Multi-Modal Engagement Prediction in Multi-Person Human-Robot Interaction

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ABSTRACT The ability to measure the engagement level of humans interacting with robots paves the way towards intuitive and safe human-robot interaction. Recent approaches achieve reasonable progress in predicting human engagement in physically situated environments. However, engagement estimation is still a challenging problem especially in an open-world environment due to the difficulty of creating and monitoring a variety of human social cues in real-time. Furthermore, the interactions may involve a group of subjects interacting simultaneously with the robot, which increases the prediction complexity. In this paper, we design a real-time engagement estimation system for humans interacting with robots with generalization capability. We propose to estimate engagement using a three-stage approach based on a combination of learning-based and rule-based approaches. Firstly, state-of-the-art deep learning methods are used to extract engagement features from input frames. Then, a simple neural network is used to estimate the focus of attention score by incorporating gaze and head pose features and assigning this score to all subjects in the scene using a face recognition algorithm. Finally, a rule-based classification approach is used to predict the engagement state of the subject to initiate/terminate the interaction with the robot. To effectively evaluate our system, we access our approach for each phase separately. Additionally, we use an online evaluation study in which subjects are allowed to interact freely with an industrial robot. Our model achieves an average of 96%, 90%, and 93% precision, recall, and F-score respectively.

INDEX TERMS Human-robot interaction, Engagement, Disengagement, cobots, Rule-based approach, Deep learning, face recognition, gaze estimation, head pose, Body pose

I. INTRODUCTION

HUMAN-ROBOT Interaction (HRI) [1]–[3] arises to tackle and enhance the meaningful interaction between humans and robots while preserving the safety for human interaction partners. These interactions include three stages of collaboration: coexistence, cooperation and responsive collaboration. Consequently, a new type of industrial robot called collaborative robot (cobot) is developed with a high level of safety to join the industry along with humans.

Using cobots aside with Artificial Intelligence opens the way for the development and creation of natural and intuitive HRI concepts. In this paper, we develop a concept that combine different features including head pose, gaze, posture, speech, and gesture to allow a multimodal and restriction-free HRI. The interactions between humans and robots are divided into four different phases: Firstly, the robot detects a potentially interested user for engagement; Secondly, the robot identifies the kind of interaction intention from the person; thirdly, the robot executes the task or gives a response to the person; Finally, human disengages from the robot after receiving the response, or after task execution. The study of engagement and disengagement phases are crucial for maintaining sustainable spontaneous interactions between humans and robots [4].

Engagement is a complex process that can be analyzed in terms of four discrete stages [5] include intention to engagement, engagement, disengagement, and re-engagement. The re-engagement phase only occurs when the disengagement is not complete which is very difficult to determine with certainty. The estimation of the engagement state requires the challenging tracking of a variety of social cues during interactions. The most common signals used in literature are
In this section, we will outline the related work regarding industrial human-robot interaction, engagement, and disenagement techniques in HRI.

II. RELATED WORK

In this section, we will outline the related work regarding industrial human-robot interaction, engagement, and disenagement techniques in HRI.
with the offline evaluation. They concluded that the simple, rule-based classifier achieves competitive performance compared with multiple trained classifiers in all the experiments. Vaufreydaz et al. [12] demonstrated that multimodal sensor data (including 32 features from multiple sensors) provides better performance than using only spatial features. Furthermore, they illustrated that seven selected features only are adequate to provide good performance for engagement detection. Li et al. [24] developed an active method where the robot interacts naturally with multiple persons. They reported that their method is capable of selecting a person as an addressee based on the perception of human visual cues. In [14], the authors created models for automatically identifying human intentions with low false-positive rates and before the engagement (3-4 seconds earlier). They used audiovisual modalities to calculate human intentions for initiating the interaction with a robot. Schuller et al. [25] offered an audiovisual approach for the identification of spontaneous engagement in human conversations. They demonstrated that balancing the training sets leads to significantly better results and also found that the combination of the audio and visual modality is better than using the single modalities, and is still real-time capable. Richter et al. [26] studied the impact of addressee identification on the robot’s performance to classify utterances directed to it from an interaction between humans. They evaluated methods to addressee identification by utilizing different types of visual cues. [14] presented a computational model for managing engagement with a situated agent in multiparty, open-world settings.

