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Master's Thesis

A Learning Support Robot Based on Behavior Update Model

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Abstract

In recent years, "Internet+" has become the next phase of the Internet development trend, "Internet+" simply means” Internet + traditional “industry." With the development of information and communication technology (ICT), the Internet can be integrated with traditional industries to create new development opportunities. With the promotion of "Internet+", all industries have given birth to new models and new vitality. Thus, Internet+ education occupies a significant position in the education industry. Compared with the traditional classroom, the online classroom takes up an increasing proportion in the education field because of its advantages, such as abundant resources, fewer time and place limitations, and the possibility of personalized teaching. With the development of robotics, there is a growing expectation that robots can help people learn. This includes companion robots that accompany students in their studies, as well as functional robots that help with learning, such as learning English and programming, so these education-supporting robots are getting more and more attention. So far, a variety of learning-supporting robots have been proposed. For example, Taki et al. proposed Interactive Emotional Communication (IEC), in which humans and robots communicate by exchanging emotional actions. Yu et al. developed a robot called an "intelligent learning partner" that can interact with learners using personalized technologies. Such as conversational agents, question-answering systems, and emotion recognition. In these researches, the robots followed predetermined rules and interacted with the learner based on their emotions and behavior. However, the effect of the robot’s interactions is different on the different learners.

This research proposes an interaction network model for learning partner robots to follow such individual differences and realize personalized interactions. The network consists of three layers representing action, words, and speech rate. It is a 3*4 fully connected network where the initial weights are set manually in advance. The weights are translated into a probabilistic form, which determines the content of the robot's interaction. We also define the "good or bad" of the previous interaction based on the learner's feedback, decide to increase or decrease the weight of the interaction network, and update the interaction network weights so that the robot can change the interaction content through the learner's feedback. Thus, it enables the robot to give the most personalized interaction to different learners.

As the partner robot in this research, we used the communication robot Sota, which has a camera, microphone, speaker, and network functions to interact with the learner with

words and actions. Sota can change the rate of speech, pitch, and volume level and customize the movements' design. For the learner's engagement prediction task, we used V. Huynh's method, a sub-challenge of the 7th Emotion Recognition in the Wild Challenge (EmotiW 2019). His method involves three basic steps: feature extraction, regression, and model combination. First, the input video is divided into multiple overlapping segments, and features are extracted for each instance. A combination of long and short-term memory (LSTM) and fully connected layers was used to capture temporal information, and regression was performed on the features from the previous step to obtain the engagement intensity. In the last step, Explain elements for this fusion to achieve better performance. In this model, the engagement intensity is divided into four levels, namely highly-engaged, engaged, barely-engaged, and disengaged. Then, the interaction network generates Sota's interactions based on the engagement intensity predicted model. After the interactions, the model re-predicts the learner's engagement intensity, determines the interaction contents are good or bad, and updates the interaction network weights to adapt to the learner's preference. Finally, we gathered 20 students and let them watch two 30-minutes instructional videos, one of which was with Sota and the other was Self-study. By comparing the conditions with and without Sota, the 20 subjects were divided into four groups to reduce the influence of the differences in the video content and learning order: Group 1: Self-study + video 1 → Sota + video 2; Group 2: Self-study + video 2 → Sota + video 1; Group 3: Sota + video 1 → Self-study + video 2; Group 4: Sota + video 2 → Self-study + video 1.

In this experiment, there are three primary objectives. 1. To evaluate the accuracy of the engagement intensity detection model. So after watching each video, the subjects were asked to refer to their facial video and score their engagement intensity at 0, 5, 10, 15, 20, 25, and 30 minutes in the learning process. The scoring criteria were 0-disengaged, 1-barely-engaged, 2-engaged, 3-highly-engaged. The data judged by the model were then compared with the data answered by the subject. The results show that out of 280 judgments, the number of correct judgments was 150, with a correct rate of 53.6%. 2. To evaluate how well the Sota performs the interaction. The goodness of Sota's interaction was evaluated from the following three perspectives. a) Which condition kept the engagement higher in Sota vs. Self-study. The data indicate that their engagement intensity was higher in the Sota condition in both cases that learners scored themselves and the neural network estimated. b) Comparison of the number of times engagement was restored during the course in Sota vs Self-study. We counted the number of changes from low to high engagement intensity in the two conditions, respectively, as a way to assess whether Sota had a positive effect on the learner's recovery of engagement intensity. The results show that in both the subject judgment and the neural network judgment, the engagement intensity was recovered more often in the condition of Sota. We can conclude that the presence of Sota helps the learner to improve the engagement intensity. c) We use the questionnaire's answer to judge whether the timing and content of Sota interactions are appropriate and whether Sota is useful for helping learners maintain a good learning state. More than half of Sota's interaction timing was positively accepted for the interaction timing. Around half of Sota's interaction contents were positively accepted for the interaction content. Furthermore, around 40% of Sota's interaction affected the maintenance of learning engagement. 3. To evaluate the effectiveness of the proposed update algorithm for the interaction model from the following two perspectives. a)According to the responses of the questionnaire, the number of Sota interactions was divided into the first third, the middle third, and the last third. To evaluate the effectiveness of the proposed update algorithm was verified by comparing the average of the subject's satisfaction with the content of these three parts. From the results, we can conclude that the subject satisfaction increases significantly in the number of interactions at the last third period as the experiment progresses. b) We summarized absolute weight changes between each engagement intensity for the 20 subjects. We found considerable variation in the weights of disengagement-criticism, engagement-criticism, and engagement-praise.

In this research, the accuracy rate of engagement intensity was 53.6%. This makes some mismatches for Sota interaction. This model also has a certain delay and is not so sensitive. Therefore, our next step is to develop a more accurate and sensitive model for future research. In future work, we expect to change the robot's interaction content based on the learner's interest in the learning content and the learning effect. In this research, each session was only 30 minutes, and we are interested in how the robot works well when learners watch longer videos.

Keyword:Deep Learning, Interaction,Interaction network,E-learning,Robot,Engagement

Contents

List of Figures

List of Tables

Chapter 1
Introduction

1.1 Research background

In recent years, Internet+ has become the next phase of the development trend of the Internet [1]." Internet+" simply means "Internet + traditional industry." With the development of information and communication technology (ICT), the Internet can be integrated with traditional industries to create new development opportunities. Through its own advantages, "Internet+" optimizes and upgrades traditional industries, enables them to adapt to the new developments, and eventually pushes modern society forward. All industries have given birth to new models and new vitality under the impetus of the Internet+.

Teaching with Internet+ occupies a significant position in the current educational institution. Compared with traditional classroom teaching, Internet teaching has various advantages, such as abundant resources, not being bound by time and place, and the possibility of personalized teaching [1].

However, unlike face-to-face teaching in a traditional classroom, the instructor cannot accurately observe the learner's states due to the limitations of the instructor’s attention. These states are communication and pedagogical feedback from learners to the instructor. However, the exchange and interaction of such information are often missing in the online classroom, negatively affecting the effectiveness of the learner's learning [2]. Computer access to online learners' learning state and emotions is a prerequisite and an essential step in improving instructional strategies[3]. Establishing a learning state and emotion recognition model could improve the quality of the classroom and enhance real-time information delivery to build personalized learning.

From 2020, online learning was implemented in many educational institutions in response to COVID-19. Especially in Japanese universities, almost all of them (98.7%) implemented or considered it [4]. According to a survey on online classes conducted by Waseda University, 92.2% of students responded that online learning was valuable [5]. Moreover, it is expected that online learning will become even more widespread. On the other hand, according to the surveys conducted by Kansai University and Hosei University, students generally study in a dispersed manner in an online education environment, and their motivation to learn decreases due to little communication [6] [7].

