An Approach to Behavioural Distraction Patterns Detection and Classification in a Human-Robot Interaction

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***Abstract*—The capacity of remaining focused on a task can be crucial in some circumstances. In general, this ability is intrinsic in a human social interaction and it is naturally used in any social context. Nevertheless, some individuals have difficulties in remaining concentrated in an activity, resulting in a short attention span. In order to recognize human distraction behaviours and capture the user attention, several patterns of distraction, as well as systems to automatically detect them, have been developed. One of the most used distraction patterns detection methods is based on the measurement of the head pose and eye gaze. The present work proposes a system based on a RGB camera, capable of detecting the distraction patterns, head pose, eye gaze, blinks frequency, and the distance of the user to the camera, during an activity, and then classify the user's state using a machine learning algorithm. The goal is to interface this system with a humanoid robot to consequently adapt its behaviour taking into account the individual affective state during an emotion imitation activity.**

Keywords-Human-Robot Interaction; ZECA Robot; Distraction Patterns; Emotional States; Machine Learning.

I. Introduction

In general, the ability of concentrating on a task for an extended period of time is a paramount skill to develop. As observed by various authors [1][2], when a person tries to reach a particular object, the observer's gaze arrives at the target before the action is completed. Additionally, the predictive gaze provides the time for the observer to plan and execute an action towards a goal.

Following this idea, the attention span and the eye gaze can be very important elements in social interaction, as they can help an individual to perceive the goals of others. However, some individual's present a low attention span, especially children with Autism Spectrum Disorder (ASD) [3] when, for example, focusing on things that do not interest them, i.e., activities that involve shared attention. Additionally, in accordance to the literature [4][5], authors suggest that individuals with ASD attend less to faces than typically developing individuals.

In an attempt to increase and captivate these individuals' interest, authors have been proposing new technological tools in the field of assistive robotics to help users with special needs in their daily activities. Assistive robots are designed to identify, measure, and react to social behaviours, being repeatable and objective offering an exceptional occasion for quantifying social behaviour [6].

They can be a social support to motivate children, socially educate them and beyond that to help transferring knowledge. Furthermore, research with assistive robots have showed that, in general, individuals with ASD express elevated interest while interacting with robots: increase attention [7], recognition and imitation abilities [8], verbal utterances [7], among others. According to studies, it was observed that children with ASD can exhibit certain positive social behaviours when interacting with robots in contrast to what is perceived when interacting with their peers, caregivers, and therapists [9]. Furthermore, few projects worldwide pursue to include robots as part of the intervention program for individuals with autism [10][11].

These robots are presented with different embodiments, varying their physical appearance from simple designs, e.g., four-wheeled mobile robots, to many levels of anthropomorphic forms, including humanoid [12], animal-like [13], and machine-like systems [14].

Recently, the research in the area of assistive robotics have moved to using robots with a humanoid design, since it can promise a great potential for generalisation, especially in tasks of imitation and emotion recognition which can be harder if the robot does not present a human form [11][12][15].

The majority of the systems proposed in the literature are controlled using the Wizard-of-Oz (WOZ) setup, meaning that in fact the robot does not adapt its behaviour to the children's actions as it does not perceive them [16]. Additionally, there have been studies with assistive robots with the goal of measuring the children eye gaze duration [17][18] and direction. However, this analysis is not performed in real-time by the robot, meaning that usually the sessions are recorded, and the metrics are manually quantified during a post-analysis of the videos.

More recently, there has been a concern in developing more adaptive approaches to interact with children with ASD. These recent approaches usually use wearable and non-wearable technologies in order to measure the children affective states.