C. DIENGAGEMENT TECHNIQUES IN HRI

Engagement breakdown occurs when humans are about to terminate their interactions with the robot. Predicting disengagement in open-world settings is a challenging problem as it involves the processing of multiple signals, including head pose, eye gaze, posture, and gestures. [13] proposed a self-supervised approach to forecast disengagement. They construct forecasting models that do not require manual annotations by deploying the robot NAO with a baseline forecasting model in an open space for five days. Furthermore, they trained logistic regression and boosted decision tree models using the data collected from 158 users interacting with the robot and compared it with the forecasting model. They conclude that the forecasting model can predict disengagement while maintaining a low false-positive rate.

Leite et al. [9] proposed three different SVM-based models for predicting disengagement of humans when interacting with social robots: a model trained with a dataset containing one subject engaging with the robot, a model trained with a dataset containing a group of three subjects engaging with the robot, a model trained with combined instances from the two datasets. The authors conclude that the model trained only with data from one engagement user might not be appropriate for group engagements. However, a model trained only with group data performs well when tested with a single user.

Furthermore, they showed that the mixed model performed better than the two models [9].

Finally, Ben et al. [11], [16], [28] presented a new dataset called UE-HRI for spontaneous interactions between humans and a Pepper robot. In [16], deep learning techniques are utilized (deep and recurrent neural networks) to predict disengagement in real-time, achieving a reasonable prediction accuracy of 78%. In addition, they further investigate the prediction of disengagement in [11] by investigating the time interval over which a user’s disengagement can be detected using supervised classifiers. They concluded that the used models were generally successful in predicting the disengagement up to 10 seconds before the user leaves the interaction.

III. COBOT SYSTEM

In our earlier Wizard-of-Oz (WoZ) study [27], we designed a mockup of a Robot System Assistant and carried out a study with 36 subjects. The subjects were permitted to use different features like gestures, speech, mimics, and gaze without any limitations to communicate with a cobot and execute different tasks like cube stacking. The subjects think that they are interacting with an artificial system, while in reality, we were controlling the cobot from a hidden room, based on the subject’s instructions. Figure 2 shows a few interactions between subjects and the cobot from our WoZ study.

In this paper, we conduct an online user study in the same way as in the WoZ study in order to evaluate our engagement and disengagement model in an open-world environment.

A. EXPERIMENTAL SETUP

Fig. 3 shows the general hardware resources used in the experimental design of the interaction. The hardware resources
include two different workstations WS1 (cobot) and WS2 each of them having a different design and purpose.

1) WS1
is responsible for the main interaction between the user and the cobot. It consists of an UR5e industrial robot with a RG6 gripper placed on a metal table in front of a TV screen. A time-of-flight (ToF) Kinect V2 camera is placed above the screen so that the user is seen fully in front of the table. On the table, there are black and white letter cubes, which can be picked up by the robot.

2) WS2
is mainly responsible for registering the subject’s facial features in the system which is crucial for the engagement estimation. Further, it is used for the questionnaires at the end of the experiments. It consists of a touch-capable smart screen with built-in speakers and another Kinect camera equipped with a microphone.

B. SCENARIO

The scenario of the experiments is divided into 3 phases as shown in Fig. 4 including registration, interaction, and the questionnaires.

1) Registration

The subject uses WS2 for registration as shown in Fig. 4(a). WS2 has an interface based on the ROS-QT visualization environment. The subject uses this interface to register his name, preferred hand, and face features to the system. In order to store all facial features, we ask the subject to look to the front and then once to the right and once to the left through the interface. Based on the stored face features, we assign a face ID to the subject that will be used during the whole experiment.

