Emotion-Aware Teaching Robot: Learning to Adjust to User's Emotional State

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Abstract. Robots today are taking more and more complex roles thus they are getting smarter and more human-like. One complex function, specific to social robots, is the role of robots in human-robot interaction. They are helpful in the process of social human-robot interaction while performing a specific task like teaching, assisting, entertaining, etc. The ability to recognize emotions has a significant role for social robots. A robot that can understand emotions could be able to interact according to that emotion. In this paper, we propose a model for robotic behavior adapting to the user's emotions. The humanoid robot Nao is used in the role of emotion-aware teacher for teaching math. Its main purpose is to teach and entertain the user while adapting its behavior to the user's emotional state derived from the facial expression. The robot uses reinforcement learning to learn which action to perform in a specific emotional state. It employs the Q-learning algorithm, maximizing the next action's award - a value that depends on the current emotional state of the user. An experimental study with a selected group of subjects is conducted to assess the proposed behavior. We evaluated the robot's ability to recognize emotions and the subjects' experience of interacting with the robot.

Keywords: Human-robot interaction · Emotional robot
Emotion-aware robot · Social robot · Teaching robot
Reinforcement learning · Emotion recognition · Face analysis
Decision making

1 Introduction

Human-robot interaction (HRI) is a study field that encompasses the study of communication between humans and robots, as well as the design and adaptation of robotic systems used by humans [8,19]. The social behavior aspect of human interaction leads the field into the development of social robots [15,18,20]. These robots are autonomous robots that interact with humans following rules originated in a social manner in order to construct a human-like interaction.

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Although we do not have a formal definition and full knowledge of the influence of emotions, studies show that emotions play a key role in many cognitive tasks of humans, such as decision-making, reasoning, memory, attention, learning, etc [35,45]. Therefore, the ability to recognize emotions has a significant role for social robots. A robot that can recognize emotion in users can be able to interact according to that emotion. There are already developed frameworks for emotion modeling for social robots [34]. Social robots that detect and adapt to the human emotions are able to perform an empathic behavior accompanied by compassion and feeling of warmth [17]. These are the key points in the social human interaction process [37]. Understanding the emotional state of the human can help in adjusting the robot's behavior to that state. This can affect the process of learning and problem solving, making it more pleasant and fun experience.

Today's methods used for recognizing emotions include emotion detection through text, where the data can be: posts, comments, messages, criticisms, certain blogs, e-commerce websites, movies, music, etc [10]. Another approach is the identification of emotions through an image, where mainly emotion is detected through certain facial expressions and body language [3,27]. A third method used to solve this problem is the emotion recognition through sound, i.e. human speech, sound features [25] and the intonation of the human voice [14]. Other methods incorporate processing of various types of physiological signals such as EEG (electroencephalogram) to detect electrical activity in the brain, ECG (electrocardiogram) to detect the electrical activity of the heart, skin conductance, changes in respiration, and so onwards [9]. It is a big challenge for a person to determine the emotional state of another person, especially because not everyone expresses their emotion in the same way and with the same intensity. Sometimes humans hide their emotions or express some emotion that is not the true emotion when interacting with other people, especially if those people are unknown to them. Knowing this, building smart solutions to enable machines and robots to determine the emotional state of the humans with greater accuracy than themselves, is a nontrivial problem that presents a big challenge [26].

Social robots are already designed and used for several tasks in different domains. Robots like Paro [48,49], Robovie [22,38], and Kaspar [12,21] are successfully adopted in the health-care and therapy domain. Keepon [29], Tega [28], iCat [7,30], Robotis OP2 [11] are utilized for educational purposes. The entertainment field includes several designed robots like Aibo [47].

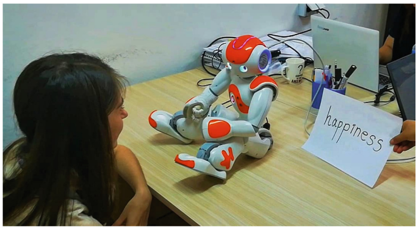
Nao is an autonomous robot developed in 2006 by SoftBank Robotics[1] and continues to develop as a small humanoid robot. This robot has been used for many research and educational purposes in numerous academic institutions. Paper [40] introduces the Nao robot with the capability of mimicking the emotions of users and providing feedback based on sentiment apprehension. Authors in [2] include the emotion conveyed through touch in the HRI between human and Nao. This robot was also designed for therapy of autistic children with good response and results [39,42,43]. The same robot is used in [5] as a tool to offer

[1] https://www.ald.softbankrobotics.com/en, last accessed: May 2018.

a tour guide for informatics laboratory, while the study in [44] explores a model for adaptive emotion expression in child-robot interaction. Another emotion and memory model intended for the robot Nao is presented in [1]. The robot adapts its behavior based on memory accounts of the child's emotional events.