With the growth of robot technology, more educational-support robots, which support learning, are getting attention. A variety of learning support robots have been proposed. For example, Taki et al. proposed Interactive Emotional Communication (IEC), in which both humans and robots communicate with each other by exchanging emotional actions, as shown in Figure1.1 [8]. Yu et al. developed a "smart learning partner" robot that can interact with an individual learner by utilizing personalized technologies such as conversational agents, question-answering systems, and emotion recognition, as shown in Figure1.2 [9]. Kashihara attempted to use robotic anthropomorphism as a medium for presentation to increase student engagement [10].

In past research on companion robots targeting learners' emotions and feelings, the robots generally follow specific rules and interact with the learners in a specific way depending on their state. For example, the robot makes a fixed A-a interaction in the A state of the learner. However, the effectiveness of the interactions made by the robot varies depending on the learners. Therefore, not all learners would prefer to the specific interactions of the robot.

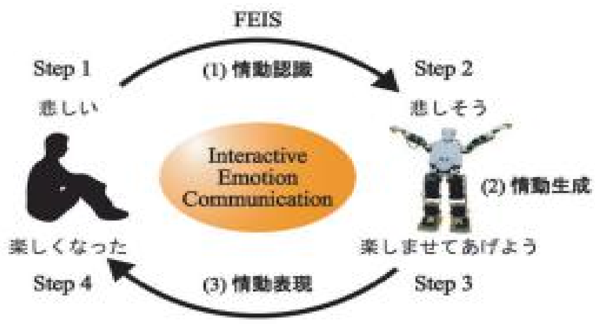

Figure 1.1 IEC model [8]

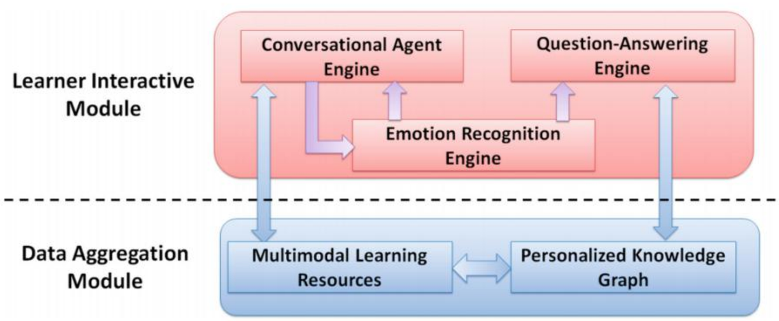

Figure 1.2 Architecture of emotion recognition [9]

1.2 Research objectives

The objective of this research is to develop a partner robot that can provide adaptive learning support by updating the robot's behavior based on the learner's responses. In order to achieve this goal, we address the following research questions:

(1) How to estimate learner engagement through a computer camera?

(2) How to develop a model to update the robot's behavior to suit the learner's individual needs?

(3) How to evaluate learning effectiveness using a partner robot?

As the learner's partner, the proposed robot estimates the learner's state and emotion and behaves according to the learner's preferences. It is expected to increase communication opportunities in online learning and increase learners' motivation to learn.

1.3 Structure of the thesis

This thesis contains the following five chapters.

Chapter 1 introduces the development and progress of distance education, presents the research background on robots in education, points out the shortcomings of educational interactive robots in research, and indicates the research objectives.

Chapter 2 introduces the development and definition of E-learning and its future direction and describes the prospects of robots in education. Then, it presents basic information about the Sota robot used in this research and introduces the basic concepts, applications, and developments of deep learning adopted in this research.

Chapter 3 proposes the model structure of the engagement intensity detection and the concept of "interaction networks," including the network structure, input and output rules, how to update the network weights, and how to acquire data in real-time.

Chapter 4 describes the experiments to verify the proposed model and algorithm through the accuracy of the engagement intensity detection model, the timing and content of Sota interactions, and the effect of Sota interaction on learners' enhancement and retention of engagement intensity.

Chapter 5 summarizes the findings of this research and future works.

Chapter 2
Related Works

2.1 E-learning

The term e-learning is most often used to refer to computer-based training that technologies support interactivity beyond a computer. According to Koran, e-learning uses electronic devices such as LAN, WAN, or the Internet for lecturing, interacting, instructing, and monitoring students' learning activities [11]. Soekartawi defines e-learning as a general term for technologically supported learning that uses a range of teaching and learning tools such as telephone bridging, audio, videotapes, teleconferencing, and satellite transmission [12].

Although e-learning has been defined in diverse ways, the common point is to facilitate and enhance learning based on computer and communication technologies with various devices and software [13].

However, many parties have not been wise in using these technologies in learning. They use this medium to download the materials needed for reading assignments or submit reports and other assignments through the Internet. These use-cases are simply replacements for traditional education, and the learning process will not be optimized [14]. The learning process expected in an Internet-based classroom is considerably challenging to manage compared to a face-to-face classroom. This includes, for example, special instructional designs that allow students to actively and independently participate in learning activities without an instructor being nearby.

In addition, e-learning has huge learning materials and less time and place constraints as advantages. However, e-learning also has disadvantages, such as a lack of interest in learning because of less communication and questions that cannot be answered in time.

2.2 Education robot

At this stage, educational robots are broadly divided into two types of instructor-assistant and learner-partner robots. Kwon et al. have shown that a robot acting as a teacher can replace a human teacher, and a robot assisting a teacher can improve students' concentration [15]. On the other hand, there are two types of learner-partner robots: one-to-many partner robots, in which one robot works with multiple learners, and one-to-one partner robots, in which one robot works with one learner. Matsuzoe and

Tanaka found that learning with a one-to-one partner robot can improve learners' motivation and learning effectiveness. As mentioned above, the robot's physicality seems a positive factor in their learning experience. The robot's presence in the real space might work on the five senses of the learner and make the support and advice more acceptable than an agent on the screen. The learner-partner robots are best suited to support home learning. If the performance of such robots is improved, they will be installed in every family to promote self-regulated learning and have great potential as a future industry. Therefore, we focus on learner-partner robots in this research.

2.3 Interaction robot: Sota

In this research, we used a robot called Sota as shown in Figure 2.1 [16]. Sota is a table-top communication robot that enables natural interaction using words, gestures, and hand gestures, equipped with cameras, microphones, speakers, and network functions. Sota is a platform that can provide a wide range of robot services through advanced integration with loT(The Internet of Things) devices and cloud AI. It has advanced functions and a cute design and can realize a completely new communication service close to people. The built-in Intel(R) Edison with Linux makes it easy to develop applications using image recognition, voice recognition, and speech synthesis. In addition, the built-in middleware for Sota enables motion creation and motion programming from Windows software “VstoneMagic.” Sota's new features can be developed using Java programming language. In this research, we have adopted the eclipse, a well-known integrated development environment, to develop the subsequent functions in Java and used the ant function of the eclipse to send implemented Java code inside Sota to run it.

Shape	280(H)×140(W)×160(D)mm
degree of freedom	Total 8 degrees of freedom (torso 1 axis, arms 2 axes x 2, neck 3 axes)
Weight	763g
CPU	Intel(R) Edison
input and output	Camera ・Monaural microphone or intelligent microphone ・Speaker ・LED (2 eyes, 1 mouth, 1 power lamp) ・Switch (power button, 2 volume buttons)
Interface	Bluetooth ・USB x 2 ・Power connector
Power supply	AC adapter (12V 4A)

Figure 2.1 Sota product specifications [16]

2.4 Deep learning and neural network

Deep learning is a new field in machine learning research. It is motivated by building and simulating a neural network that mimics the human brain for analysis and learning. It mimics the mechanisms of the human brain to interpret data, such as images, sounds, and text.