2) Interaction

The subject switches to WS1 to start doing three different collaborative tasks with the cobot including:

1) Have Cobot give you a block as in Fig. 4(c).
2) Spell a specific word with the alternating color of blocks as in Fig. 4(e).
3) Build a 3-2-1-Pyramid with black-white-black layers as in Fig. 4(g).

We add one more step to this phase that the subject switches to WS2 to read the instruction for the next task and then return to WS1 to execute the task. This step will add more challenges and complexity to the deployed engagement model.

3) Questionnaires

Finally, the subject switches to WS2 to answer questionnaires as in Fig. 4(b). Additionally, a module-specific questionnaire was taken to allow the subjects to evaluate each module separately after finishing the experiment.

IV. APPROACH

We propose a new model that utilizes simple rule-based policies to predict human engagement state of humans interacting with a cobot. Our model is easy to use approach as it employs visual data that is available on various robot platforms. It can track the engagement state of humans starting from willing to engage until disengaging. Further, our model can predict the re-engagement state based on the subject identity features obtained from a face recognition algorithm. Our model consists of three stages include feature extraction, feature processing, and engagement classification:

1) Stage 1: we extract crucial features for classifying engagement including human head pose, gaze, and face ID using state-of-the-art convolution neural networks. Further, we use Kinect v2 to extract the body pose feature.
2) Stage 2: we output the most important signals for the engagement including the focus of attention and fused body signals using a feed-forward neural network.
3) Stage 3: we classify the engagement state of subjects using a simple rule-based policy based on the output of stage number two.

Fig. 5 shows the overall architecture of our multimodal three-stage engagement and disengagement prediction model.

A. FEATURE EXTRACTION

Various cues could represent the subject’s engagement intentions, which could be used to model engagement and disengagement. Using more features to estimate engagement may increase the prediction accuracy. However, it will increase the computational cost, which will harm the overall model performance. Consequently, we extract the most crucial features to characterize engagement as mentioned in most of the literature including gaze, head pose, body posture, and face ID as shown in Table 1. To extract robust features,
we apply state-of-the-art deep learning methods to the raw signals obtained from the resources.

### TABLE 1. Extracted feature streams.

| Stream | Feature | Description |
|--------|---------|-------------|
| Gaze   | Gaze    | 2 features [yaw, pitch] (in degrees) |
| Head   | Head    | 3 features [yaw, pitch, roll] (in degrees) |
| Face   | Face ID | 1 feature $\in \mathbb{Z}_{>0}$ |
| Body   | Body Joints | 25 features [x, y, z] |

1) **Gaze**

Gaze is the most crucial cue used in predicting engagement and disengagement, as it defines the person’s current visual focus of attention. The direction of gaze defines the initial intention of humans to engage with the robot. We propose to use a robust gaze estimation method designed by Petr et al. [29] which they extract gaze using a convolution neural network (CNN). As seen in the table 1, we estimate 3D gaze direction as spherical coordinates (pitch, yaw) relative to the camera view.

2) **Head pose**

Head pose is a good approximation of the person’s focus of attention, especially when the gaze is missed or inaccurate. The direction of the head pose combined with the gaze can deduce the interaction willingness of the person to start/terminate the interaction with the robot. A lot of methods and techniques were proposed to estimate 3D face poses from images. We propose to use a robust method developed by albiero et al. [30] which is a real-time, six degree of freedom (6DoF) head pose estimation. Then, we convert the 6DoF estimated by the model to the head pose Euler angles (pitch, roll, yaw) as seen in Tab. 1.

