaiting FCA', in this stage the face is already detected and it is ready for the further processes. Then, the dialogue enters the 'geometric-based facial distance measurement' stage to obtain the each facial parts' distance measurements. Once this stage is completed, at the 'Physiognomic interpretation' stage physiognomic interpretation of the facial measurements is interpreted. At the last stage, the 'FCA-Terminal' step provides the corresponding FCA results.

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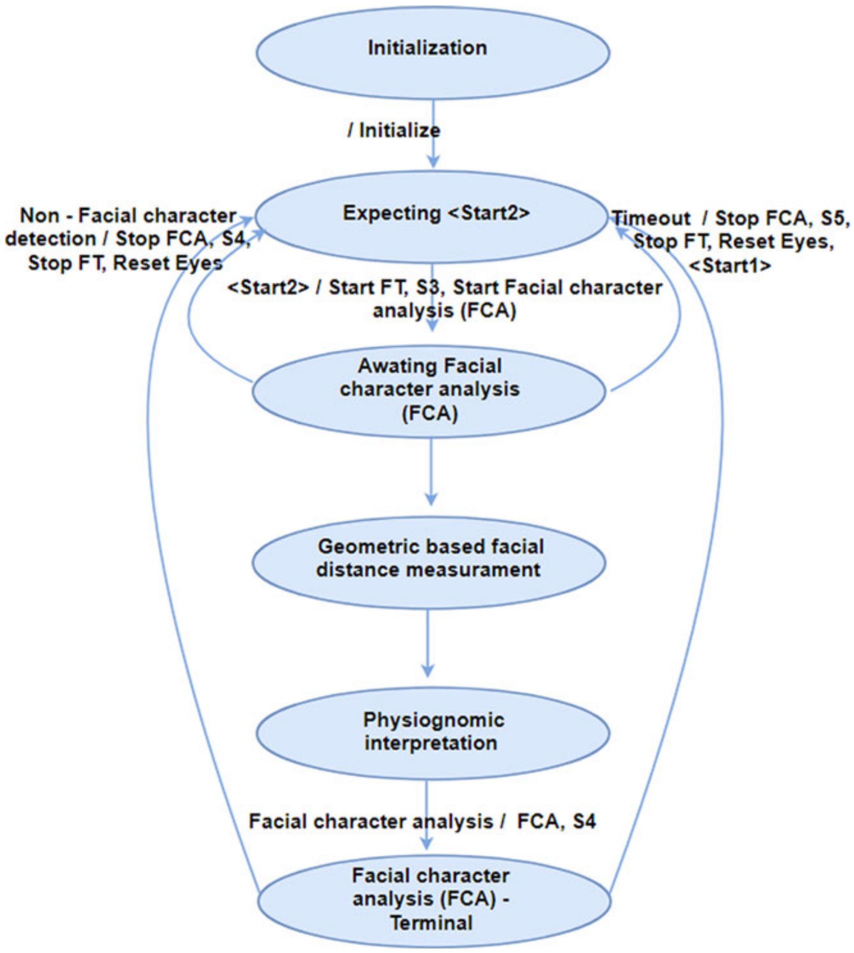

Fig. 15. Dialogue model of the FCA stage.

Within the figure: 'FT' stand for 'Face Tracking', 'FCA' stands for 'Facial Character Analysis', 'S3' stand for the statement 'Ok, please stand in front of me, I will try to analyze your facial characteristics', 'S4' stands for the statement 'I analyzed your facial characteristics, listen to me!', and 'S5' stands for the statement 'Sorry, I could not analyze your facial characteristics'. After displaying the FCA results, it moves back to the FCA-initialization stage.

6. Simulation and Experimental Results

This section evaluates the FCA algorithm both in the simulation and experimental environments. Initially, the experimental setting is introduced and then the results are assessed.

6.1. Simulation and experimental settings

Five persons' FCA are performed for five times at random intervals of a day to take into account the effects of the tiredness, changing possible mood, varying light and impact of distance between the persons and the camera.

Table II shows various facial distance measurements obtained with the geometric-based technique for the FCA.