The concept of deep learning originated from the study of artificial neural networks. A neural network is an operational model consisting of a large number of nodes (or neurons) interconnected with each other. Each node represents a specific output function. Each connection between two nodes represents a weighted value for the signal passing through the connection, called a weight, which is equivalent to the memory of an artificial neural network. The output of the network varies depending on the input, weight, and excitation function of the network [17]. For example, a multilayer perceptron with multiple hidden layers is a deep learning structure. Figure 2.2 shows a deep learning model with multiple hidden layers. Deep learning uses a hierarchical structure similar to a neural network. The system consists of a multilayer network with an input layer, a hidden layer (multilayer), and an output layer. Only nodes in adjacent layers are connected to each other, and there are no connections between nodes in the same and across layers. Each layer can be considered as a logistic regression model. This hierarchical structure is closer to that of the human brain. In this research, deep learning techniques are applied for the intensity detection of the learner's engagement, and some features of neural networks are referenced in the proposed interaction network model.

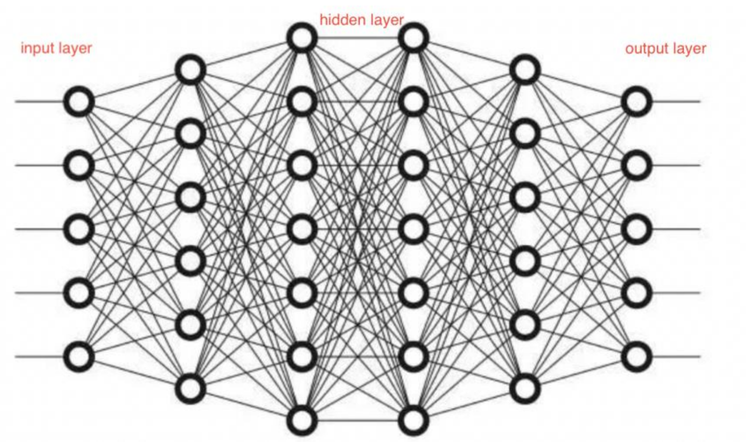

Figure 2.2 Neural network [17]

Chapter 3
Proposed Model

3.1 Engagement intensity prediction

This research needs to detect the learner's learning engagement as the first step. Thus, we choose the model of V.Huynh [18] as an excellent model to detect the learner's engagement intensity.

Their research presented a method for engagement prediction "in the wild" environment, a sub-challenge in 7 the Emotion Recognition in the Wild Challenge 2019. Their approach took advantage of the state-of-the-art architectures and frameworks in computer vision to solve the problem. Their results demonstrated a strong effect of facial and eye gaze-related features in engagement prediction and got the best performance in the challenge with an MSE of 0.0597 [18].

3.1.1 Method overview

In this method, each video frame is passed to [19], a facial behavior analysis toolkit that implements MTCNN [20] for face detection, [21] for facial sign detection and tracking, [22] for eye gaze estimation, and [23] for facial action unit detection. Based on the face regions extracted by OpenFace, facial features are obtained by a pre-trained SEResNet-50 model [23,24,25]. They divided the video sequence v into ℓ segments s1,s2,... . sℓ, si∩si+1 |=r, si=si+1 |, i=1, ℓ 1. The features of each frame are counted based on OpenFace features and SE-ResNet features to further obtain the features of each segment. Figure 3.1 shows the pipeline of the engagement prediction system.

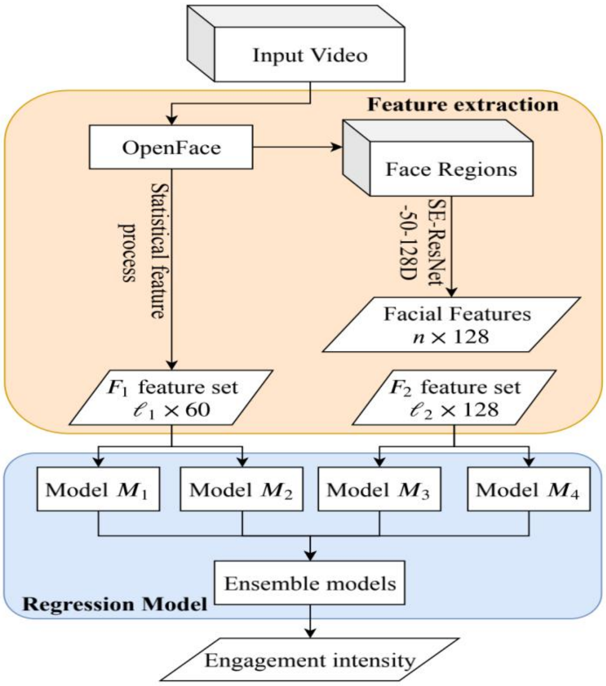

Figure 3.1 Engagement prediction system pipeline [18]

3.1.2 Feature extraction

This method extracts the line of sight and head features using a convolutional neural network. 56 landmarks (2D landmarks in pixels) and real-world landmarks (3D landmarks in millimeters) are provided by OpenFace to determine the eye position for each frame. It will calculate the view vectors and the realized angles for both eyes, and these features are called the F1 features. The mean and standard deviation of head position, rotation, binocular gaze vector, and gaze angle are calculated for each clip to capture head pose and gaze direction changes. The shape and position of the eyes in the frame and the actual situation are the key factors to achieving the changes in feature orientation. These features are calculated based on the mean, standard deviation, and minimum to maximum values for each segment. Table 3.1 shows the dimensions of each feature type in F1.

The feature set F2 is obtained from the face region by CNN. These faces are obtained from 68 landmarks provided by Open Face. Before putting them into the neural network, we need to do pre-processing. First, resize the face image so that its short size is 256 pixels, then crop the central 224x224 part of the image. Facial feature extraction was performed by SE-ResNet-50 [24,25,26]. It puts the Squeeze-and-Excitation (SE) block into ResNet-50 by modeling the relationship between the channels of its convolutional features and recalibrates the feature responses of the channels. The performance of the

SE block in object and scene classification has been demonstrated in the ILSVRC 2017 classification competition. To take advantage of the SE block and existing state-of-the-art deep architectures, they used SE-ResNet-50, which was trained on MS-Celeb-1M [27], a large-scale dataset of real-world face images, and then fine-tuned on the VGGFace2 dataset, a large-scale with considerable variation in pose, age, illumination, race, and occupation face recognition dataset.

Table 3.1 A summary of F1 feature set extracted based on OpenFace [18]

Feature type	Feature information	Dim
Gaze direction	mean, standard deviation	16
Eye landmarks 2D and 3D, distance from eye to camera	mean, standard deviation, coefficient of variation, ratio between the min and max values	32
Head pose	mean, standard deviation	12

3.1.3 Engagement intensity regression models

In this model, they deploy two different networks, “A1, A2” for each feature set. one model is LSTM-FC, which is learned in the original feature set, while the other extends the dataset by using a fully connected right-front LSTM (FCLSTM-FC) to learn in the new dataset, as shown in Figure 3.2, and uses ReLU activation in each FC layer and LSTM layer using the functions. The engagement changes over time in the videos due to changes in the learning content. To capture these changes, they use 2 LSTM layers followed by 2 FC layers to learn, obtain relationships between successive segments, and make predictions for each segment generated by the last FC layer. These values are passed to an ensemble layer, which takes their average and outputs the intensity of participation for the whole video. In this work, they take a multi-level ensemble approach to improve the prediction based on the results of every single model.