The purpose of this research is to build an emotionally conscious teacher with the help of the humanoid robot Nao. The robot Nao used in our experiments is shown in Fig. 1a. The main task of the robot is to try to teach and entertain the user adapting to its current emotional state. The emotional state is recognized using the facial expression while the behavior is determined using optimal policy learned with reinforcement learning. The prime target group are children from primary school. However, in order to initially test the model and build a safe environment for children, the experiments for determining the ability of robot's learning and emotion recognition are carried out with adults. Testing the proposed robot behavior with children remains our aim for future work.


(a) Nao robot.



(b) Nao robot in the experimental setup.

Fig. 1. Nao robot utilized in this study.

The rest of the paper is organized as follows. Section 2 describes the model of the robotic behavior. The details of the implementation are included in Sect. 3. Section 4 presents the experimental study and evaluation of the results. Suggestions for the future work are given in Sect. 5, and at the end, Sect. 6 concludes the study.

2 A Model for Robotic Behavior

A model for robotic behavior based on user emotions is proposed in this paper. The complete workflow of the robot's behavior is shown in Fig. 2. The model is formulated with a set of robotic actions and states. Robot's learning is implemented as reinforcement learning, where the emotional state of the user is taken as a reward. Each part of the proposed behavior is described in details in the following subsections.

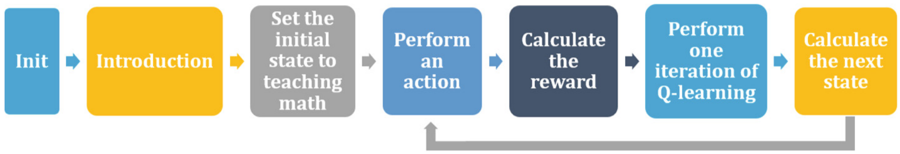


Fig. 2. Robot workflow.

2.1 Reinforcement Learning

The central element of robot control is the robot's learning. The robot should perform actions with fewer mistakes over time, utilizing the knowledge derived from previously gained experience. The learning of a robot can be categorized into two groups: offline and online learning. In this paper, we implemented reinforcement learning [41], which is an online learning method. The idea of this type of learning is to maximize the award that the robot receives for the actions it takes, that is, to build an optimal policy (behavior) with which the robot performs actions that give the best reward.

A mathematical framework for defining a solution for a reinforcement learning scenario is Markov Decision Processes, composed of:

- finite set of states S
- finite set of actions A
- function $f(s, s')$ for determining the reward r for transiting from state s to state s'
- policy π, which is a function that takes the current environment state to return an action
- value $V^{\pi}(s)$ - state-value function that returns the expected value from state s following policy π

One model of reinforcement learning is Q-learning [6,50]. The basis of Q-learning is learning the Q value that represents the value of a given action in a given state. The state-value function $V^{\pi}(s)$ is determined as

$$V^{\pi}(s) = \sum_{a \in A} \pi(a|s) * Q^{\pi}(s, a) \tag{1}$$

where s refers to the state, a is an action, A is the set of all possible actions, π represents the policy, and $Q^{\pi}(s, a)$ is the is the action-value function following the policy π in a given state s. First, the robot begins with initial values and then over time, it learns by exploring the space state-action and updates the values accordingly.

Q-learning is implemented with a simple version of the algorithm. The essential components are the defined states S, the possible actions A and the function $f(s, s')$ for determining the reward for mapping a given state and action. Having the current state s, after performing the action a the robot receives a reward r (the value of the function $f(s, s')$) and changes the state from s (previous state) to s' (current state). If the value of r is a penalty, then for the previous state s and the action a, the value Q is updated so that it is decreased. Therefore, the next time the robot finds itself in that state, the other actions will have a greater Q value and they will be selected. On the other hand, if r represents a reward, then the value for that combination of state-action increases and that action is favorable for the given state s.