The work developed by [19] consisted in controlling the robot reactions and responses, by using a combination of hardware, wearable devices, and software algorithms to

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measure the affective states (e.g., eye gaze attention, facial expressions, vital signs, skin temperature, and skin conductance signals) of children with ASD. The wearable devices that the authors used were a sensorized t-shirt to acquire the subject physiological signals (ECG and respiration rate), wireless electrode bands to collect the user's skin temperature and Electro Dermal Activity (EDA) and the HATCAM, a system composed of a hat with markers and a grid of cameras to estimate the user's gaze. The developed system, FACET, includes a multisensory room in which a psychologist drives a stepwise protocol involving the android FACE and the autistic subject. This interaction between the robot and the subject is tailored by the therapist. A preliminary test was conducted with six male subjects: four individuals with ASD aged between 15 and 22 years old and two typically developing individuals aged between 15 and 17 years old. By analysing the results, the authors conclude that the subjects were calm during the activity and responded well to the robot. Additionally, the results confirmed that the system can be used as an innovative tool during the intervention sessions with subjects with ASD.

Bekele and colleagues [20][21] developed and later evaluated a humanoid robotic system capable of intelligently managing joint attention prompts and adaptively respond based on gaze and attention measurements. The system is composed of a humanoid robot with augmented vision by using a network of cameras for real-time head tracking using a distributed architecture. In order to track the child's head motion, a hat with markers was used. Thus, based on the cues from the child's head motion, the robot adapts its behaviour to generate prompts and reinforcements. A pilot usability study was conducted with six children with ASD. The results allowed to conclude that the children directed their gaze towards the robot when it prompted them with a question. The authors suggested that robotic systems, endowed with enhancements for successfully captivating the child's attention, might be capable to meaningfully enhance skills related to coordinated attention.

Following this trend, the present work proposes the development of a framework that uses a RGB camera to interface with the humanoid robot ZECA (Zeno Engaging Children with Autism). Generally, in order to track the user's attention patterns, the literature approaches combine the use of several wearable sensors, which can be invasive, with non-wearable sensors. Thus, in order to become less invasive, the present approach uses only one camera to estimate eye gaze, head motion, the blinks frequency and the distance of the user to the camera. The proposed system allows to infer children distraction patterns (if any) when performing a task and to adapt the robot behaviour accordingly.

The final goal of the present work is to collect the selected patterns (head pose, eye gaze, blink frequency, and distance of the user to the camera), and based on these patterns classify the user state, attentive or distracted, during a laboratorial activity.

The paper is organized as follows: in Section 2 the experimental set-up is presented. Section 3 presents the experimental methodology describing the system modules as well as the robot behaviour. The results and their discussion are presented in Section 4. The conclusion and future work are addressed in Section 5.

II. EXPERIMENTAL SETUP

The proposed structure (Figure 1) was designed to use only an RGB camera to detect patterns of user distraction in order to adapt the behaviour of the robot during the activity.

In addition to an RGB camera, the experimental setup uses a computer and the ZECA humanoid robot.

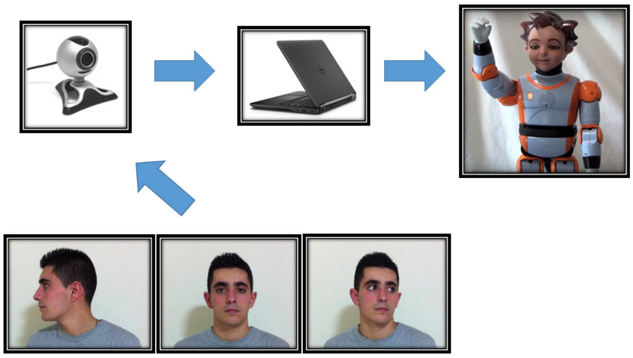

Figure 1. Experimental setup: starting from the left, the RGB camera; in the centre, the computer; and on the right, the humanoid robot ZECA.

The camera used in the present work is a RGB camera, more specifically the Microsoft VX-1000 camera. This device has a minimum resolution of 320 by 240 pixels and a maximum resolution of 640 by 480 pixels. The camera dimensions are 5.5 cm of width, 6.8 cm of height, and 5.3 cm of depth. For a better detection and feature extraction, the camera is placed on the robot chest, being at the same level as the user's face.

