

Proceedings of the
SECOND INTERNATIONAL CONFERENCE
ON
**RECENT TRENDS IN MULTI-DISCIPLINARY
RESEARCH AND INNOVATION**
ICRTMRI' 25

19th September 2025

in Association with



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AN AUTOMATIC SOCIAL ENGAGEMENT MEASUREMENT DURING HUMAN - ROBOT INTERACTION CONCEPT IN ARTIFICIAL INTELLIGENCE

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Abstract

Social engagement refers the expressions of existing interpersonal relationships during the interaction which represents the actual interesting of human in the interaction. However, social engagement measurement is a significant concern in social human-robot interaction (HRI) because of its role in understanding the interaction's trend and adapt robot's behavior accordingly. Hence, we achieved the two main objectives of this study. Firstly, enrichment the theoretical literature and related concepts. Secondly, proposed a robust neural network model which is multi layer perceptron (MLP) classifier to measure social engagement state during interaction. PInSoRo dataset was used for training and testing purpose. In particular, the parameters of MLP model were meticulously crafted to recognize the social engagement accurately. We evaluated the model's performance by several metrics and the result showed an interesting accuracy reached 94.85%. Given that, it supports the robot to has adaptive and responsive behavior in real time applications which is improving HRI eventually.

Keywords: Human-Robot Interaction, Neural Network, Social Engagement, Social Robotics User Engagement

INTRODUCTION:

Recently, social services robots as an assistant or a companion have been integrated to our services environments. They are pervasively turning into part of everyday tasks in education, work, and healthcare. Human-robot interaction (HRI) and social robotics study how robots support human through social interaction with an insight on developing an interaction with individuals in different contexts effectively. Generally, social robots are designed as user-friendly even for users without technological background such as children. Researches in these fields have focused on the factors that influence individuals' behavior and perception toward robots. Definitely, child-robot interaction is an essential and critical research field as social robots are significantly employed to work with. Children are interacting with robots in different way since they have different immature cognitive development and daily living skills as well as they have high ability to adapt and learn new technology. Normally, children do not interact with robot as device with a computer program, but the characteristics of robot these are usually expected to be similar to any living system. Furthermore, the perspectives of children toward robots are far different from those of adults. Hence, expanding this knowledge to children's behavior is crucial to positively engage with robot. Generally, robot's attitude affected directly on engagement of child with the robot.

There are several forms of engagement such as affective engagement, social engagement, and cognitive engagement. Since the concept of engagement itself is yet unclear, thus there is no plain explanation for each form with its features and there is an overlapping in the definition of each form. However, most of existing work concentrated on cognitive and emotional engagement since these forms are more defined and understood to some extent so they are easier to be recognized while the social engagement form has gotten less attention. On other hand, by perusing the literature, researchers used diverse methods to measure the state of engagement forms. Machine learning and deep learning models have been employed in the most

due to the fact that they have been proven their efficiency in field of pattern recognition specially with the quick and massive advancement in the computation hardware

Nevertheless, the vast majority of the previous studies have been measuring the engagement state, regardless its form, by using binary classification of two classes which are engaged or not engaged while there are a range of engagement states in between, each one could be improved differently.

BACKGROUND AND RELATED STUDIES

It begins with theoretical background such as the engagement concept in HRI, its forms, measurement approach. Eventually, it highlights the related studies, identifying the main methods, findings, and existing problems:

Engagement in human-robot interaction

In the development of social intelligent technology such as (robot, computer, or virtual agent), there are different issues shall be considered in order to personalize the interaction. Indeed, engagement is one of main these issues that broadly utilized as a key social phenomenon in the HRI field. The research filed of engagement robots with people (users) is obtaining an intensive attention and interest among researchers . Regardless the common use of engagement, there is no explicit meaning or interpretation concept. Conversely, the definition of engagement is yet characterized by ambiguity and big variation . However, some studies define the concept of engagement with the technologies and its role in particular contexts. To demonstrate, Sidner et al. was from the earlier to define engagement concept, in general form, as “the process by which two (or more) participants establish, maintain and end their perceived connection during interactions they jointly undertake”.

Definitely, the ultimate goal of HRI is to establish a high level of engagement during interaction, consequently, achieve the interaction’s task successfully. Hence, reinforcement of engagement enhances the quality of interaction which reflected eventually on increasing the possibility of achieving interaction’s goal . So that, measuring user’s engagement can give insight for developing the user interaction where as literatures amply concluded the positive relationship between user engagement and task achievement. Robots may formulate interaction strategy to sustain the users engaged or improve the engagement level, if they got the ability to measure the state of user engagement during interaction. An accurate engagement measurement can support robots to adapt their behavior in order to increase the success of interaction’s task and enhance user experience .