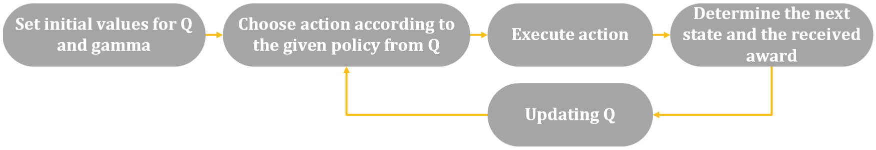


Fig. 3. Q-learning algorithm steps.

The equation for updating Q is given as

$$\mathbf{Q}(s, a) = \mathbf{Q}(s, a) + \alpha[r + \gamma \max_{a} \mathbf{Q}(s', a) - \mathbf{Q}(s, a)] \tag{2}$$

where s refers to the previous state, s' is the current state, $\mathbf{Q}$ is the matrix with state-action values, r represents the award from the environment, γ is a gamma factor $(0 < \gamma < 1)$ and α is the learning rate from the reinforcement learning. The goal is to learn an optimal policy which maps the states S into the robot's actions A. Selecting an action according to the values in $\mathbf{Q}$ is obtained according to the most beneficial action from the mappings in $\mathbf{Q}$ using ϵ-greedy policy (ϵ is the probability to select a random action), given the current state and possible actions. The algorithm is presented with the diagram on Fig. 3.

2.2 User's Emotional State

The ability to recognize user's emotion plays a significant role in the robotic behavior. Being aware of that emotional state the robot can choose its next action in accordance with it. When the robot is able to perceive the user's emotional state, it will determine how well the user is satisfied with the performed action. Positive emotion, if for example, the user is happy, signifies that the robot chooses an appropriate action. On the contrary, negative emotion indicates that the action should be changed in order to improve the emotional state of the interlocutor.

The emotion felt at a specific time by the user, i.e. its emotional state, represents a reward for the robot in the learning process described in the previous subsection. After every performed action, the user's emotional state is analyzed. Subsequently, the reward is calculated based on five emotions: happiness, neutral, surprise, sadness and anger. The probability of each emotion is calculated from facial expressions. The final reward is defined as a weighted sum of these probabilities as follows:

$$r = P(h) * 10 + P(n) * 5 + P(su) * 5 - P(sa) * 5 - P(a) * 10 \tag{3}$$

where $P(h)$, $P(n)$, $P(su)$, $P(sa)$ and $P(a)$ are the probabilities for happiness, neutral, surprise, sadness and anger, respectively.

2.3 States and Actions

The main purpose of the robotic behavior presented in this paper is teaching math. Therefore, we define three different states for the robot:

1. **Teaching math** - the robot teaches the user basic math concepts for addition and subtraction with examples
2. **Solving math tasks** - in this state, the robot sets math tasks which should be solved by the user
3. **Playing/Taking rest** - the robot and the user play, i.e. they take rest

Schematic view of the states is displayed in Fig. 4. The robot takes actions and as a result it can change its state. We define two actions which are performed by the robot:

1. **Stay in the same state**
2. **Change state**

According to this, if the robot is, for example, in the state **Teaching math** it can perform one of the three actions:

- *Stay in the same state* - with this action the state is not changed. The new state is again **Teaching math**.
- *Change state into **Solving math tasks*** - with this action the state is changed from **Teaching math** to **Solving math tasks**.
- *Change state into **Playing/Taking rest*** - with this action the state is changed from **Teaching math** to **Playing/Taking rest**.

3 Implementation

The Nao robot[2] has a special operating system called NAOqi, which is Linux based. Also, the robot has a software package that includes a graphical programming tool called Choregraphe[3] [36], simulation software package and SDK.

[2] http://doc.aldebaran.com/2-1/home_nao.html, last accessed: May 2018.
[3] http://doc.aldebaran.com/2-1/software/choregraphe/index.html, last accessed: May 2018.

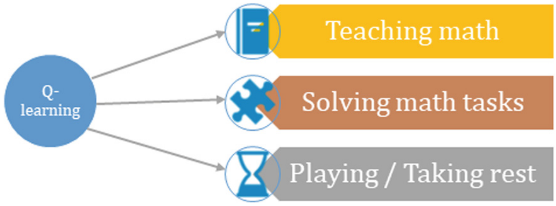


Fig. 4. Changing states with Q-learning.