The Zeno R50 RoboKind humanoid child-like robot ZECA is a robotic platform that has 34 degrees of freedom: 4 are located in each arm, 6 in each leg, 11 in the head, and 1 in the waist. The robot is capable of expressing facial cues thanks to the servo motors mounted on its face and a special material, Frubber, which looks and feels like human skin, being the major feature that distinguishes Zeno R50 from other humanoid robots.

III. EXPERIMENTAL METHODOLOGY

Since the purpose of this work is to know whether the user is distracted, a study was done to determine which patterns best fit in this evaluation. The following patterns were identified: the eye gaze, the head orientation, the eyes blinking frequency, and the distance of the user to the camera. These patterns will be detected during an emotion imitation activity.

After the extraction of these patterns, the classification was done using an algorithm based on machine learning, thus classifying the user as attentive or distracted.

The design of this activity consists in ZECA displaying a facial expression and asking the child to imitate it. Then, the robot automatically verifies if the answer is correct and responds accordingly. Meanwhile, if the system detects any distraction pattern in the child, the robot adapts its behaviour, encouraging the child to return and participate in the activity.

A. Affective state detection and classification

Figure 2 presents the block diagram of the overall system considering the detection of distraction patterns, as well as the classification of the emotional state of the chid during an activity.

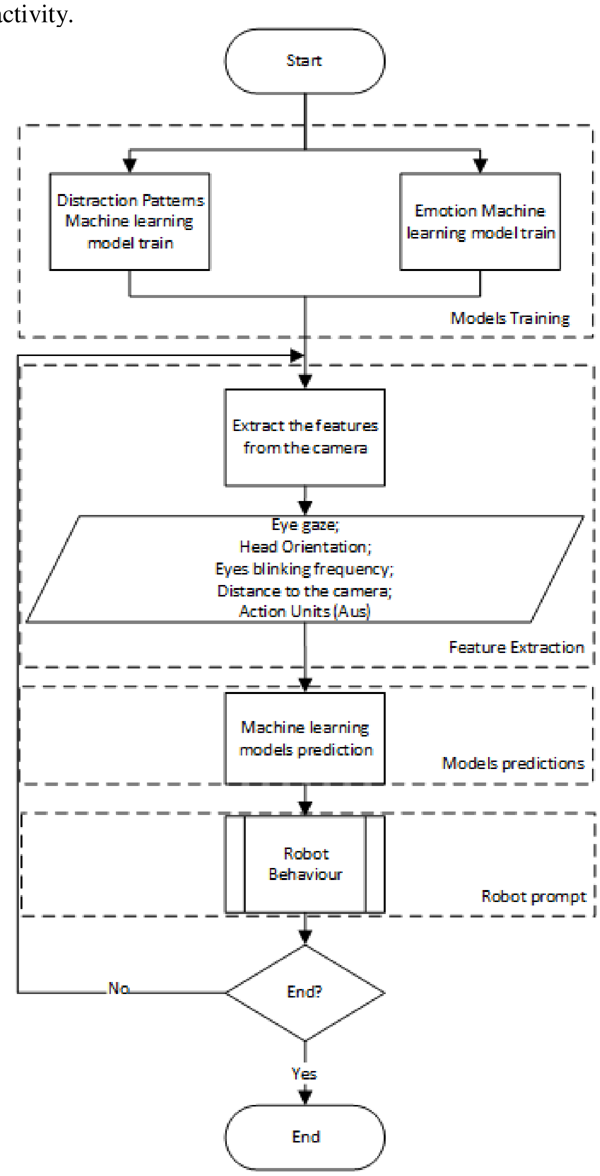

Figure 2. System flowchart highlighting the defined modules for detecting distraction patterns and emotional states: Models training, Feature extraction, Models predictions, and Robot prompt.

The first module, Models Training, consists in training each machine learning model with a previously defined database.

Three other modules are defined: Feature Extraction, Models predictions, and Robot prompt.

For the feature extraction an algorithm based on the OpenFace [22]-[25] library is used to track the face and eyes of the user, as well as the user's Action Units (AUs).