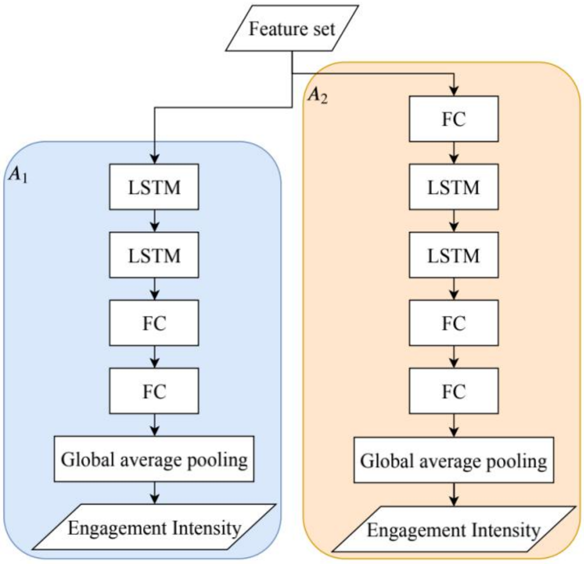

Figure 3.2 The pipeline of A1,A2.[18]

3.1.4 Environment and Implementation

The environment of the prediction system was running on python 3.8, TensorFlow 2.0, and ubuntu 20.04 OS with Inter i7-9900k, 32G RAM and Nvidia GeForce RTX 2080 (6GB).

So, the source codes of OpenFace and Huynh's model were downloaded from GitHub and installed as instructed. Figure 3.3 shows the output of OpenFace2.2.0, which captures facial features through the camera. The system outputs two engagement scores through the neural network and takes the average as the final engagement intensity, as shown in Figure3.4.

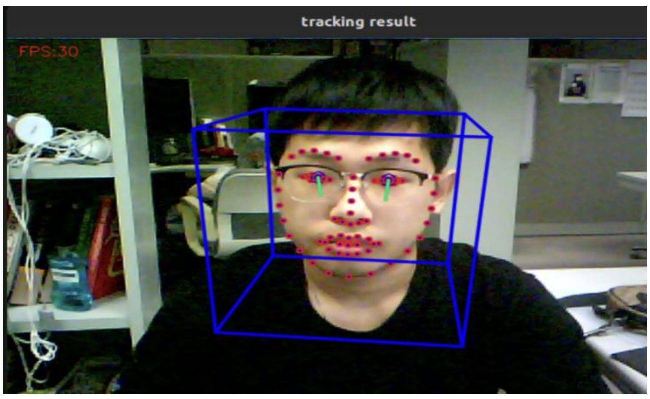

Figure 3.3 The effect of using Openface

The engagement-level is classified into four levels: Disengaged, Barely-engaged, Engaged, and Highly-engaged as follows by Van Thong:[17]

0 <= engagement-intensity < 0.4 : Disengaged =0

0.4 <= engagement-intensity < 0.6: Barely-Engaged =1

0.6 <= engagement-intensity < 0.83: Engaged =2

0.83 <= engagement-intensity <=1.00 :Highly-engaged =3

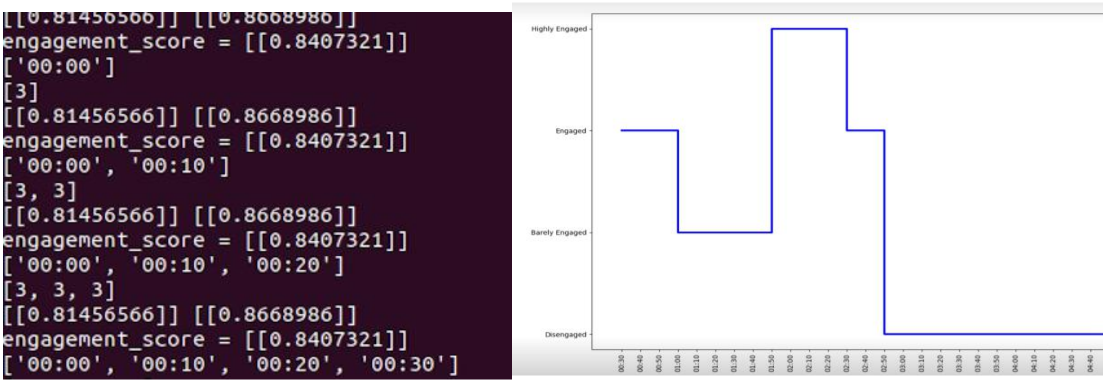

Figure 3.4 The model 's output

3.2 Interaction network

As described in the research background, there has been much research on educational robots to solve various teaching problems and improve students' interest in learning. In those research, the robots generally follow specific rules to interact with learners in a particular way, depending on their state. For example, the robot interacts with the learner in state A with a fixed "a" interaction, B with "b," and C with "c," respectively, as shown in Figure 3.5. Of course, these predetermined interactions must be consistent with most human minds and behaviors. However, the effectiveness of the robot's interactions varies from learner to learner, and not all learners will prefer the specific robot's interactions. For a particular learner in state A, the interaction that better fits his mind and behavior would be b, not a. If the robot gave the interaction an in state A, it would reduce that learner's engagement. To solve this problem and to allow the robot to give the most appropriate interaction for the learner in any state, we designed the interaction network to update the interaction strategy in real-time by adjusting the network weight parameters according to the feedback from the learner's interaction.

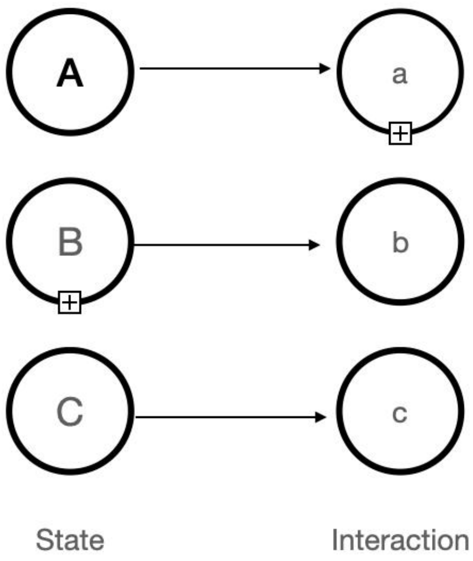

Figure 3.5 Interaction behavior

3.2.1 Interaction network model

Firstly, the interaction network is located behind the engagement intensity model. Using the model's output as the network input, we construct a three-layer fully connected network including words, action, and speech rate, as shown in Figure 3.6. The weights to each path between the layers are pre-assigned. The sum of the path weights to the next layer is 1. The magnitude of the weight is used to choose the node in the next layer as a probability. The advantage of deciding the path as a probability is that it increases the variety of interactions and allows more opportunities for the robot to find the most appropriate interaction for the learner. However, there are also some disadvantages since there may be surprising and confusing interactions in the beginning and middle stages. Figure 3.6 indicates the composition of weights at a particular engagement intensity. For the sake of illustration, it is assumed that the node will choose the path with the highest probability of weight. Then the output of this interaction at this engagement intensity is support, action_A, and general speech rate.

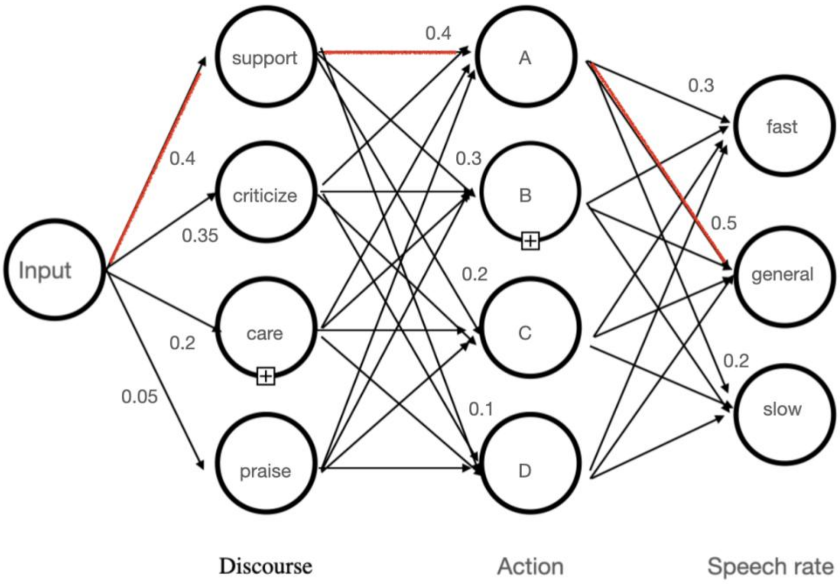

Figure 3.6 lnteraction network model

In [28], we can learn that the teacher's interaction style and manner affect the students' learning efficiency. In [29], it is stated that criticism will make a deeper impression on students, and appropriate criticism will help students improve their learning in some cases. In [30], it is claimed that care, support, and praise will enhance students' goodwill and thus promote learning interest. Therefore, in this research, we used four types of emotional expressions: criticism, encouragement, care, and compliments. In addition, in the sota_action class that comes with Sota, we selected four actions that go best with these four emotions. Moreover, the interaction content is shown in Table 3.2, the content of the words is shown in Table 3.3.