Engagement Components

Cognitive engagement

This component of engagement has been typically involved conscious components like investment, attention, and effort for instance when users invest their cognitive resources during the interaction away from emotional ,physical ,or social resource store in force the role of performance(e.g.I have to work hard) . On the whole, cognitive engagement concerns of how the users build their connection during interaction, thinking actively, answering the questions, and resolving the problems . It can be defined as the efforts to understand and analyze the interaction concept including meta-cognitive behaviors such as how the user set’s goal, plans, and organize their effort to achieve the task. It was also defined as an intensity of engrossment, concentration, and focus to achieve the task during interaction .

Behavioral Engagement

Generally, it refers to user attention towards tasks completion during the interaction. Behavioral engagement has been defined as a proactive predisposition of user to adopt with the changes and experiences during the interaction, in addition, the desire to be enhanced toward these changes. It is considered the encouragement that motives the participation in the task Behavioral engagement is addressed at the task level when there are a goal-oriented tasks for

establishing the engagement. Therefore, as long as behavioral engagement increases, the more positive impact it has on task achievement. This component of engagement has been found in nature, purpose, lack of difficulty, and familiarity of the task, while it misses emotional and social factors. The key feature of this type is that the human can resume the behavioral engagement and completing the task after any interruption.

Affective engagement(emotional)

The emotional engagement is defined as the mirror of affections and reaction among users (humans) and robots who are the parts of interactions which might be an internal and an external. In particular, the emotional engagement comprises of several affective states, to name few, enjoyment, mood, the feelings, and attitudes of the users who are joining the interaction. Nevertheless, the enthusiastic feeling and the enjoyment are the dominant affective states which have been investigated in the vast majority of the done studies. The theory, that says “positive emotions give a signal of purpose and excitement to the brain, accelerating learning and enhancing motivation”, ensures the tight association between the positive emotions and engagement level. Hence, the affective engagement amounts of user’s enjoyment in the interaction environment.

Generally speaking, social engagement is the way of interaction between the human and its environment (other human, technology or task) in an adequate contextually approach and shows complicated internal dynamics which indicates the occupation of interaction state. It is a main metric for measure the human’s cognitive and socio-emotional state collectively. Also, it is defined as the quantity and quality of verbal and non-verbal social interaction with robot. In HRI term, social engagement refers to the involvement of the human with robots which have a friendly and sociable interaction capability. Additionally, it is added to the other engagement components due to its reference to the human dynamics and consider the engagement as an expression of existing interpersonal relationships during the interaction. Furthermore, it differs from other engagement components because of having different conscious concentricity through the interaction. Whereas the other components disregard a significant factor to assess the engagement during interaction which is the actual interesting and readiness of human to begin the interaction.

Engagement measurement approaches

There are different approaches to measure engagement state during the HRI. Thereafter, each category has divided into sub-categories considering the data modalities and techniques used. Here, this study highlights a general overview and key points of each category:

Manual measurement

It is a traditional and ubiquitous approach to measure the engagement state of user during HRI. The predominant techniques in this approach are observational techniques and self-report and questionnaire. This approach has been widely employed in various fields; HRI included. In case of observation methods, the interaction’s administrator relies on the observation to measure the level of user’s engagement. An example of Ethograms, video coding incorporating observed emotions that indicates to analyzing and labelling the video recording to categorize the emotion state for the individuals in the video.

On the other hand, the example of observational rating scales is observational measurement of engagement which uses an observation checklist to measure level of engagement. On other hand, self-report and questionnaire involved the interaction’s user such as user engagement scale. This approach endures some drawbacks such as the subjectivity of the administrator, time-discrepancy issue as the engagement is measured after the interaction, and lack of adaptability for robot during the interaction.

Automatic measurement

In order to overcome the limitations of manual engagement measurement, several studies began with development of an automatic measurement methods. In fact, the idea of automatic

measurement of engagement in HRI is relatively recent then it has earned more attention . Mostly, the studies utilize video and audio modalities of data as well as the neurological and physiological data for measurement such as heart rate, relative motion index(RMI), and electroencephalogram (EEG).However, the diversity of social robotics' applications has drawn more attention toward the visual data since each social robot has a built-in camera. Accordingly, the vast majority of latest studies use a cue-based approaches to recognize the social cues which could measure the social engagement level as well as other types of engagements .

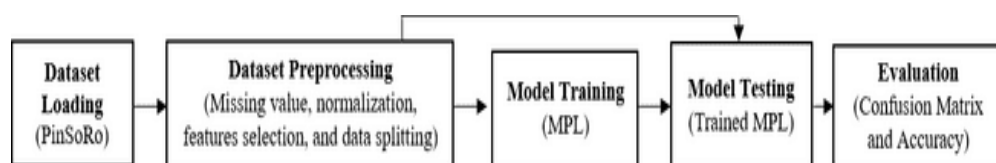
A development of intelligent robots, that socially interacted with human and autonomously adapted its behavior during the interaction, requires an ability to measure the engagement state in proper and continuous way which is consider as a key challenge for social robotics researchers. The transition to automatic measurement offered an ability to determine if the user already engaged to the robot and waiting for its response within the interaction time. Thereupon, the robot can use the engagement state to adapt its behavior conveniently toward enhancing the interaction outcome.

