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Context-Sensitive Personalities and Behaviors for Robots

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Abstract

This paper proposes Context-Sensitive Behaviors for Robots (CSBR), a method for generating diverse behaviors for robots in indoor environments based on five personality traits. This method is based on a novel model developed in this work that reacts to a synthetic genome that defines the personality of the robot. The model functions return different answers and reactions, depending on a given spoken request. The responses of the robot included spoken answers, facial animations, gestures, and actions. The novelty of this method lies in its capacity to adapt the behavior of the robot according to the context of the request. Moreover, the model is scalable since its functions not only return spoken answers but also physical responses, such as opening a gripper, saying hello with gestures, or animating a face that represents an emotion according to the context. Changes in the parameters of the synthetic genome produce different behaviors. By defining different synthetic genomes, robots can adapt to different people's moods. In this work, we introduce two scenarios for human–robot interaction in two domestic environments (house and office) through spoken requests from a human user. We implemented our method in Care-O-Bot 4 and defined three synthetic genomes to produce three behaviors: friendly, detached, and hostile. In the considered scenarios, we asked the robot the same set of requests for every synthetic genome. Not only did Care-O-Bot 4 answer according to its personality, but it also proved that our method produces different behaviors. For these scenarios, we assume that the given request includes its connotation. Since our method has characteristics influenced by context, we show that the robot's behavior changed according to the human mood and the environment.

Keywords: Robotics; Personality; Human-Robot-Interaction; Social Robotics; Affective Computing

1. Introduction

In human–robot interaction (HRI) and affective computing, personality is an essential characteristic that allows robots to adapt to different people and contexts [1]. Moreover, the next generation of artificial intelligence and robotics

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should be able to adapt to society [2]. The human ability to infer intentions from others, their facial expressions, and connotations from their speech allows people to make inferences about how to react to a given situation [3],[4]. Hence, robots that are shown to be more extroverted and more similar to the user's personality tend to be more accepted [5],[6],[7]. Adding personality to robots can also provide users with a better understanding of the robot's behavior [8],[9]. Robots with personality adaptability used in teaching [10] show that when a robot adapts its personality to its users, the HRI arouses more interest. For robots' personalities, there are more factors that affect the impression of users, such as the velocity of its gestures [11],[12].

Human and robot collaboration takes place not only in factories but also in domestic environments [13]. However, there are still concerns about whether humans will totally accept robots as collaborators [14]. Nevertheless, there are studies [15] that show the positive psychological effects of the use of robots that look like animals. These robots improved the moods of elderly people. Even though the benefits of personality applied to social robots are well known, there are still research gaps in areas such as context [16]. Given a particular context, the personality of a robot may change since the mood of a person is also part of the context of the situation. Although many studies [17],[18],[19],[20] focus on the reaction of users, the models to produce robot personalities and adaptable reactions are significantly different, which presents another gap in the research.

Personality is usually represented by the Big Five personality traits: openness, conscientiousness, extraversion, agreeableness, and neuroticism (OCEAN) [21]. Openness is correlated with curiosity and imagination [22]. Conscientiousness stands for people who are self-aware of their own actions [23]. Extraversion refers to how outgoing someone is. Introversion is the opposite of extraversion. Agreeableness refers to how friendly someone is [24]. Neuroticism is related to someone's lack of patience and self-esteem [25]. Particularly relevant to this paper, the Big Five personality traits have been applied as a metrical tool in social robotics [26],[27],[28]. In the literature, several attempts have been made to emulate the personality or behavior of an artificial agent using artificial genomes [29],[30]. Besides, affective computing studies the development of systems that emulate, process, and recognize human emotions and moods[31]. In the literature there exist several methods that involve affective computing and robotics[32], which show that existing models in affective computing stereotype personality types and behaviors[33]. Therefore, there is a necessity to develop adaptable methods to adjust the behavior of robots.

In this paper, our contribution is a method called Context-Sensitive Behaviors for Robots (CSBR), which uses a scalable model to represent a request-return process based on the personality of the robot, and two deterministic algorithms that are designed to react to a manually created Q&A dataset. We also define the structure of the Q&A since the scalability of CSBR relies on the information contained in the dataset. The model reads the synthetic genome of the robot, which represents five aspects of personality. The synthetic genome of the robot can change at any moment, depending on the context. This change in synthetic genome values produces diverse behaviors. The synthetic genome has values from zero to one, which represent the probability of showing a certain personality trait. The model contains four groups of spoken answers: positive polite, positive unpolite, negative polite, and negative unpolite. Moreover, the model also supports physical answers, such as showing emotions with its face, moving any part of its body, or navigating. All the characteristics of the model react to the synthetic genome of the robot. The novelty of this method is its simplicity in representing a request–return process that varies with the synthetic genome of the robot. Furthermore, our method not only provides control for spoken answers but also for its gestures. Finally, we define two scenarios, use our method to implement three synthetic genomes for Care-O-Bot, ask the same set of questions, and examine the behavior of the robot.