To perform the FCA, measurements determined with the geometric-based technique for the eyes, nose, mouth, and forehead are recorded. In terms of the measurements for the eyes, distance ratio of Left Eye_c1 (left rect corner distance to the center of the eye), Left Eye_c2 (left rect corner distance to the center of the eye), Right Eye_c1(right rect corner distance to the center of the eye), and Right Eye_c2 (right rect corner distance to the center of the eye) are used to find the center of the eyes and distances to each other. Similarly, for the mouth measurements, left mouth (left rect corner distance to the center of mouth), right mouth (right rect corner distance to the center of the mouth), upper mouth (TopRect corner distance to the center of mouth), and lower mouth (BottomRect corner distance to

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Table II. Experimental data obtained with the geometric-based facial distance measurement technique.

Geometric-based facial distance measurement results for five persons											
Markers	**Left Eye_c1**	**Left Eye_c2**	**Right Eye_c1**	**Right Eye_c2**	**Left nose**	**Right nose**	**Left mouth**	**Right mouth**	**Upper mouth**	**Lower mouth**	**Forehead**
Persons	**Distance ratio**	**Distance ratio**	**Distance ratio**	**Distance ratio**	**Distance ratio**	**Distance ratio**	**Distance ratio**	**Distance ratio**	**Distance ratio**	**Distance ratio**	**Distance ratio**
1	0,53	0,52	0,51	0,52	0,33	0,32	0,59	0,62	0,22	0,19	0,31
2	0,45	0,49	0,44	0,42	0,34	0,31	0,59	0,57	0,23	0,19	0,33
3	0,51	0,52	0,49	0,45	0,38	0,36	0,61	0,66	0,21	0,21	0,41
4	0,51	0,55	0,47	0,45	0,31	0,28	0,59	0,56	0,22	0,19	0,36
5	0,47	0,56	0,51	0,48	0,35	0,34	0,63	0,64	0,21	0,21	0,35

Table III. Geometric-based facial distance measurements for 1 person.

Geometric-based facial distance measurement results for 1 person in 5 trials											
Markers	**Left Eye_c1**	**Left Eye_c2**	**Right Eye_c1**	**Right Eye_c2**	**Left nose**	**Right nose**	**Left mouth**	**Right mouth**	**Upper mouth**	**Lower mouth**	**Forehead**
Trials	**Distance ratio**	**Distance ratio**	**Distance ratio**	**Distance ratio**	**Distance ratio**	**Distance ratio**	**Distance ratio**	**Distance ratio**	**Distance ratio**	**Distance ratio**	**Distance ratio**
1	0,53	0,52	0,51	0,52	0,33	0,32	0,59	0,62	0,22	0,19	0,31
2	0,53	0,52	0,51	0,51	0,33	0,32	0,58	0,61	0,21	0,19	0,31
3	0,52	0,52	0,52	0,52	0,32	0,33	0,59	0,61	0,21	0,21	0,32
4	0,52	0,51	0,52	0,51	0,33	0,32	0,61	0,61	0,21	0,21	0,32
5	0,53	0,52	0,52	0,51	0,32	0,32	0,59	0,62	0,22	0,19	0,31
Average	0,526	0,518	0,516	0,514	0,326	0,322	0,592	0,614	0,214	0,198	0,314
Std dev	0,005477	0,004472	0,005477	0,005477	0,005477	0,004472	0,010954	0,005477	0,005477	0,010954	0,005477

Table IV. FCA results for 1 person for 5 trials.

Facial characters	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5
Balanced, talented	89,95	89,91	89,92	89,93	89,9
Clear talking, conservative	90,75	90,74	90,74	90,56	90,6
Modest	89,75	89,61	89,59	89,74	89,76
Moderate	90,27	90,27	90,29	90,29	90,26

Table V. Statistical analysis of the FCA results for each character.