3) **Face ID**

Person identification is crucial, especially when dealing with multi-subject HRI. We adopt a face recognition framework based on three stages including face detection, face alignment, and face identification. Firstly, we utilize RetinaFace [31] to detect and localize the faces in the input frames, which is one of the most accurate face detection methods. Furthermore, we use MobileNet-0.25 [32] as a backbone to achieve real-time HRI. Secondly, the bounding boxes with high confidence are aligned by a practical facial landmark detector [33]. The aligned faces are cropped to a size of 112 VOLUME 4, 2016

FIGURE 4. Typical human-robot interactions scenario with three phases including registration, interaction, and questionnaires.
x 112 to be more consistence with the next stage. Finally, the face features are extracted from the cropped faces by means of the ArcFace model [34] and outputs the corresponding feature embedding vector of 512 features. We compare the embedding vector against the gallery embedding to predict the face ID as shown in Tab. 1.

To the best of our knowledge, all related works that estimated engagement and disengagement do not consider the face identification feature in their techniques.

4) Body posture
The body posture provides a good indication of the person’s engagement degree, especially when the face is missed. Body posture is estimated with the Kinect v2 using the native Kinect for Windows SDK. The resulting skeleton contains 25 points mapped in the 3D coordinate system relative to Kinect. Each joint can have a tracking state: “tracked”, “inferred” or “not tracked”, thus determining the overall quality of the tracked skeleton.

Fig. 6 presents the four features extracted from streams in order to predict engagement and disengagement.

**B. FEATURE PROCESSING**
Using the extracted features, we generate two important binary signals to characterize engagement. These signals include the focus of attention (FA) and fused body face (BF), which are crucial for engagement estimation. Our model uses these signals aside with rule-based policy to make engagement decisions.
face array to prevent double IDs. Only a body with an ID, matched to the body and the face is then removed from the transforms its head coordinates into 2D camera space. For each input must be matched to a corresponding user. It management, safety and is necessary in order to maintain an face ID to skeleton matching plays a crucial role in user have a valid skeleton and a valid registered face ID. We refer not engaged with the system, we only consider users who to prohibit (accidental/mischievous) input from a skeleton, To prevent an accidental mix-up of the detected skeletons and focusing its attention on the robot.

Algorithm 1 Skeleton S and Face F{x, y, ID} Fusion

1: Faces ← All detected Faces
2: Bodies ← All tracked Kinect Skeletons
3: for all S in Bodies do
4: \( x_S, y_S \leftarrow \text{Transform}_{2D}(S.\text{Head} \{x, y, z\}) \)
5: \( d \leftarrow \infty \)
6: for all F in Faces do
7: \( \delta_F \leftarrow \sqrt{(x_s - F.x)^2 + (y_s - F.y)^2} \)
8: if \( \delta_F < d \) and \( \delta_F < 30 \) pixels then
9: \( d \leftarrow \delta_F \)
10: \( S.\text{ID} \leftarrow F.\text{ID} \)
11: end if
12: end for
13: if \( S.\text{ID} \neq \text{null} \) then
14: remove \( F(S.\text{ID}) \) from Faces
15: Users.add(S)
16: end if
17: end for

1) Focus of attention signal

In every frame, a simple model is used to deduce whether the attention of each subject in the scene is pointed to the (WS) robot or not. This inference is currently based on a simple neural network model trained using a manually labeled dataset. We concatenate the extracted 3D gaze direction and 3D head pose angles to form a 5-dimensional feature vector. We build a simple classification neural network containing 6 fully connected layers followed by a ReLU activation layer. The network takes the gaze and head pose vector as an input and outputs a binary attention signal. We create an attention score counter for each subject based on the face ID feature. At every frame, the attention score counter is incremented if the face of the subject is frontal and the gaze is directed to the robot and decremented vice-versa. If the attention score reached a specific threshold we publish the subject ID to the robot and decremented vice-verse. If the attention of each subject in the scene is pointed to the

Algorithm 2 Engagement

1: Users ← All fused bodies
2: A ← Focus of Attention
3: for all Workstations W do
4: if W.current_user \( \neq \) null then continue
5: end if
6: for all Fused Bodies B in Users do
7: if B.ID == A.ID then
8: if is_registered(B) then
9: W.current_user ← B
10: welcome(B)
11: else
12: send_to_registration(B)
13: end if
14: end if
15: end for
16: end for