Supported working languages are C++, Python, Java, MATLAB, Urbi, C, .Net. To implement the emotion-aware behavior of the robot, we used Choregraphe and the Python programming language. This tool enables simple application development using already implemented modules, as well as the ability to define custom modules. Figure 5 shows a visual representation of the implemented modules.

An initialization module is executed before the start of the interaction with the robot. This module sets predefined values for the parameters to be used. To begin interacting with the robot, the user needs to touch the robot at the front of the head. In this way, the interaction with the robot starts and the robot firstly introduces itself. Then, it performs tasks that are part of the first state - teaching math. The tasks for this state, as well as for other states, are implemented in the form of modules.

Within the state for teaching math, which is the initial state, the robot randomly chooses one of the two topics (addition or subtraction) to teach the user. Then, for the selected theme, the robot tells a brief explanation and illustrates it with an example. The robot interaction includes talking, which is done with the *AlTextToSpeech*[4] module which enables the robot to speak. Choosing the mathematical tasks for the user is part of the second possible state. In this state, in a similar way as in the previous one, the robot selects the theme for the task question. After selecting the topic (addition or subtraction), the task is randomly selected. Next, the robot waits for an answer. Information for the correctness of the answer is received by a third person in the following way: the touch of the front of the head indicates that the child answered correctly while the touching the back of the head indicates that the answer is wrong. After receiving information about the answer, the robot informs the child about the correctness of the answer. Within the third possible state - taking rest, the robot plays music that aims to entertain the child.

Next follows the estimation of the emotional state of the user. This is defined in a separate module that gains information about the five emotions defined previously and calculates the robot's reward. The module *ALFaceCharacteris-*

[4] http://doc.aldebaran.com/2-1/naoqi/audio/altexttospeech.html, last accessed: May 2018.

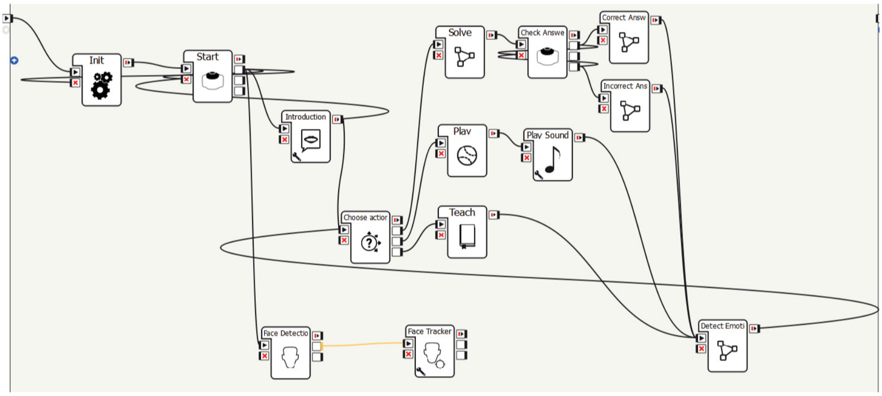


Fig. 5. The modules of the robot behavior in Choregraphe.

tics[5] is used to recognize and calculate the intensity of the emotional state of a person. This module analyses the person's characteristics for the people who are near the robot. *ExpressionProperties* represents one attribute of the conducted analysis. This attribute contains a list that holds the probability of a certain emotion for each of the five emotional states: neutral, happiness, surprise, anger, and sadness. It should be noted that the facial recognition and facial features analysis modules are sensitive to room illumination. This means that brightness can influence whether a person near the robot is detected and whether the values as features (probabilities of emotions) are obtained at all.

A specific module defines the Q-learning algorithm and the selection of next action. This module takes the previously calculated award and uses it to update the Q values. Depending on these values, the next action is selected. The parameters used in the multiple modules are stored in the robot's memory.

In parallel with these modules, the *ALFaceDetection*[6] and *ALFaceTracker*[7] modules are executed. These modules serve to detect and track people in the proximity of the robot. The memory of the robot contains the information about each of the "reachable" people.