Facial character classification				
No:	**Features of facial characters**	**Mean**	**Root mean square**	**Variance**
1	Authoritarian	90,11	0,005	0,121
2	Balanced, talented	80,43	0,031	0,203
3	Generous	89,78	0,015	0,134
4	Clear-talking, conservative	80,56	0,029	0,201
5	Intellectual, strong imagination	90,05	0,006	0,118
6	Modest/humble	88,45	0,017	0,142
7	Perfectionist	89,06	0,019	0,131
8	Social	89,56	0,016	0,129
9	Strong self-confident	90,02	0,006	0,116
10	Very careful, punctual	90,05	0,008	0,118

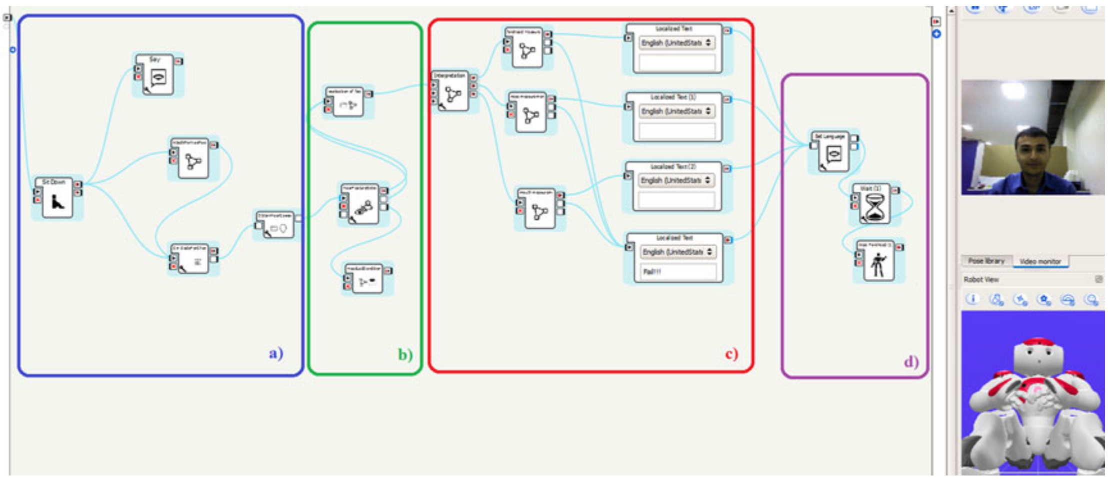

Fig. 16. FCA application using Choregraphe: (a) represents the face detection stage, (b) is for the facial distance measurement stage, FCA interpretation is applied in (c) and results are given from the NAO HR as in (d).

the center of the mouth) distance ratios are used to determine the size of the mouth (width–height). For the nose measurements, left nose (left rect corner distance to the center of the nose) and right nose (right rect corner distance to the center of the nose) are obtained. Finally, to specify the measurements for the forehead, eyes locations, face center, and head size are used. Similarly, distance ratios of each facial parts from the center point to the left eye, right eye, nose, mouth, and above and below mouth are approximately 0.52, 0.48, 0.33, 0.60, and 0.20, respectively, for five persons.

In order to test the reliability of the FCA results for each individuals, the facial distance measurements are taken for five times for each person as shown in Table III.

6.2. Results

After obtaining the facial distance measurements, the physiognomy science assesses these measurements to reach a decision about the character of the persons. Additionally, as can be seen from Table V, three simple statistical features (mean, root mean square, and variance) are determined to analyze FCA results for each character.