2) Fused body signal

To prevent an accidental mix-up of the detected skeletons and to prohibit (accidental/mischievous) input from a skeleton, not engaged with the system, we only consider users who have a valid skeleton and a valid registered face ID. We refer to the combination of the two as “fused body”. Consequently, face ID to skeleton matching plays a crucial role in user management, safety and is necessary in order to maintain an efficient interaction between one operator and the system. It also plays an important role in multi-user scenarios where each input must be matched to a corresponding user.

The algorithm 1 takes a valid and tracked skeleton and transforms its head coordinates into 2D camera space. For the corresponding head coordinates, the closest face is found and checked for deviation (< 30 pixels). The face ID is then matched to the body and the face is then removed from the face array to prevent double IDs. Only a body with an ID, referred as fused body, is further considered for interaction and are considered for input. For each Frame, the fused body is checked for integrity. If the matched face or the skeleton is missing for more than 3 frames, the fused body is removed from the user array. Since the face ID is the primal identification feature and is by definition constant, it is only necessary to track this ID for any interaction.

C. ENGAGEMENT CLASSIFICATION

We model the problem of engagement and disengagement as a binary classification. Using the focus of attention and fused body signals, we create a rule-based approach to predict engagement in each workstation. Each workstation monitors its current active engaged subject and the corresponding ID. The system is designed according to two constraints including:
- The system must be free, i.e., no one is already engaged with it.
- The user must be registered and, if necessary, have an appropriate clearance for the workstation.

1) Engagement

The engagement process, as explained in algorithm 2 happens automatically when a subject starts interacting with the system and thus accumulates a focus of attention and fused body. If multiple subjects are engaging at the same time, the one with the highest focus of attention score gets chosen. The system reacts to the engagement process by turning on the monitor, turning the robot towards the subject, and greets the subject with the name, chosen during the registration process. If the person engaging with the system is unknown, the system guides him to WS2 for the registration process.

2) Disengagement

The examination for disengagement, the process explained in algorithm 3, starts after a subject engages with a system and is repeated every frame. For the interaction to take place, a valid fused body and positive focus of attention scores are
Algorithm 3 Disengagement

1: Users ← All fused bodies
2: A ← Focus of Attention
3: for all Workstations W do
4:    B ← W.current_user
5:    if B == null then continue
6:    end if
7:    if A = null or B /∈ Users then
8:        start disengagement timer
9:        display message: “Are you still there?”
10:   end if
11:   if disengagement timer timeout then
12:        W.current_user ← null
13:   end if
14:   if B.ID == A.ID then
15:       stop disengagement timer
16:   end if
17: end for

necessary. If either of them is missing, a reminder timer gets started. If either of the features returns, then the timer is stopped and the subject notices no difference in interaction. In the case of a timeout, a message “Are you still there?” is displayed, asking the subject to return to the scene or to become attentive again. During the message display, a logout timer is started, after which the subject ID is removed as active from the corresponding workstation, if the focus of attention or the fused body-face are still missing.

After the disengagement, the robot and the monitors go to an idle state or the next attentive subject fulfilling the prerequisites becomes engaged with the system.

V. RESULTS

Our engagement prediction model is a three-stage approach including feature extraction, feature processing, and engagement classification. In order to effectively assess our model, we access our approach for each phase separately focusing on the methods and techniques used during this stage.

A. FEATURE EXTRACTION

We present the evaluation to the CNNs used to extract four engagement features used in our model.