2. Context-Sensitive Behaviors for Robots

This section introduces CSBR, the Care-O-Bot 4 setup, the elements that integrate the synthetic genome, a description of the characteristics of the set of questions and answers used to build request-return objects with our model, two algorithms used by CSBR, and a description of how to use the request-return model.

2.1. Robot setup

The robot used in this paper is Care-O-Bot 4 (Figure 1.a), which is a service robot designed for domestic environments. Care-O-Bot 4 has two arms, two grippers, one omnidirectional base, three lidar sensors, four depth cameras, a microphone, two speakers, and a screen that represents the face of the robot. Every arm has seven degrees of freedom and a payload of 5 kg. Moreover, the robot's omnidirectional base has lidar sensors attached every 120 degrees, such that the lidar sensors send data about all the objects surrounding the robot. The depth cameras are Intel Real Sense cameras that also provide RGB images. The robot has a text-to-speech module to interact with the speakers. Finally, Care-O-Bot 4 can display 21 different emotions on the screen, and their animation velocity can also be controlled.

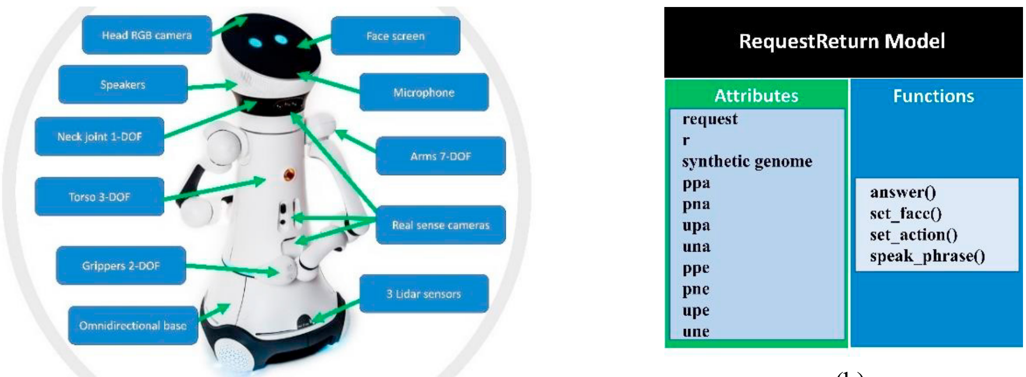
2.2. Synthetic genome

The main purpose of a synthetic genome is to numerically influence the robot's behavior. We define the synthetic genome as a 5-tuple $\langle o, c, \epsilon, a, n \rangle$ based on the five traits of personality, where o is the openness, c is the consciousness, ϵ is the extraversion, a is the agreeableness, n is the neuroticism, and $\{o, c, \epsilon, a, n\} \in (0,1)$. For the robot in this paper, o represents how aware the robot is of the context. The higher the value of o, the more attention a robot puts into the context. In terms of consciousness, c represents the level of attention a robot puts into its own actions: a value closer to one will result in most actions taken by a robot being stored and recorded, and a value closer to zero will result in actions being rarely stored. Moreover, c influences the capacity of the robot to register the context together with its actions. Extraversion for the robot directly correlates to the frequency the robot shows a face reaction according to the request and is represented with ϵ. When the ϵ value is high, the robot shows a face animation reaction to most of the requests.

Table 1. Synthetic genome example

Personality trait	Synthetic genome value
Openness	0.6
Consciousness	0.1
Extraversion/Introversion	0.3
Agreeableness	0.9
Neuroticism	0.2

When ϵ is low, the robot rarely shows facial expressions. In this paper, agreeableness corresponds to politeness for the robot. Hence, when a is close to zero, the robot picks more unpolite answers, and when a is close to one, the robot tends to pick more polite answers. The last personality trait value n refers to the patience of the robot. When n is one, then the robot will stop answering the same request after a few repetitions, and when n is zero, then the robot is going to answer all the requests. Furthermore, n is also proportional to how fast the robot shows gestures and face animations. In Table 1, we provide an example of a synthetic genome and its values.



(a) (b)

Fig. 1. Robot setup and *RequestReturn* model. (a) shows the Care-O-Bot 4 robot configuration. (b) shows the *RequestReturn* model, its attributes, and its functions.