Table 3.2 Interaction content

Words	Support	Criticize	Care	Praise
Action	Call	Presen	Talk	Bye
Speechrate	Fast	General	Slow	

Table 3.3 Word content (in Japanese)

Support	応援しているよ	負けないで	いつも力になるよ
Criticize	このままダメだよ	試合が終わっていいの?	いつから頑張る?
Care	無理しないで	休憩しませんか	大変ですね
Praise	よくできた	さすがいいね	このまま行こう

3.2.2 Initial weight

The output rules of the proposed interaction network are based on the conversion of the magnitude of the weights into a probability. The interaction network does not require prior weights training, and its weights are updated during interaction in the learning process. Therefore, the design of the initial weights is necessary.

So, we set the initial weights of the interaction network through research on how teachers' behaviors and expressions affect students' emotions and how they should communicate with students when they have negative emotions, as shown in Table 3.4 [31][32]. In addition, we decide to leave the robot without any interaction and let the learner continue to learn in this state so as not to disturb the learner when the model detects that the learner is highly engaged.

Table 3.4 Initial weight

Words / Engagement	Support	Criticize	Care	Praise
Disengaged	0.4	0.35	0.2	0.05
Barely-engaged	0.45	0.3	0.15	0.1
Engaged	0.2	0	0.1	0.7

words \ action	call	presen	talk	bye
support	0.4	0.3	0.2	0.1
criticize	0.2	0.3	0.1	0.4
care	0.35	0.4	0.15	0.1
praise	0.25	0.3	0.4	0.05

action \ speechrate	fast	general	slow
call	0.3	0.5	0.2
presen	0.5	0.4	0.1
talk	0.2	0.4	0.4
bye	0.5	0.3	0.2

3.2.3 Weight update

In the previous subsection, we set the initial weights for the interactive network. In this subsection, we will introduce the rules for updating the weights. In the proposed method, we determine whether the interaction content is appropriate for the learner in the current state by comparing the change in learner engagement before and after the interaction with Sota through an engagement intensity detection model. If the learner's engagement remains the same or decreases after the interaction, we decrease the weights of all the paths through which the interaction takes place and increase the weights of the other paths to keep the sum of weights at 1. The weights of the other paths are increased so that the robot will give other interaction strategies in the same situation next time. Of course, depending on the engagement change before and after the interaction, the change in the weights varies. Figure 3.7 shows the specific change rules.

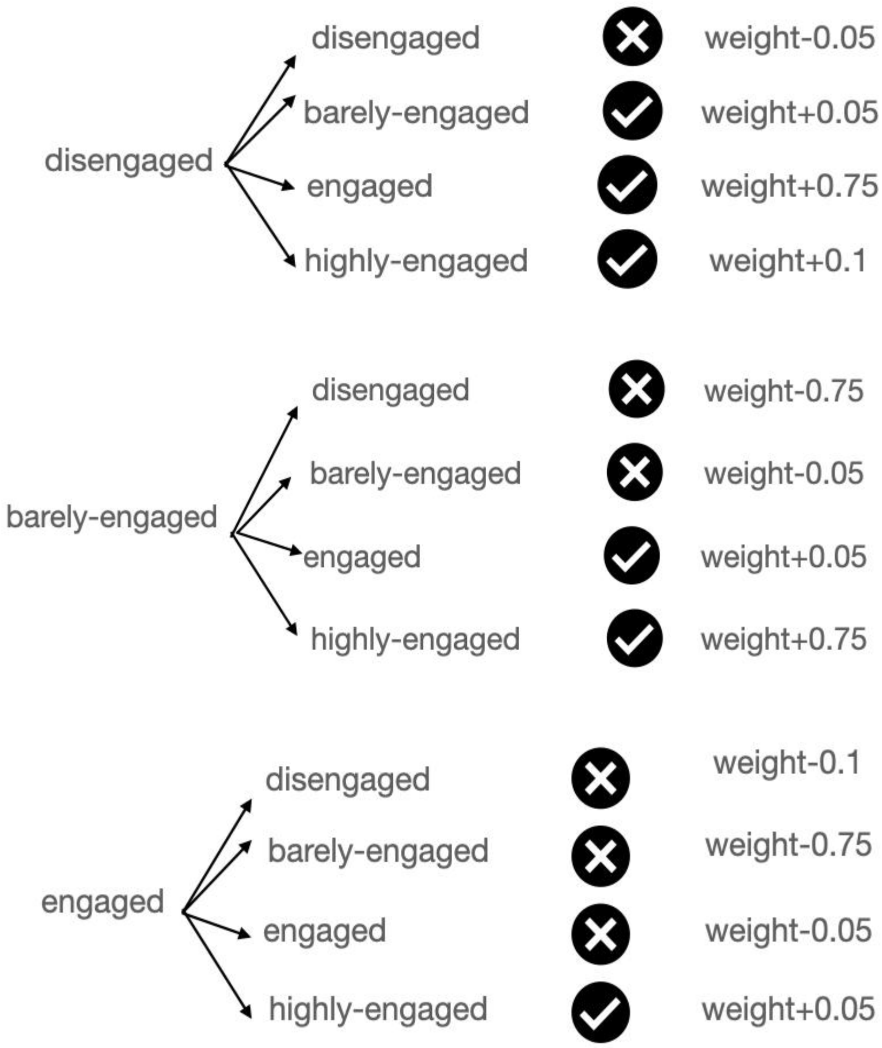

Figure 3.7 Wight update rule

Through this approach, the interactive network can slowly find the most suitable interactive content for current learning to achieve an excellent interactive experience for each different learner's personality. However, there will be some unpleasant interactions during the weight adjustment process, but this will get better as the learner's use increases over time.

3.3 Sota interaction development

The API of Sota consists of diverse classes, such as sota_say to control the content of Sota speech, sota_scene to control the action of Sota, sota_speechrate to control the speech rate, sota_intonation to control the pitch of Sota speech, and sota_color to control the color of Sota LEDs. This research uses only the three classes, sota_say, sota_scene, and sota_speechrate, since the interaction content is only statements, actions, and speech rate.

First, we use the engagement intensity detection model to capture the learner's face through the webcam and determine the engagement intensity of the learner. Then, the engagement intensity is uploaded to the webserver as the input to the proposed interaction network model. Next, Sota fetches JSON data once a minute by the gson library from the server and parses the data to generate interaction based on the output of the interaction network.

Chapter 4
Experiment and Evaluation

This chapter discussed the experiment and evaluation with the following perspectives.

1. Accuracy of the engagement intensity detection model.
2. How well Sota performs interaction with learners.
3. Effectiveness of the proposed update algorithm for the interaction model.

4.1 Experimental method

We gathered 20 students from JAIST and let them watch two 30-minutes instructional videos(a college physics instructional video and a high school chemistry instructional video), one of which was with Sota and the other was Self-study as the within-subject design. By comparing the conditions with Sota and Self-study, the 20 subjects were divided into four groups to reduce the influence of the differences in the video content and learning order:

Group 1: Self-study + video 1 → Sota + video 2;

Group 2: Self-study + video 2 → Sota + video 1;

Group 3: Sota + video 1 → Self-study + video 2;

Group 4: Sota + video 2 → Self-study + video 1.