1) Gaze

We use a CNN that consists of a ResNet-18 as a backbone followed by two fully connected layers for outputting gaze direction. We utilize pinball loss as a network loss function that estimates the gaze direction and error bounds together, which improves the gaze performance. Further, we train our model using the gaze360 dataset which is collected under unconstrained settings, to improve our model generalization capabilities. We follow the same evaluation criteria as in [29] by dividing the dataset into train-val-test sets. We train the network for 100 epochs with a batch size of 80 and a constant learning rate of 0.0001. Our gaze estimation model achieves a performance of 15.3° mean angular error on the gaze360 dataset.

2) Head pose

We utilize a CNN that consists of a ResNet-18 as a backbone and exploit a stochastic gradient descent with a mini-batch of two images. Further, we train our model using the WIDER FACE dataset [35], which contains image samples with high diversity in scale, pose, and occlusion. We train the model for 35 epochs with a batch size of 512 and a variable learning rate starts from 0.001 and decreased by a factor of 10 if the performance does not increase over 3 epochs. Our head pose estimation model achieves a performance of 3.913 mean absolute error on the AFLW2000-3D dataset which is a challenging dataset with a diversity of illumination, head pose, and facial expression.

3) Face ID

We use a deep CNN for recognition feature extraction. To achieve real-time inferring, we utilize MobileFaceNet [36] as a backbone learned by ArcFace [34] loss function. MobileFaceNet can infer face feature embedding within 2.4ms with a model size of 112MB. Further, we train our model using the MS-Celeb-1M dataset [37] which contains about 100k identities with 10 million images. The model was trained for 30 epochs with a batch size of 512 and a variable learning rate starting from 0.001 and decreased by a factor of 10 at 100K, and 160K iterations. Our face recognition model achieves a performance of 95.45% and 92.07% on CPLFW and CALFW datasets respectively. CPLFW and CALFW datasets show higher pose and age variations with the same identities as the LFW dataset.

4) Body posture

We use the native Kinect2 for Windows SDK to estimate the 25 points for body posture. Further, we removed any skeletons containing more than eight inferred points for a short period of time to deal with the problem of Kinect falsely detecting skeletons in inanimate objects. This is due to the fact that the false detections, while having a stable torso, usually do not have a stable limb detection. These false limbs are then estimated as vigorously shaking around, while having the “inferred” status. To further reduce a possible false-positive body detection, a rage for expected body position values, or basically an “interaction zone” of \(2m \times 2m \times 2m\) was set up. No chairs or doors or other inanimate objects were considered as bodies after this implementation, while the real person detection rate was not reduced.

B. FOCUS OF ATTENTION

Furthermore, we evaluate the focus of attention neural network as it is an important stage in our model. We use binary labels for modeling the FA which includes two classes: looking toward the robot and looking somewhere else. To train and evaluate our network, we used two public datasets with gaze and head pose annotations: Gaze360 [29] and
Based on the range of head pose angles and gaze direction, we manually annotated the FA for 50400 images in two classes: looking towards the robot (35367 images) and looking somewhere else (15033 images). The annotated dataset distribution is unbalanced and biased toward the first class. To avoid this problem, we apply oversampling technique by increasing the number of instances of the second class. We split the annotated data into 2 parts: 80% for training and 20% for testing. We train the network using Adam optimizer for 25 epochs with a batch size of 128 and a learning rate of 0.00001. In order to evaluate the FA network, we calculated the FA prediction accuracy as well as the F-score. Our FA network achieves an average accuracy of 91%, and an F-score of 0.89.

C. ENGAGEMENT CLASSIFICATION

In order to evaluate this stage, an online study was set up in the lab space of Neuro-Information Technology research group, Otto-von-Guericke University, Magdeburg, Germany. We have conducted on-site experiments with 11 subjects aged between 20 and 34 years following the scenario mentioned in Sec. III. Data has been recorded during the experiments using dedicated ROS message data structures and saved in bags, the primary mechanism in ROS for data logging. Since each message comes with a specific timestamp of its generation, all streams can be easily synchronized. An example of the recorded multimodal features is shown in Fig. 7. When the subject’s focus of attention deviates from the robot for a while, the model predicts a subject disengagement which is highlighted in the figure by the pink color.