2.3. RequestReturn model

The goal of this subsection is to introduce the *RequestReturn* model (Figure 1.b). This model can be implemented as a class and instantiated from any programming language to create different request-return objects. The functions of the model can produce physical or spoken responses.

The *RequestReturn* model has thirteen attributes: $request$, r, $synthetic\ genome$, attempts, polite positive answers (ppa), polite negative answers (pna), unpolite positive answers (upa), unpolite negative answers (una), polite positive expressions(ppe), polite negative expressions (pne), unpolite positive expressions (upe), unpolite negative expressions (une) and ges_{vel}. The attribute request is a string containing a question or a physical requirement (e.g., “How are you?”, “Where are you from?”, “Come here!”).

To distinguish when the robot may execute a physical action or return a spoken answer, we set $r \in \{0,1\}$. When r is a physical action, its value is one; otherwise, it is zero. The synthetic genome value is the tuple of personality traits defined in the last subsection. The maximum number of attempts $attempts_{max}$ is given by:

$$attempts_{max} = \lceil \alpha e^{1-n} \rceil, \quad (1)$$

where α is a tuning hyperparameter that increases or decreases the maximum number of allowed attempts, and n is the neuroticism. When n is close to zero, then the number of times the robot answers to that question is closer to $attempts_{max}$, and when n is close to one, the number of times the robot answers is closer to zero. The attributes polite positive answers, polite negative answers, unpolite positive answers, and unpolite negative answers are lists that contain elements with diverse manners to answer a question or a physical request positively or negatively in a polite or unpolite manner. Table 2 shows an example of the configuration of these attributes; the answer lists contain multiple answers to the same question. The data are taken from the data set that is explained in the next subsection.

Table 2. Attributes setting example.

Attribute	Value
request	“Open right gripper”
polite positive answers	“Yes, I will do it,” “Of course”
unpolite positive answers	“Fine,” “Yeah, whatever”
polite negative answers	“Excuse me, but I will not do it,” “It has been too much of that for today”
unpolite negative answers	“No, I won’t,” “Never again”

The *RequestReturn* model has four functions: *set_face(), set_action(), speak_phrase()* and *answer()*. The function *set_face()* uses elements from Table 5 and the attribute ges_{vel}. The function *set_face()* sets a facial animation on the robot screen. The function *set_action()* receives one of the elements from Table 3 as input and sends an action to the robot. Care-O-Bot 4 has several predefined physical actions for every part of its body. Specifically, the physical actions of the robot are related to its right arm, left arm, right gripper, left gripper, torso, and neck.

The function *speak_phrase()* uses the speech-to-text library of Care-O-Bot 4 to generate a spoken answer, whose input is a string with a spoken answer from one of the answer attributes (*ppa*, *pna*, *upa*, or *una*). The function *answer()* interactively calls set*_face()*, *set_action()*, or *speak_phrase()*, and reacts according to its $synthetic\ genome$ attribute.

Table 3. Care-O-Bot 4 mobile elements and choices.

Right Arm	Left Arm	Right Gripper	Left Gripper	Torso	Neck
“home”	“home”	“home”	“home”	“home”	“home”
“side”	“side”	“open”	“open”	“right”	“back”
“folded”	“folded”	“close”	“close”	“left”	“right”
“hello”	“hello”			“bend”	“left”
“wave”	“wave”				

2.4. Questions and Answers data set

The Questions and Answer (*Q&A*) data set used contains one hundred questions. Every question has a polite form and an unpolite form. For all the questions, we added several possible positive and negative answers manually, all with polite and unpolite versions. The Q&A data set structure is designed to be compatible with Algorithm 1. Moreover, the data set already provides between one to five possible answers to multiple requests. The answers are classified in four groups: "Polite positive", " Polite negative", "Unpolite positive" and "Unpolite negative". Table 4 provides a set of *Q&A* examples. In addition, we provide a value for the parameter "Politeness", which is 1 when the request is polite and -1 otherwise. Multiple answers in the data set were completed with information from an ontology that represents the robot capabilities and personal data. For example, since the ontology contains the name of the robot and its nationality then we can concatenate "My name is "+RobotName, "I am "+RobotAge+" years old", or "I am from "+RobotNationality. Moreover, the ontology also contains information about the battery state of the robot, and its physical capacities. For example, if the request is "What can you do?", then the answer will be "I can "+RobotCapabilities. The ontology assists the automation of the generation of some answers of the data set. With a combination of manually written questions, information taken from the ontology, and manually coded scripts, we generated the Q&A data set to meet the purposes of our experiments. Even though our method's scalability relies on the Q&A data set and there exits several methods to classify text and its sentiment analysis, we assume that this information is already given, and we focus on the reaction of the robot. It is especially important to consider the manner in which a human requests something such that a robot can react accordingly.