4 Experimental Results

To evaluate the proposed behavior, we performed an experimental study with a group of 17 subjects from different gender and age. The distribution of age and gender is displayed in Fig. 6. We evaluated the robot's ability to recognize

[5] http://doc.aldebaran.com/2-1/naoqi/peopleperception/alfacecharacteristics.html, last accessed: May 2018.

[6] http://doc.aldebaran.com/2-1/naoqi/peopleperception/alfacedetection.html, last accessed: May 2018.

[7] http://doc.aldebaran.com/2-1/naoqi/trackers/alfacetracker-api.html?highlight=tracker, last accessed: May 2018.

emotions and the experience of interacting with the robot. The results from these experiments are explained in details in the following subsections.

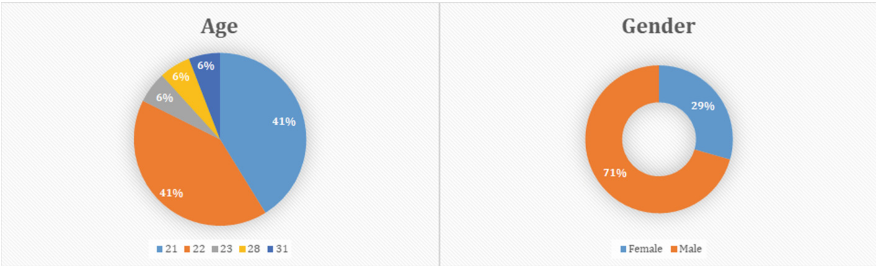


Fig. 6. Distribution of age and gender of the subject participating in the experimental study.

4.1 Experimental Procedure

The subjects were divided into two groups (of size eight and nine), and two sessions for interaction with the robot Nao were performed. Each subject had approximately five minutes for interacting with the robot during which he or she had to act all five defined emotions. The robot was placed on a desk in a sitting position which guarantees that the robot will stay safe during the experiments. The subjects were sitting in front of the robot at less than 1-meter distance. The environment of the experiments is presented in Fig. 1b. As discussed previously, the brightness influences the robot's ability to detect a face and emotions appropriate to that face. It is important to make sure that the room in which the experiments are performed is bright enough. Therefore, the experiments were performed during the day additionally with lamps light. The interactions were recorded to be analyzed later. After the interaction, all subjects were asked to fill in a questionnaire.

The order of the acted emotions was previously defined. In the first session, the order was as follows: *happiness*, *sadness*, *surprise*, *neutral* and *anger*. Throughout the first session, we noticed that acting **sad** after acting **happy** was difficult for the most of the subjects. Therefore, in the second session, the order of emotions was changed into the following sequence: *happiness*, *neutral*, *sadness*, *surprise* and *anger*.

4.2 The Ability to Recognize Emotions

In this subsection, the robot's ability to recognize emotions is discussed. One of the key influences on the emotion recognition is the user's ability to act emotions. Therefore, if the subject does not act the emotion properly, the robot would not be able to recognize it.

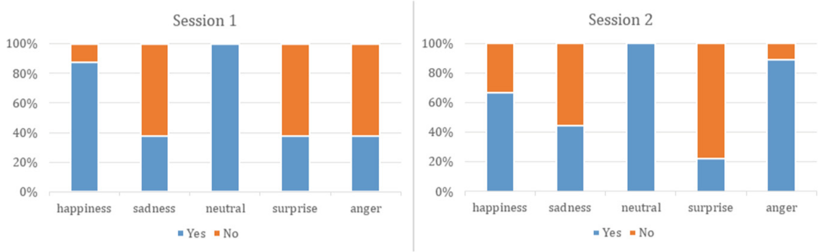
By examining the recordings of the sessions, it can be seen that not all subjects are good at acting emotions. There were cases when the emotion was not acted good enough, leading to a confusion of emotions. An example is recognizing **neutral** for some of the subjects, although the expected emotion is **sad**. When evaluated by a human, the emotion was also classified as **neutral**. For such situations, we gave a second chance for acting the same emotion, which in the most cases led to better results.