The OpenFace is an open source library that makes available a collection of facial landmarks (a total of 68 facial points) and AUs based on the Facial Action Coding System (FACS). The FACS system, developed by Ekman and Friesen [26], allows researchers to analyse, and classify facial expressions in a standardized framework. This system associates the action of the facial muscles to the changes in facial appearance. The basic metric of the FACS system are the AUs which are actions performed by a muscle or a group of muscles. Ekman also proposed the six basic emotions [26], also considered the six universal emotions – happiness, sadness, anger, surprise, fear, and disgust.

Additionally, OpenCV is also used due to its suitability and applicability in computer vision solutions.

Generally, some researches use machine learning techniques in order to infer the user emotional states [27]. Then, by using machine learning methods, for example Support Vector Machines (SVM) or k-Nearest Neighbours (k-NN), the attention patterns and the user facial expression will be recognized.

Once the patterns corresponding to distraction and emotional states are detected, the robot should trigger the corresponding action (robot prompt module) to acknowledge the emotion, to give reinforcement and, if necessary, to capture the user's attention again.

B. Robot Behaviour

The general procedure during an activity is: 1) ZECA greets the researcher and the user; 2) ZECA asks which activity shall be played; 3) The selected activity starts and continues until the experimenter decides to end it.

In the activity, the robot prompts a different behaviour accordingly to the results, the child attentiveness, and response. Thus, according to the classifier output, four conditions may occur:

- the user is attentive and answer to the robot prompt;
- the user is attentive but does not answer to the robot prompt;
- the user is distracted and does not answer to the robot prompt;
- the user is distracted but answer to the robot prompt.

In order to adapt the robot behaviour accordingly to the four different conditions mentioned, a state machine model is proposed [28].

After classification it is necessary to take an action, that is, if the robot classified the user as attentive, then it will continue the activity. Then, ZECA revises the patterns, so as to always know if the user is attentive. If it has previously considered the user inattentive, then it will trigger an action in order to capture the user's attention again.

At the end of the cycle, it is always checked if the activity is complete; if it is accomplished, the robot does not need to revise the defaults; if it is not, then the robot will have to continue to analyse the user defaults. Figure 3 depicts the general procedure that happens during an activity.

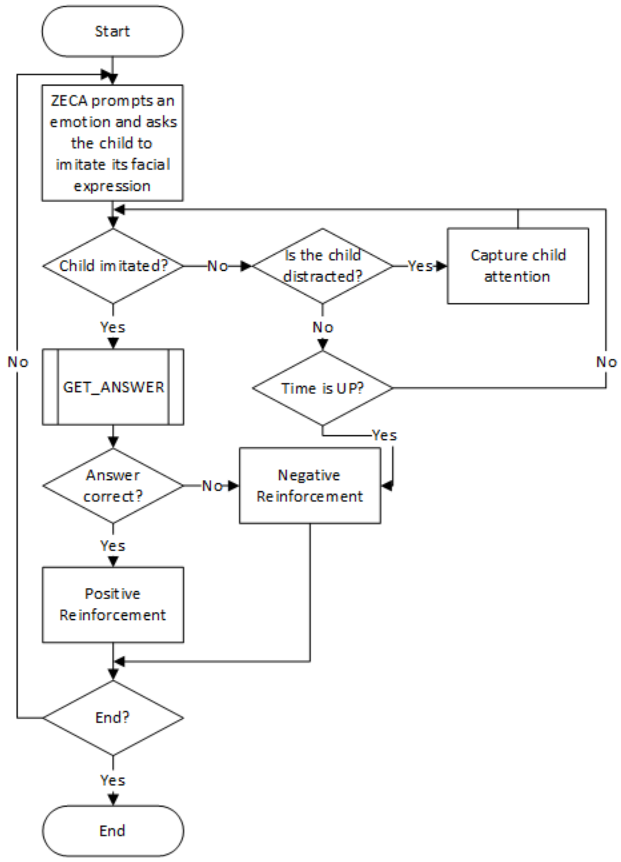

Figure 3. Robot behaviour flowchart.