The detailed time schedule is shown in Table 4.1

Table 4.1 Experiment schedule

Time	Project
0:00-20:00	Introduce Sota and questionnaire1
20:00-50:00	Watch video1
50:00-70:00	Break and questionnaire2
70:00-100:00	Watch video2
100:00-110:00	Questionnaire3
110:00-140:00	Check engagement data and questionnaire4
140:00-180:00	Questionnaire5 and check all the data

The Edison version of the Sota, a webcam, and two computers were used as experimental tools. Figure 4.1 shows a block diagram for equipment in the experiment.

Diverse data, including the responses to the questionnaires, the output of the engagement intensity detection model, and the facial video of the subjects, were recorded during the experiment to evaluate three experimental perspectives. The sheets for the questionnaire and agreement for cooperation in the experiment are attached in the appendix.

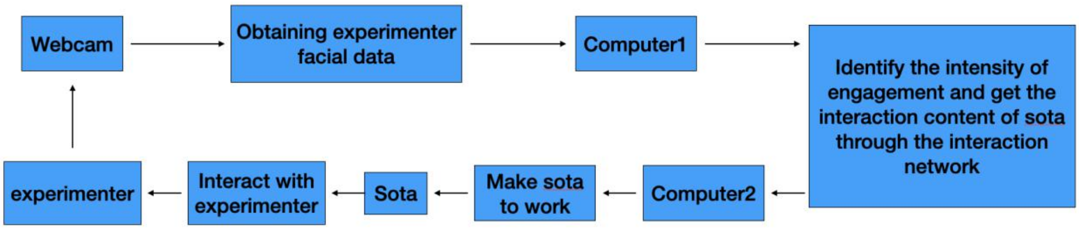

Figure 4.1 Functional diagram of experimental equipment

4.2 Experimental evaluation

4.2.1 Evaluation of Experimental perspective 1

After watching each video, the subjects were asked to refer to their facial video and score their engagement intensity at 0, 5, 10, 15, 20, 25, and 30 minutes in the learning process. The scoring criteria were 0-disengaged, 1-barely-engaged, 2-engaged, 3-highly-engaged.

The data judged by the model were then compared with the data answered by the subjects. The results show that out of the total 140 judgments made in the Self-study, the number of correct judgments was 77, with a correct rate of 55%. Out of the 140 judgments studied with Sota, the number of correct judgments was 73, with a correct rate of 52.1%. In total, out of 280 judgments, the number of correct judgments was 150, with a correct rate of 53.6%, as shown in Table 4.2 and Figure 4.2.

Table 4.2 The accuracy of the model

	Number of judgments	Number of concordance determinations	accuracy
self-study	140	77	0.55
with sota	140	73	0.521
total	280	150	0.536

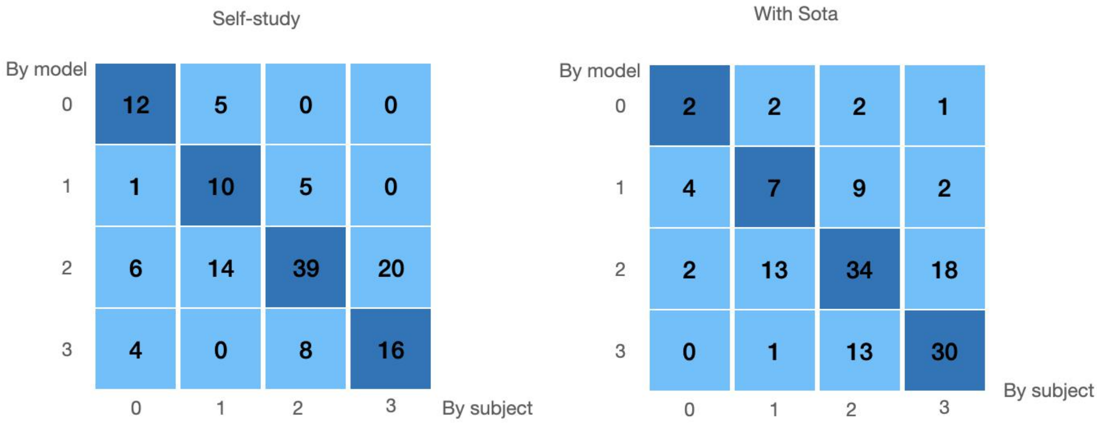

Figure 4.2 The accuracy of the model

From Figure 4.2, we can see that although the correct rate is only 53.6%, 93.6% of the errors are 1. We think we can say that and the model's judgment is "roughly accurate.” However, in the actual experiment, we found that "roughly accurate" also affects the interaction timing and content of Sota, thus affecting the interaction feeling of the subjects. As for errors, the model seems to estimate the subject's engagement optimistic since there are a certain number of cases where the subjects were barely-engaged, and the model was engaged. Therefore, we have to improve the model's accuracy to obtain better results in future work.

4.2.2 Evaluation of Experimental perspective 2

The goodness of Sota's interaction was evaluated from the following three perspectives.

a) Which condition kept the engagement higher in Sota vs. Self-study.

Table 4.3 shows the mean of the engagement intensity in Sota and Self-study conditions.

With model judgments, the intensity of learning engagement was significantly higher with Sota (M=2.06, SD=0.66) compared to Self-study (M=1.81, SD=0.83), t(139)= -2.4205, p=0.01614.With subject judgments, the intensity of learning engagement was significantly higher with Sota (M=2.07, SD=0.78) compared to Self-study (M=1.71, SD=1.05), t(139) = -3.11479, p=0.00203 by T-test. We can conclude that there is significant variability in this data set.

Table 4.3 Mean and standard deviation of the engagement intensity

	With sota		Self-study	
	Mean	SD	Mean	SD
Model	2.06	0.66	1.81	0.83
Subject	2.07	0.78	1.71	1.05

b) Comparison of the number of times engagement was restored during the course in Sota vs Self-study since engagement usually goes down.

We counted the number of changes from low to high engagement intensity in the two conditions, respectively, as a way to assess whether Sota had a positive effect on the learner's recovery of engagement intensity, as shown in Table 4.4.

With model judgment, the number of recoveries of engagement intensity was significantly higher for Sota (M=1.25, SD=0.59) compared to Self-study (M=0.8, SD= 0.56), t(19)=-1.8311, p=0.03747. With subject judgments, the number of recoveries of engagement intensity was not significantly higher for Sota (M=1.32, SD=0.41) compared to Self-study (M=1.1, SD=0.99), t(19)=-0.77562, p=0.44290 by T-test.

The results show that in the model judgment, the engagement intensity was recovered more often in the condition of Sota. However, the engagement intensity recovered has no difference in both conditions in the subject judgment. We can conclude that the presence of Sota helps the learner to improve the engagement intensity from the outside but is not very obvious from the inside.

Table 4.4 Mean and standard deviation of the number of participatory recoveries

	With sota		Self-study	
	Mean	SD	Mean	SD
Model	1.25	0.59	0.8	0.56
Subject	1.32	0.41	1.1	0.99

c) Whether the timing and content of Sota interactions are appropriate and whether Sota is useful for helping learners maintain a good learning state.

Figure 4.3 shows the result of questionnaire A: How about the point in time when Sota performs the interaction? And merge the following paragraph. The mean of answers is 3.43, and the standard deviation is 0.608. Thus, more than half of Sota's interaction timing was positively accepted. Because the model accuracy is not very high, this model also has a certain delay and is not so sensitive. Sota did the interaction at an inappropriate time, and we think this is why a few of Sota’s interactions were not positively accepted.