The most difficult emotion to act, and therefore to be recognized, was **surprise** with less than 40% recognition rate in the first session and less than 25% in the second session. This emotion was mostly confused with **neutral**. The percentage of correctly identified emotions in each session is displayed in Fig. 7a. These percentages are calculated as follows. For all emotions acted by the subjects, the emotion to be acted and the corresponding recognized emotion by the robot are compared, assuming that all of the emotions were acted properly. But, as stated previously, there were subjects whose acting was not good enough. The assessment of the acting was done with human judgment by re-examining all previously filmed videos. Removing the results of subjects whose acting was not good enough caused an increase in the emotion recognition rate, as presented in Fig. 7b. The recognition rate for **surprise** increased from 37% to 42% in the first session and from 22% to 33% in the second session. For **happiness**, the recognition rate in both sessions increased up to 100%. However, despite all circumstances, there were subjects for which most of the emotions were successfully identified. For 75% of the subjects in the first session and 78% in the second session, three or more emotions were successfully recognized by the robot.

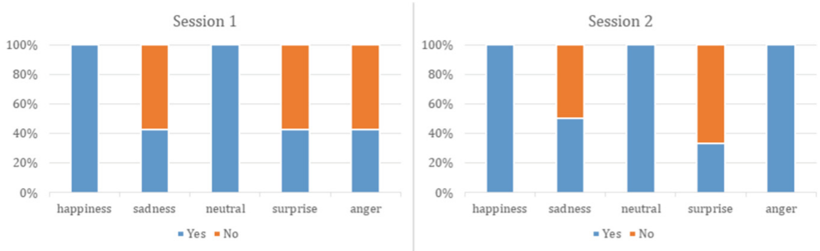
Further, to test whether the emotion acting influences the emotion recognition, the *Pearson's chi-squared test of independence* was performed and the *Pearson's correlation coefficient* was calculated. Two different scenarios were evaluated:

1. Two binary random variables are defined as follows. The first random variable represents the goodness of acted emotion - *"Yes"* if the emotion is acted properly or *"No"* otherwise. The second random variable shows the correctness of the recognized emotion - *"Yes"* if the emotion is detected properly or *"No"* if not.
2. For this scenario, the first random variable illustrates the goodness of acted emotions per subject (*"Yes"* if the emotions are correctly acted or *"No"* otherwise). The second random variable is numerical with values in the range [1,4] that represent the number of correctly identified emotions per subject.

For both scenarios, the null hypothesis is *"The occurrence of the outcomes is statistically independent"*. It is rejected according to a significance level of 0.05 with a p-value of 0.009 for the first scenario and 0.021 for the second. This indicates that the series are not independent. The correlation analysis confirms the conclusion that dependence between detecting and acting emotions exists, i.e. we cannot give a concrete justification for the detection of emotion because it is not independent of the acting. For both scenarios the correlation coefficient



(a) All subjects.



(b) Removed subjects whose acting was not good enough.

Fig. 7. Percentage of recognized emotions. "Yes" - the emotion is recognized, "No" - the emotion is not recognized.

is positive - 0.313 for the first and 0.742 for the second scenario, indicating a relation between the acting and detection of the emotions.

Besides the ability of emotion recognition, the ability to adjust to the user's emotional state can be also evaluated with the performed experiments. The robot's reward is increased if the emotion is *positive* (happiness, neutral, surprise) and decreased if the emotion is *negative* (sadness, anger). In the beginning, the robot is in an initial stage of learning to adjust to the subject's emotional state. Consequently, the next action is randomly selected. As the interaction continues, the robot starts to learn the emotional state of the subject. Hence, if the emotion is positive, the state of the robot is not changed. On the contrary, when the emotion is negative, the state changes with the decreasing of the reward. This part of the model behaves as expected - adapting to the user's emotional state. One possible negative influence may be caused by detecting emotions. In fact, if the emotion is not correctly determined, the robot will get an inappropriate reward and therefore choose an irrelevant action. The errors of the emotion recognition model, including its weaknesses like room illumination, may produce erroneous action selection.