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```
Hello, I am Nao. I can do facial character analysis.
Do you want me to analyse your facial character?
y/n ?
y
Ok, I am analysing...
This is what I get:
********
 Balanced, talented
 Clear talking, conservative
 Moderate
 Modest / Humble
********
Do you want to learn your weak side ?
y/n ?
y
********
You are a little bit obsessive :(
********
Do you want me to analyse the face again ?
y/n ?
n
Ok, let's back to the beginning.
Hello, I am Nao. I can do facial character analysis.
Do you want me to analyse your facial character?
y/n ?
```

Fig. 17. Python output results of the FCA using the geometric-based facial distance measurement technique.

As can be seen from Table IV, despite the small differences between the facial measurement values (as shown in Table III) for each trials, these changes do not affect the result of the FCA.

Now, the algorithms for the face detection, facial distance measurements, and physiognomy-based character analysis are transferred to the NAO HR's interface through Choregraphe as shown in Fig. 16. In this application, all steps are represented with boxes, where each box has its own functions and these functions are connected to each other. Furthermore, as shown in Fig. 17, an additional dialogue is created in Python dll environment and all the data results are printed to also visualize the application.

7. Conclusion and Further Research

In this paper, for the first time in the literature, an FCA algorithm for HR is proposed and implemented to an HR in real time. The developed algorithm, initially, detects the face with the Viola–Jones algorithm, and then measures the important facial distances with the geometric-based facial distance measurement technique. Finally, the measured facial distances are evaluated with the physiognomy science to reveal the characteristic properties of the person. Even though the proposed algorithm can be implemented to all HR, in this research, it has been specifically applied to the NAO HR. The reliability of the FCA is verified by analyzing each terminal decision about the character analysis and the facial distance measurements.

This research will be extended and applied to various sophisticated HRI cases in near future. Please visit the below YouTube link to see how the NAO HR interacts with a person during FCA.

https://www.youtube.com/watch?v=u3RYJu3plaE&feature=youtu.be

Acknowledgments

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References

1. P. Viola and M. J. Jones, "Robust real-time face detection," *Int. J. Comput Vis*. **57**(2), 137–154 (2004).
2. O. H. Jensen, Implementing the Viola-Jones Face Detection Algorithm, *Master's thesis* (Technical University of Denmark, DTU, DK-2800 Kgs. Lyngby, Denmark, 2008).
3. H. Schneiderman and T. Kanade, *A Statistical Method for 3D Object Detection Applied to Faces and Cars. CVPR* (IEEE Computer Society, Washington, D.C., USA, 2000). ISBN: 0-7695-0662-3.

https://doi.org/10.1017/S0263574719000304 Published online by Cambridge University Press

4. H. A. Rowley, S. Baluja and T. Kanade, "Neural network-based face detection," *IEEE Trans. Pattern Anal. Mach. Intell*. **20**(1), 23–38 (1998).
5. T. Kanade, *Picture Processing System by Computer Complex and Recognition of Human Faces* (Kyoto University, Kyoto, 1974).
6. R. E. Schapire, "Explaining AdaBoost," **In:** *Empirical Inference* (B. Schölkopf, Z. Luo and V. Vovk eds.) (Springer, Berlin, Heidelberg, 2013) pp. 37–52.
7. R. Brunelli and T. Poggio, "Face recognition: Features versus templates," *IEEE Trans. Pattern Anal. Mach. Intell*. **15**(10), 1042–1052 (1993).
8. J. C. Lavater, *Essays on Physiognomy (T. Holcroft, Trans.)* (William Tegg, London, England, 1869). (Original work published 1772).
9. R. D. B. Wells, *Faces we Meet and How to Read Them* (Vickers, London, 1870) p. 14.
10. B. Gonsior, S. Sosnowski, C. Mayer, J. Blume, B. Radig, D. Wollherr and K. Kühnlenz, "Improving aspects of empathy subjective performance for HRI through mirroring emotions," *Proceedings of IEEE Intern. Symposium on Robot and Human Interactive Communication, RO-MAN 2011*, Atlanta, GA, USA (2011).
11. M. Valstar and M. Pantic, "Fully automatic facial action unit detection and temporal analysis," *Proceedings of IEEE Computer Vision and Pattern Recognition Workshop*, New York, NY, USA (2006) pp. 149.
12. I. J. Cox, J. Ghosn and P. N. Yianilos, "Feature-based face recognition using mixture-distance,". **In**: *Proceedings CVPR'96, 1996 IEEE Computer Society Conference Computer Vision and Pattern Recognition*, San Francisco, CA, USA (1996, June) pp. 209–216.
13. M. Barasch, "Character and physiognomy: Bocchi on Donatello's St. George a Renaissance text on expression in Art," *J. Hist Ideas* **36**(3), 413–430 (1975).
14. A. Oommen and T. Oommen, "Physiognomy: A critical review," *J Anat. Soc. India* **52**(2), 189–191 (2003).
15. S. Angle, R. Bhagtani and H. Chheda, "Biometrics: A further echelon of security," **In**: *UAE International Conference on Biological and Medical Physics*, Dubai, United Arab Emirates (2005, March).
16. E. Charles, *Major Psychological Assessment Instruments* (Allyn & Bacon, Boston, MA, USA, 1996).
17. L. S. Mong, *The Chinese Art of Studying the Head, Face and Hands* (Eagle Trading Sdn Bhd, Malaysia, 1989).
18. R. Brunelli and T. Poggio, "Face recognition: Features versus templates," *IEEE Trans. Pattern Anal. Mach. Intell*. **15**(10), 1042–1052 (1993).