IV. RESULTS AND DISCUSSION

In order to display the user's information and to monitor the activity, a Graphical User Interface (GUI) was developed. Figure 4 shows the GUI where the head pose angles (pitch, roll, and yaw), the number of blinks, the gaze estimation, the distance of the user to the camera, and the prediction of the classification model are displayed.

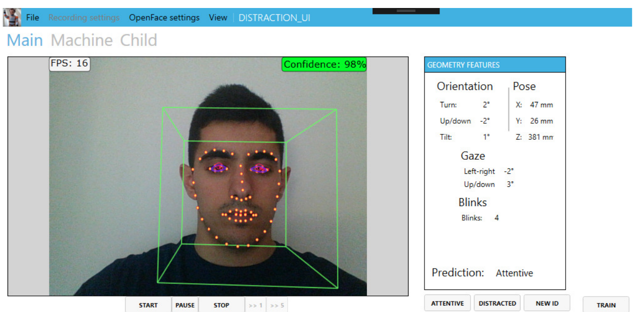

Figure 4. The GUI displaying the webcam feed, the user's eye gaze, the head pose, the number of blinks, the distance of the user to the camera, and the prediction of the classification model.

Several distraction and attention behaviours were simulated in a laboratorial environment, where the user sat in front of the camera. The corresponding patterns were stored in a training database (head pose, eye gaze, blink frequency, distance of the user to the camera). This database was built with six different subjects with 500 samples each. Then, with Accord [29], two classification methods, Gaussian SVM and k-NN [27], were used.

To test the robustness of the system a test database was created and tested with these two methods, in order to find out the best method for this type of classification. This new database was composed by three different subjects and with 100 samples each. The same patterns were stored in the test database (head pose, eye gaze, blink frequency, distance of the user to the camera).

Tables 1 and 2 represent the confusion matrix for the Gaussian SVM method with the two databases created.

TABLE I. CONFUSION MATRIX FOR GAUSSIAN SVM METHOD WITH TRAINING DATABASE.

Predicted Class	Actual Class	
	Attentive	*Distracted*
Attentive	81.0%	5.1%
Distracted	19.0%	94.9%

TABLE II. CONFUSION MATRIX FOR GAUSSIAN SVM METHOD WITH TEST DATABASE.

Predicted Class	Actual Class	
	Attentive	*Distracted*
Attentive	63.5%	0%
Distracted	36.5%	100%

By analysing Table 1, it is possible to see that the results are satisfactory, since the accuracy of the attentive and distracted classes are above 80%. Regarding the confusion matrix with the test database (Table 2), it is possible to see that the accuracy of the distracted class is 100%. Conversely, the accuracy of the attentive class has decreased. Although, in the test database (Table 2), the accuracy of the attentive class decreased, the distracted class accuracy increased, meaning that the system can accurately detect when the user is distracted which is the main goal of the proposed system.

In Tables 3 and 4, it is presented the confusion matrix for the k-NN method with the two databases created.

TABLE III. CONFUSION MATRIX FOR K-NN METHOD WITH TRAINING DATABASE.

Predicted Class	Actual Class	
	Attentive	*Distracted*
Attentive	100%	0%
Distracted	0%	100%

TABLE IV. CONFUSION MATRIX FOR K-NN METHOD WITH TEST DATABASE.

Predicted Class	Actual Class	
	Attentive	*Distracted*
Attentive	65.3%	2.8%
Distracted	34.7%	97.2%

Analysing Table 3, the k-NN performed better in the training step in comparison to the Gaussian SVM method. However, by analysing the performance of the k-NN method in with the test database (Table 4), the performance, in general, decreased.

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Tables 5 and 6 present the values of accuracy, the Matthews Correlation Coefficient (MCC), the sensitivity, the specificity, the precision, and the Area Under the Curve (AUC) obtained with the Gaussian SVM and the k-NN methods for the training and test databases, respectively.

TABLE V. METRICS OBTAINED WITH THE GAUSSIAN SVM METHOD FOR THE TRAINING AND TEST DATABASES.