4.3 The Experience of Interacting with the Robot

This subsection presents the results obtained by the questionnaire. The main purpose of this questionnaire is to evaluate the experience of interaction with the robot. It consists of five questions:

- *Question 1: "How well, on a scale of 1 to 5, do you think that the robot can recognize your emotion?"* - for this question, 10 of the subjects gave"4" as a grade, 3 of the subjects evaluated the ability to recognize emotions with grade "5" and"3". One subject reported a grade "2", while grade"1" was not chosen by any of the subjects.
- *Question 2: "Do you think that the robot can learn to adjust to your emotional state?"* - the most of the subjects (12) responded with"Yes", 4 reported that the adjustment is not sufficient and 1 participant stated that (s)he does not know. The last option is "No" which was not selected by any of the subjects.
- *Question 3: "How well, on scale from 1 to 5, do you think that the robot is useful in the context for which it is intended?"* - grades"1" and "2" were not chosen by any of the subjects, while grades"3", "4" and"5" were chosen by 1, 7 and 9 subjects, respectively.
- *Question 4: "Do you think that the robot Nao can have a role of social assistant/teacher?"* - to this question, 13 of the subjects responded with"Yes" and 4 with "Maybe". Options"No" and "Don't know" were also available, but not selected by any subject.
- *Question 5: "Would you, if possible, use a robot as a teacher instead of a human?"* - most of the participants (9), to this question, answered with"Maybe". The rest of the participants responded as follows: 5 with "Yes", 3 with"No" and no one with "Don't know".

From the results, it can be concluded that the overall experience is positive. Relatively large percentage of the subjects consider that the robot is able to recognize and adjust to their emotional state. Moreover, most of the subjects consider that the robot is suitable in the context for which it is intended and can have a role of social assistant. The results from this questions are summarized in Fig. 8.

5 Future Work

As mentioned previously, the emotion detection module has several weaknesses. Therefore our future work will include designing a more robust solution for solving the problem with greater accuracy. The aspired direction is building models with deep learning networks, as they show satisfactory results for facial expression emotion detection in many research studies including [4,23,31]. Another thing to consider is the implementation of Q-learning and reinforcement learning with deep neural networks. This approach is favorable if we increase the number of states and actions, making the robot more capable of intelligent interaction

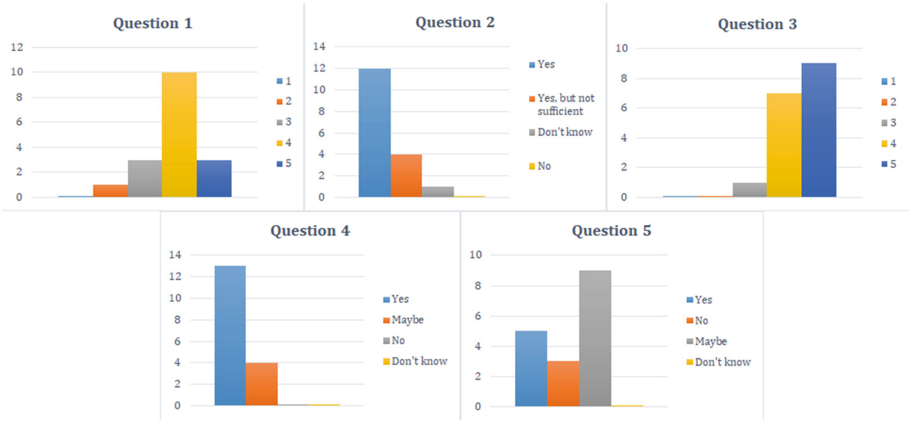


Fig. 8. Questionnaire results.

and multi-task accomplishment. Implementations that utilize this method are presented in [32,33,46].

Social assistive robots are already adopted and tested for the child-robot interaction [13,16,24]. Our future work can include research where the target group are children, that is, Nao would interact with the child as an educational tutor or as an entertainer.

6 Conclusion

This research addresses the use of the Nao robot in the role of an emotionally aware teacher. The learning of the robot is implemented as a reinforcement Q-learning. For this implementation, the robot needs to be able to determine a particular reward according to which it will update its knowledge. The corresponding reward of the robot is calculated through the emotional state of the user determined by the facial expression. Hence, the robot should adapt to the current state of the user and learn how to act at a specific time. The Q-learning method enables the robot to learn whether its behavior at some point was good, that is, whether it managed to adapt to the emotional state of the user.

An experimental study was performed to evaluate the proposed behavior of the robot. The results show that the overall experience is positive. The qualitative analysis points out that some of the subjects in the experiments were not able to act certain emotions. Despite the difficulties of recognizing emotions in some cases, in general, the robot is able to detect the correct emotion from the facial expression and therefore to adapt to the user's emotional state. Solutions of the problems in this model are considered in our future work that also includes ideas for upgrading the model.

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