For the purpose of automatic measurement rule-based, machine learning, and deep learning are used. Firstly, the rule-based techniques that choose various rules among the presence of the main social signals. Then, each rule is measured by a state machine that calculate the final engagement level. Also, it can adopt a threshold-based rule for measurement purpose. Secondly, machine learning models are largely used in engagement measurement since it enriches the development of HRI and affective computing studies that automatically characterize the human behavior. Finally, deep learning that is somewhat late in engagement measurement studies. However, both machine learning and deep learning use by mapping the features of raw data to get the target level of engagement. Deep learning sparked by the weakness of machine learning.

GENERAL RESEARCH WORKFLOW METHOD:

There are several libraries have been used during the experiment process such as mainly Num Py and Pand as for data preprocessing and handling -learn library for design and implement classification model, Mat plot lib library for visualizing the results and others libraries for other particular tasks. A multiclass classification using MPL classifier whereas each class represents a different state of child's social engagement as detailed in next sections.

Figure1.General research workflow



Data set description

For sake of training and testing the proposed model, a publicly available dataset, named PInSoRo, has been used. This dataset was collected during a series of under specified free-play child-child and child- robot interaction. However, it recorded an over45 hours of social interactions among 45 child-child pairs and 30 child-robot pairs. Besides, it used a hand-coded recordings occurring in natural social inter actions between children. It has a video recording, skeletal information, 3D recordings of the faces, and full audio records. The key strength of considering visual and audio data is that the setup of interaction environment will be relatively comfortable and close to reality. Eventually, the dataset is rich because of many characteristics such as covering a vast range of interaction situation, demonstrating complex social dynamics, natural and original behaviors due to the unspecificity, and wealth of multimodal interactions .

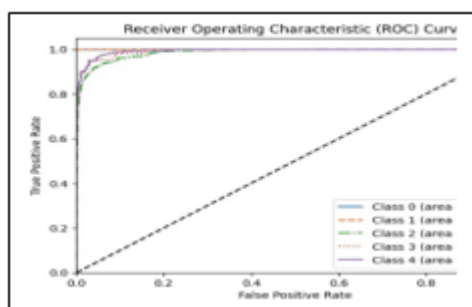
Data pre-processing

Prior to feed the network by the dataset, several pre-processing techniques have been applied on the raw dataset toward enhancing network's performance. Initially, different action has been taken for different data type, for instance, cleaning the data, handling the missing values, and managing the categorical features. However, imbalance dataset is a key challenge in engagement measurement, then the dataset has passed through some steps to be balanced and normalized. Additionally, principal component analysis (PCA) technique has been utilized to reduce the high dimensional issue in the raw dataset. On the other hand, the irrelevant features have been eliminated from the dataset.

Measurement metrics

In order to evaluate the performance of proposed model for automatic social engagement measurement, several approaches have been applied. Firstly, comparing the classification result with the actual classes by calculating the accuracy, precision, recall, and F1-score as the following equation. Overall, the model achieved an impressive classification accuracy rate of 94.85%. In the same context, precision—which defines the model's performance by calculating the ratio of true positives (TP) to the total predicted positives (TP+false positives (FP)), as shown in (1)—reached 93.00%. Likewise, recall, which measures the ratio of TP to the total actual positives (TP+false negatives (FN)),

It provides a visualized depiction that plainly reveal insight into the number of predicted classes to the number of actual classes. However, in respect to our model's performance the confusion matrix presents a breakdown in details of measuring the social engagement state of children. Lastly, we apply the receiver operating characteristics (ROC) to visualize the measurement performance considering the correct and incorrect measurement rate. ROC plotted the trade between the true positive rate and false positive rate.



RESULTS AND DISCUSSION:

The neural network met the expectation whereas it has shown a remarkable result which verified during the evaluation phases as detailed in the previous section. Also, the evaluation of our model's experimental demonstrated an out performance in the overall classification accuracy comparing to the result the fact that the number of cooperative class samples in the dataset are the least.

The core of social engagement, its features, and difference about other components of engagement are presented which reflected on the setting of model and the accuracy's improvement eventually. Secondly, developing a high accurate measurement model for social engagement state during HRI. Yet, the results highlight a limitation in measurement of onlooker state that has a slight decline as shown in the recall (89.00%). Overall, the proposed model holds promises for social engagement measurement in HRI.

CONCLUSION AND FUTUREWORK:

In real time application which enhances the HRI at last place. It presented the definition of engagement in HRI field and dived deeper to each component's characteristics. However, the

measurement process has been considered as multiclass classification issue. MPL model was used to tackle this problem and was achieved a distinguish results. The proposed model utilized a multi modal dataset which consists of visual and audio data for training and testing purpose. The overall accuracy is 94.85% that appeared an improvement comparing to other done studies. The result is promising toward building a more sociable and adaptable robot and leverage the interaction. In future, we will work to measure the social engagement state in integrated way which means measuring the states in between the distinct states such as (onlooker and parallel) or (associative and cooperative) at the same time and test the model with real application, then simulate the proposed model to the virtual robotics environment such as ROS.

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