Table 4. Q&A data set samples.

Request	Politeness	Polite positive	Polite negative	Unpolite positive	Unpolite negative
"How are you?"	1	"I am very good thank you"	"I am busy"	"Awesome"	"It's none of your business"
"What's up?"	-1	"Hello"	"Nothing"	"What's up? Really?"	"Who cares?"
"Where are you?"	1	"I am at the laboratory"	"I do not want to tell you"	"Right here?"	"That's very obvious"
"Come here"	-1	"Yes of course"	"No, I will not do it"	"Yeah, whatever"	"Not that again"

2.5. Contextual behavior generator

In this subsection, we present two deterministic algorithms: Algorithm 1 "*behavior generator*" and Algorithm 2 "*contextual personality*." Algorithm 1 is designed to react to ϵ, a, and n parameters. Algorithm 2 is designed to react to o, c (parameters related to the context of the situation), and the gesture velocity. Both algorithms are designed to react to the structure and content of the Q&A dataset. Openness and consciousness (o and c values) react not only to one request but also to the whole human robot interaction process. Furthermore, o and c are the connection between the context (human way of expression and location, e.g., office, hospital, home) and the behavior of the robot. The higher the value of o, the more attention the robot will dedicate to the human connotation and to the environment. Consequently, o must affect a, n, and gesture velocity values. When the user is polite, then o tends to increase the

Table 5. Care-O-Bot 4 "mimic" faces classified by attribute.

polite positive expressions	polite negative expressions	unpolite positive expressions	unpolite negative expressions
"yes"	"blinking"	"no"	"asking"
"happy"	"busy"	"surprised"	"confused"
"laughing"	"searching"		"asking"
"blinking_right"			"bored"
"blinking_left"			"angry"

value of a and increase the value of n, since the robot perceives good treatment from the user and responds accordingly. When the user is not polite, then the robot's patience n and agreeableness a will drop, causing the robot to answer unpolitely and to stop executing tasks. When the value of o is too low, then the robot will not react to any human mood. The facial expressions of the robot have already been defined and classified. The Care-O-Bot 4 library "*mimic*" provides these facial animations (Table 5).

The contextual affectation from the user $C_{user} \in \{-1,1\}$ is the connotation of the request, which is -1 when the request is unpolite and 1 when it is polite. The effect of C_{user} in a is given by:

$$a = \begin{cases} a + \lambda_3(1-a)o, & C_{user} > 0 \\ a - \lambda_4 a o, & C_{user} < 0 \end{cases} \tag{2}$$

The effect of C_{user} in n is given by:

$$n = \begin{cases} n - \lambda_5 n o, & C_{user} > 0 \\ n + \lambda_6(1-n)o, & C_{user} < 0 \end{cases} \tag{3}$$

The effect of C_{user} in the velocity of the gestures ges_{vel} is given by:

$$ges_{vel} = \begin{cases} (ges_{vel} - 1)n, & C_{user} > 0 \\ (2 - ges_{vel})n, & C_{user} < 0 \end{cases} \tag{4}$$

Algorithm 1 Behavior generator

```
input: ⟨o, c, ϵ, a, n⟩, ppa, pna, upa, una, ppe, pne, upe, une, r
Set attempts_max according to equation (1);
attempts ← 0;
if attempts <= attempts_max then
    Set threshold to a random number between 0 and 1;
    if threshold < a then
        Choose an answer from ppa and call speak_phrase(r);
        Set threshold to a random number between 0 and 1;
        if threshold < ϵ then
            Randomly pick a face from ppe and call set_face();
    else
        Choose an answer from upa and call speak_phrase(r);
        Set threshold to a random number between 0 and 1;
        if threshold < ϵ then
            Randomly pick a face from upe and call set_face();
else
    Set threshold to a random number between 0 and 1;
    if threshold < a then
        Choose an answer from pna and call speak_phrase(r);
        Set threshold to a random number between 0 and 1;
        if threshold < ϵ then
            Randomly pick a face from pne and call set_face();
    else
        Choose an answer from una and call speak_phrase(r)
        Set threshold to a random number between 0 and 1;
        if threshold < ϵ then
            Randomly pick a face from une and call set_face();
end if
attempts ← attempts + 1;
```