Metrics	**Database**	
	Training	***Test***
Accuracy	88.1%	80.3%
MCC	76.9%	66.6%
Sensitivity	81.0%	63.5%
Specificity	94.9%	100%
Precision	93.8%	100%
AUC	88.0%	81.8%

TABLE VI. METRICS OBTAINED WITH THE K-NN METHOD FOR THE TRAINING AND TEST DATABASES.

Metrics	**Database**	
	Training	***Test***
Accuracy	100%	79.9%
MCC	100%	64.7%
Sensitivity	100%	65.3%
Specificity	100%	97.2%
Precision	100%	96.5%
AUC	100%	81.3%

Analysing both Tables, it is possible to conclude that, in general, the SVM with the Gaussian kernel achieved better results with an accuracy of 80.3% when compared with the k-NN method (accuracy: 79.9%) with the test database. Although the k-NN method obtains excellent results with the training database, the same does not happen with the test database, having lower results in some of the metrics. The Gaussian SVM method, despite obtaining slightly lower results with the training database when compared to the k-NN, the overall performance is slightly better and more consistent than the k-NN method with the test database. Thus, in general, it can be concluded that the results obtained with the test database, using Gaussian SVM method, are overall better than when using the k-NN method.

As the Gaussian SVM trained model showed better results, it was used in a real-time laboratorial environment evaluation. The user sat in front of the camera and performed simulated behaviours, attentive and distracted. The system automatically classified the user state. Some of the results for different positions obtained using this method are shown in Figure 5.

Figure 5. The GUI displaying the classification considering different poses (results using Gausian SVM method). The classifier output is presented in the interface (red rectangles).

V. CONCLUSION AND FUTURE WORK

The ability of concentrating on a task for an extended period of time is a paramount skill to develop. In general, when a person tries to reach a particular object, the observer's gaze arrives at the target before the action is completed. Thus, the predictive gaze provides the time for the observer to plan and execute an action towards a goal. During a social interaction, the predictive gaze and the attention span can be crucial elements, as they can help an individual to perceive the goals of the others.

However, some individuals present a low attention span, especially children with Autism Spectrum Disorder (ASD), and in general they attend less to faces than typically developing individuals.

Researches have been using robotic platforms for promoting social interaction with individuals with ASD. Furthermore, it has already been proven that the use of robots encourages the promotion of social interaction and skills lacking in children with ASD. However, most of these systems are controlled remotely and cannot adapt automatically to the situation. Even those who are more autonomous still cannot perceive whether or not the user is paying attention to the instructions and the actions of the robot. Additionally, some of these systems use an array of cameras and a hat with markers in order to infer the user gaze.

The present paper concerns the development of a framework to estimate the user/child affective states. The system is based on a camera to detect and follow the face and contours, and extract the user head orientation angles (yaw, pitch, and roll), eye gaze, action units, blinking frequency, and the distance between the user and the camera. It applies an algorithm based on Opencv functions and OpenFace library. Using the features extracted from the user, and a machine learning model (Gaussian SVM or k-NN) it is possible to recognize these patterns and classify the user as distracted or attentive.

In general, the method that registered a better accuracy was the SVM with the Gaussian kernel (accuracy: 80.3%); the k-NN method had slightly lower results (accuracy: 79.9%) both with the test database.

As future work, it is necessary to recognize these patterns (distraction and emotional states) during a triadic emotion imitation activity with children with ASD (child, researcher and robot ZECA), where the child facial expression is recognized through facial features in real-time. Robot behaviour will be constantly adapted taking into account child affective state. Through the use of a friendly interface, the teacher/therapist will be able to access the child's performance as well as to monitor the running intervention activity.

To accomplish this, the developed system is going to be evaluated in different scenarios in order to assess its performance. A first evaluation is going to be conducted in a school environment with typically developing children with the purpose of detecting the system constraints and to tune the conditions of the experimental scheme. After this first validation in a controlled environment, a second test should be developed in a real-world context with individuals with ASD.

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