It is hard to annotate a person’s engagement with the robot as it is subjective and requires trained annotators. We introduce a benchmark to evaluate our model based on certain engagement and disengagement events that can be easily annotated. During the experiments, the subject was expected to engage with WS2 five times during the whole experiment: one time for registration, three times for interaction, and one time to answer The questionnaires. Also, the subject was expected to engage with WS1 four times for the task execution. Consequently, the subject will have nine engagement and disengagement events.

In addition, we design a way to track the engagement and disengagement actions during the study. If the robot, infers that the user wants to engage, it turns toward the user; otherwise, it does not turn. To assess the performance of our model, data is extracted from the bags and classified into True Positives (TP), False Positives (FP), False Negatives (FN), and True Negatives (TN). Based on the classification results, we calculate the model precision, recall, and F-score for each subject separately. We calculate these metrics as follows:

\[ \text{Precision} = \frac{TP}{TP + FP} \]  
\[ \text{Recall} = \frac{TP}{TP + FN} \]  
\[ F = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}} \]

Fig. 8, 9, 10 shows the precision, recall, and F-score for each subject separately and the average of all subjects. As can be seen, our model achieves an average of 96%, 90%, and 93% precision, recall, and F-score respectively.
Table 2. Average execution time of individual methods used in the first stage of our model

| Module                | Avg time |
|-----------------------|----------|
| Face detection        | 5.2 ms   |
| Face recognition      | 5.5 ms   |
| Gaze                  | 3.5 ms   |
| Head pose             | 7 ms     |
| Kinect V2             | 33 ms    |

The study conducted has a complex scenario and hardware setup which include a human interacting with two workstations synchronized together using the ROS operating system. It includes a total of 18 engagement events for each subject in an ideal scenario. In addition, extracting features during the experiments is a challenging task due to the lighting conditions, extreme deviation in head pose and gaze angles, and occlusion. However, the performance assessment mentioned above has illustrated the effectiveness of the proposed model in inferring the subject’s engagement and disengagement in a multi-person environment. Our model can predict engagement and disengagement in real-time.

Some engagement decisions caused a long delay during the experiments due to the model computational cost and the network overhead. Although, two of the subjects were wearing a face mask for the whole experiment, our model succeeded to characterize their engagement with reasonable accuracy.

The advantage of our model is that it depends on simple rule-based policies which do not require manual and costly annotations. Furthermore, subjects were more satisfied with the engagement process based on the subject assessment questionnaire.

Due to the limited number of subjects in this study, future work would contain a new study with a large number of subjects to effectively assess the performance of the model. Also, the future study could contain different human-robot interaction scenarios to test the generalization capabilities of the proposed model. Finally, future work should assess the performance of our model in comparison to learning models obtained from the labeled ground truth.
VII. CONCLUSION
In this paper, we present a robust three-stage model for predicting engagement and disengagement in an open-world environment. Our model consists of a combination of deep learning and rule-based approaches. Firstly, state-of-the-art deep learning models are utilized to extract robust engagement features including gaze, head pose, body posture, and face ID. Secondly, a feedforward neural network is used to estimate the subject’s focus of attention using visual data including head pose and gaze direction. In order to handle engagement in a multi-subject interaction, we use the face recognition technique for person identification to track all the subjects in the scene. Further, a rule-based policy is used to match face ID with the body to maintain an efficient interaction between one subject and the cobot. Finally, a rule-based algorithm is adopted in order to make engagement and disengagement decisions (i.e. when and whom to engage with).

To show the robustness of our model, we validate the methods used in each stage of our model. Regarding the final stage, we conduct an online study with subjects doing collaborative tasks with a cobot. Our model achieves an average of 96%, 90%, and 93% precision, recall, and F-score respectively. The experimental results have shown that our model is able to predict real-time engagement state effectively in a multi-subject environment.

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