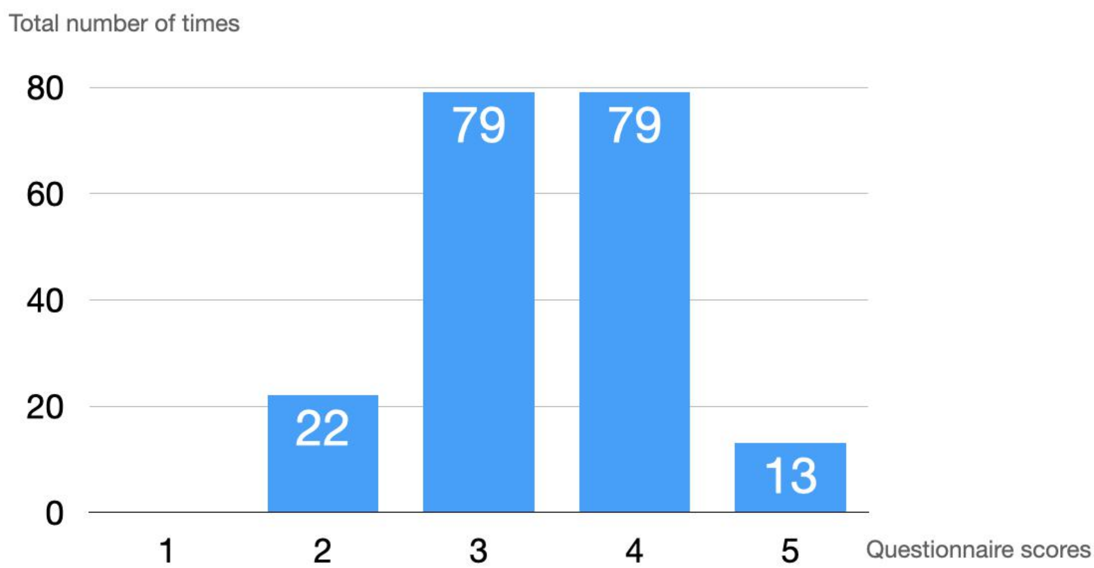

Figure 4.3 About Sota’s interaction timing

Figure 4.4 shows the result of questionnaire B: How about the content of Sota’s interaction? The mean is 3.24, and the standard deviation of 0.728. Thus, around half of Sota's interaction contents were positively accepted. In the initial stage, Sota's interaction content is not suitable for everyone's preference. Then, there are some strange interaction contents in updating interaction network weights. This might make some of Sota's interaction content negatively accepted.

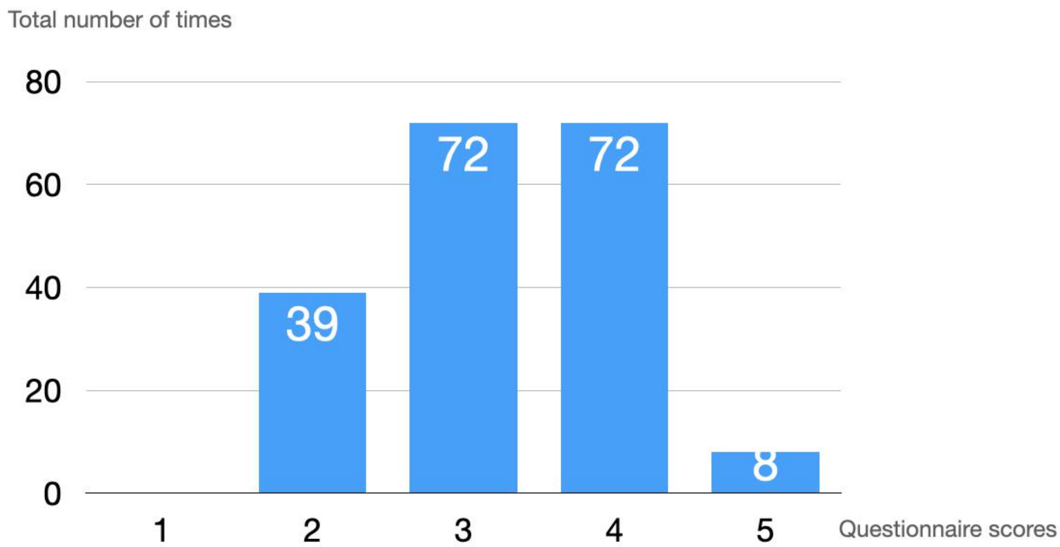

Figure 4.4 About Sota’s interaction content

Figure 4.5 shows the results of questionnaire C: How about your engagement after Sota’s interaction. The mean is 3.26, and the standard deviation is 0.472. Thus, around 40% of Sota's interactions affected the maintenance of learning engagement. About 13% of Sota’s interaction reduce the intensity of learning engagement. Because Sota did the interaction at an inappropriate time, and the setting of the initial weight of the interaction network affected the acceptance of the interactive content.

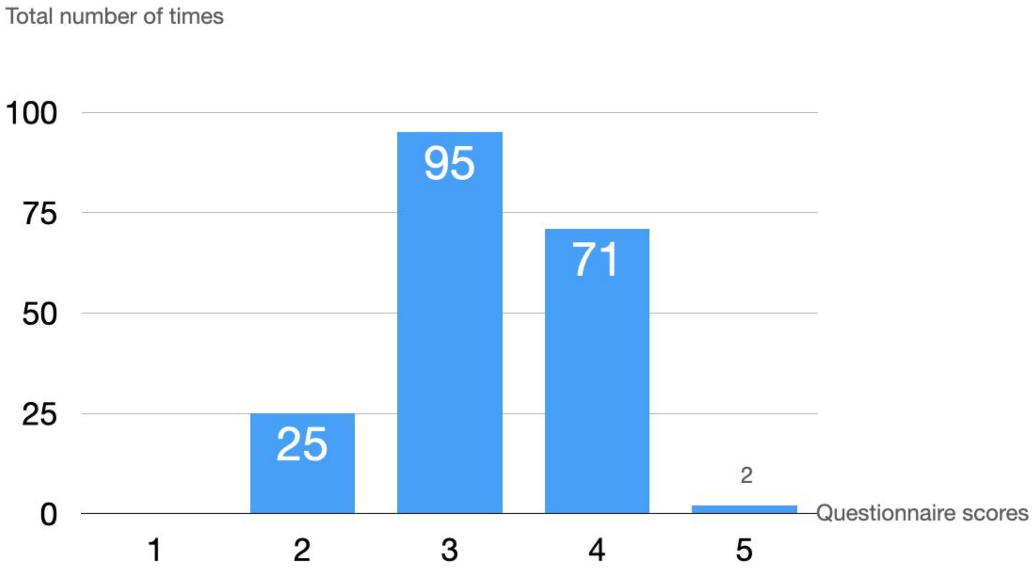

Figure 4.5 About learning engagement after Sota interaction

4.2.3 Evaluation of Experimental perspective 3

a) According to the responses of the questionnaire, the number of Sota interactions was divided into the first third, the middle third, and the last third. To evaluate the effectiveness of the proposed update algorithm was verified by comparing the average of the subject's satisfaction with the content of these three parts.

Table 4.5 indicates that in the first third of the interaction M1=3.17, Std=0.814; in the middle third of the interaction M2=2.84, Std=0.879; in the last third of the interaction M3=3.70, Std=0.706.

Table 4.5 For the mean and std.

Items	N	Mean	Std.Dev.
First third	63	3.17(M1)	0.814
Middle third	61	2.84(M2)	0.879
Last third	63	3.7(M3)	0.706

First, we confirmed the data were normal distribution through the Jarque-Bera test. We tested the data with the unpaired ANOVA to compare the three groups, showed that the f-ratio value is 18.8644. The p-value is $< .00001$. The result is significant at $p < .05$. Comparing the specific differences, the samples all showed significant differences. By using Tukey's HSD, we compare the data of each two stages as shown in Table 4.6. The Q-value between M1 and M2 is 3.34 (p=.04984), the Q-value between M1 and M3 is 5.22 (p=.0085), and the Q-value between M2 and M3 is 8.56 (p=.00000). Thus, we can say their satisfactions in these periods were significantly different.

Table 4.6 The table of the HSD test

Pairwise Comparisons	HSD.05=0.3383 HSD.01=0.4224	Q.05=3.3414 Q.01=4.1717
M1=3.17 M2=2.84	0.34	Q=3.34(p=0.04984)
M1=3.17 M3=3.70	0.53	Q=5.22(p=0.0085)
M2=2.84 M3=3.70	0.87	Q=8.56(p=0.0000)

From these results, we can conclude that the subject satisfaction increases significantly at the last third period as the experiment progresses. We analyze the reason for the decrease in satisfaction in the middle of the experiment. Many strange interactions reduced their satisfaction while adjusting the weights in the middle of the experiment. However, this situation was solved by increasing the number of interactions.

b) We summarized absolute weight changes between each engagement intensity for the 20 subjects. Table 4.7 indicates considerable variation in the weights of disengagement-criticism, engagement-criticism, and engagement-praise.

Table 4.7 Weighting change

	Initial weight	Absolute value of change
disengaged—support	0.4	0.03
disengaged—criticize	0.35	0.18
disengaged—care	0.2	0.12
disengaged—praise	0.05	0.03
barely-engaged—support	0.45	0.11
barely-engaged—criticize	0.3	0.08
barely-engaged—care	0.15	0.02
barely-engaged—praise	0.1	0.01
engaged—support	0.2	0.02
engaged—criticize	0	0.15
engaged—care	0.1	0.11
engaged—praise	0.7	0.28

By comparing the data of the subject 12 and 19 in Table 4.7, we found that despite the significant difference in their weight changes, the change in their satisfaction with the content of Sota interactions was consistent as the number of interactions increased, as shown in Table 4.8, 4.9. This illustrates the individual variability and validates the effectiveness and practical relevance of the proposed algorithm.

Table 4.8 Weight changes for No.12 and No.19

weight	NO.19	NO.12
engaged—support	0.2-0.23	0.20-0.18
engaged—criticize	0-0.03	0-0.42
engaged—care	0.1-0.01	0.1-0.25
engaged—praise	0.7-0.73	0.7-0.15

Table 4.9 Changes in No.12 and No,19 interaction content satisfaction

Interaction content satisfaction	First	Middle	Last
NO.19	3.33	2.67	4
NO.12	3.33	2.75	3.5

Chapter 5
Conclusion

This chapter gives a general overview and summary of this research, followed by a description of the remaining issues that emerged from this research and future expectations.

5.1 Summary

With the development of robotics, there is a growing expectation that robots can help people learn. So far, a variety of learning-supporting robots have been proposed. In these researches, the robots followed predetermined rules and interacted with the learners based on their emotions and behavior. However, the effects of the robot interactions are different on the individual learners since it is difficult to fit individual preferences.

This research proposes an interaction network model for learning partner robots to follow such individual differences and realize personalized interactions. The network consists of three layers representing action, language, and speech rate. It is a 3*4 fully connected network where the initial weights are set manually in advance. The weights are translated into a probabilistic form, which determines the content of the robot's interaction. We also define the "good or bad" of the previous interaction based on the learner's response, decide to increase or decrease the weight of the previous interaction, and update the interaction network weights so that the robot can change the interaction content through the learner's feedback. Thus, it enables the robot to give the most personalized interaction to different learners.

Section 1.2 describes the three primary research questions. Through this research, we have these conclusions.

Q1: How to estimate learner engagement through a computer cameras?

A1: We adopted Huynh's engagement intensity detection model. Engagement intensity is divided into four levels: highly-engaged, engaged, barely-engaged, and disengaged. We compared the data from the model judgments with the subjects' judgment through the experiment. The results showed that out of 280 judgments, the number of correct judgments was 150, with a correct rate of 53.6%. However, 93.6% of errors are neighbors, and the model's judgment can be said "approximately correct."

Q2: How can we develop a model to update the robot's behavior to suit the individual needs of the learner?

A2: We proposed a model called the interaction network, which interacts with learners based on the output of the engagement intensity detection model. After the interactions, the robot again judged the learner's engagement intensity to determine whether the interaction content was reasonable and updated the interaction network weights to adapt to each learner's preference. The number of Sota interactions was divided into the first third, the middle third, and the last third in the experiment to evaluate the effectiveness of the proposed update algorithm. The results could conclude that the subject satisfaction increased significantly in the number of interactions at the last third period as the experiment progressed. This illustrated the individual variability and validated the effectiveness and practical relevance of the proposed algorithm.

Q3: How to evaluate learning effectiveness using a partner robot ?

A3: According the answer of the questionnaire, we compared which condition kept the engagement higher in Sota vs Self-study, and we also compared the number of times engagement was restored during the course in Sota vs Self-study. We counted the number of changes from low to high engagement intensity in the two conditions, respectively, as a way to assess whether The results show that Sota can help the learners maintain engagement.

5.2 Future Topics

In this research, we adopted Huynh's model to identify the learner's engagement intensity. Due to the lack of data set, we used his pre-training model. The accuracy rate of engagement intensity was 53.6%. This makes some mismatches for Sota interaction. This model also has a certain delay and is not so sensitive. Therefore, our next step is to develop a more accurate and sensitive model for future research. Moreover, the designed interaction network had only three layers, which made the content of the interaction a little less and did not meet the requirements of some learners for Sota. In future research, we will deepen the number of layers of the network and add more content and ways of interaction. Furthermore we found that the initial weights affect the interaction perception of learners at the initial stage, while the update speed and rules of the weights affect the interaction perception of learners at the later stage, so we expect to find the optimal weights settings in the future work.

In this research, we updated the interaction content based on the change in the intensity of the learner's engagement after the robot interactions. We expect to change the robot's interaction content based on the learner's interest in the learning content and the learning effect in future work. In this research, each session was only 30 minutes, and we are interested in how the robot works well when learners study longer.

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Appendix

Agreement for cooperation in experiments

実験協力承諾書

研究課題名：振る舞い更新モデルに基づいた学習支援ロボット
実施責任者：北陸先端科学技術大学院大学　先端科学技術研究科　長谷川研究室　YAOBOWEI
実施日時：令和　　年　　月　　日　　時　　分
実験時間：約３時間
実験内容：ロボットと一緒に学習
詳細
(1) 実験内容解説

　実験協力者の方に、本実験で行ってもらう課題の内容、ロボットの機能の解説等を行います。

(2) 実験

実施責任者が準備した PC を用いて実験協力者の方に、ロボットと一緒に勉強します

(3) アンケート・聞き取り

　実験協力者の方に、勉強の体験と内容の理解度についてアンケートを実施します。また、アンケート内容によっては実施責任者から実験協力者にいくつか質問させて頂く場合があります。

謝礼：３000 円

　本実験では実施責任者が準備した PC で示した動画について、PC の動画と協力者の顔を映像で録画して、アンケートの答えを収集します。

　本実験で収集したデータは、本研究と関連しない目的には使用しません。

以上の実験について協力することを承諾します。

令和　　年　　月　　日

氏名＿＿＿＿＿＿＿＿＿＿＿＿

Questionnaire

A. インタラクションのタイミングはどうでしたか？

5	4	3	2	1
とても よかった	よかった	どちらでも ない	悪かった	とても 悪かった

B. インタラクションの内容はどうでしたか？

5	4	3	2	1
とても よかった	よかった	どちらでも ない	悪かった	とても 悪かった

C. インタラクション後はの学習状態はどうなりましたか？

5	4	3	2	1
とても 良くなった	良くなった	どちらでも ない	悪くなった	とても 悪くなった