Algorithm 2 Contextual personality

```
input: A, ⟨o, c, ϵ, a, n⟩, δ
Initialize a buffer memory M^actions;
Calculate c_env according to equation (5);
a ← a + c_env;
c ← c + δ(1 − c)o;
ges_vel ← 1;
while human and robot interact do
    Get request;
    if request ∈ A then
        Set threshold to a random number between 0 and 1;
        if threshold < c then
            Get request connotation β;
            Set a according to equation (2);
            Set n according to equation (3);
            Set g_vel according to equation (4);
        Set threshold to a random number between 0 and 1;
        Call answer() function from request;
        if threshold ≤ c then
            Save request and return into M^actions;
end while
```

Where $\lambda \in (0,1)$. All λ values assist with the control of the effect of context over a and n. Algorithm 1 takes r, $\langle o, c, \epsilon, a, n \rangle$, ppa, pna, upa, una, ppe, pne, upe, une as inputs, where $r \in \{0,1\}$. The parameter r is 0 when a sole spoken answer is required and 1 when an action is required. Algorithm 1 indirectly reacts according to equations (2) to (4). Nevertheless, contextual effects come not only from the user but also from the environment. Given this, let c_{env} be the contextual effect from the environment given by:

$$c_{env} = \delta o(1 - a) \tag{5}$$

where $\delta \in (0\,,1)$ is the formality. When the robot is in an office environment, the formality increases, and when the robot is in a house environment, the formality decreases. Finally, let:

$$A = \{r_1, r_2, \ldots, r_i\} \tag{6}$$

be the set of all the *RequestReturn* instances that the robot can answer. Then, Algorithm 2 takes A, $\langle o, c, \epsilon, a, n \rangle$, δ as inputs. The purpose of the $M^{actions}$ buffer is to contain all the requests that the human user asks the robot. The size of $M^{actions}$ depends on the level of consciousness. An initial modification of a is also important, since the value of c_{env} is going to be higher or lower depending on the location of the robot. During the while loop, the robot dynamically receives requests from the human user, and depending on the human connotation of the requests, the value of its agreeableness will vary and modify the behavior of the robot. The rest of the elements of the synthetic genome remain invariable, which maintains the essence of the initial personality traits of the robot.

3. Validation

We used two scenarios for our experiments: the first scenario is a house environment and the second is an office environment. Furthermore, we set three synthetic genomes and provided the same set of requests to the robot. The set of requests is a sample of 20 questions from the Q&A data set and is repeated five times to assess the neuroticism of the robot and its sensibility to the user. The robot is supposed to change its behavior depending on the connotation of the user, the environment, and its own synthetic genome.

This section presents the results of implementing our method to modify the behavior of Care-O-Bot 4 in two domestic environments with different user inputs. The implementation of CSPR was done through Robot Operating System (ROS). Both algorithms were coded in Python and run as ROS nodes. Care-O-Bot 4 packages include *cob_scrip_server*, which is a ROS and Python compatible interface that allows the operation of the robot from code. This package provides control for the arms, torso, base, face animations and robot's voice of Care-O-Bot 4. For speech recognition we used the *speech-to-text Google API*. Finally, we used *flair* (a Python compatible library) to perform sentiment analysis on the answers of the robot.

3.1 Synthetic genomes

We defined three behaviors (friendly, detached, and hostile) whose synthetic genomes are shown in Table 6. The purpose of these synthetic genomes is to assess the behavior of the robot and its changes according to the environment and the user. With friendly behavior, Care-O-Bot 4 is expected to show good manners, depending on the context. Detached behavior may affect Care-O-Bot 4's level of perception of the environment, the user, and itself. Hostile synthetic genome values are selected to affect the patience of Care-O-Bot 4 and its agreeableness when answering requests.

Table 6. Synthetic genome example

Personality trait	Friendly	Detached	Hostile
Openness	1.0	0.5	0.4
Consciousness	0.9	0.1	1.0
Extraversion	0.8	0.5	1.0
Agreeableness	0.9	0.5	0.3
Neuroticism	0.1	0.5	0.9

3.2 CSBR test

To measure the change in the behavior of the robot according to the user connotation and the environment, we considered two scenarios for Care-O-Bot 4 and a human user. Figure 2.a shows an interval from 0 to 1 and was obtained from the sentiment analysis evaluation of *flair* to the answer of the robot, the closer to 0 the more negative the answer is. We took the value from the total interaction for every behavior. The friendly behavior of Care-O-Bot 4 achieved the highest values in the sentiment analysis results. Moreover, a friendly personality is also sensitive to an unpolite user, since there is a decrease in the sentiment analysis value. Detached behavior is shown to be less sensitive to the environment, since the level of consciousness is lower. A hostile personality produces a lower sentiment analysis score and is more sensitive to users. Even though the office environment influenced the robot's behavior, the robot tended to answer more unpolitely than the other two behaviors.

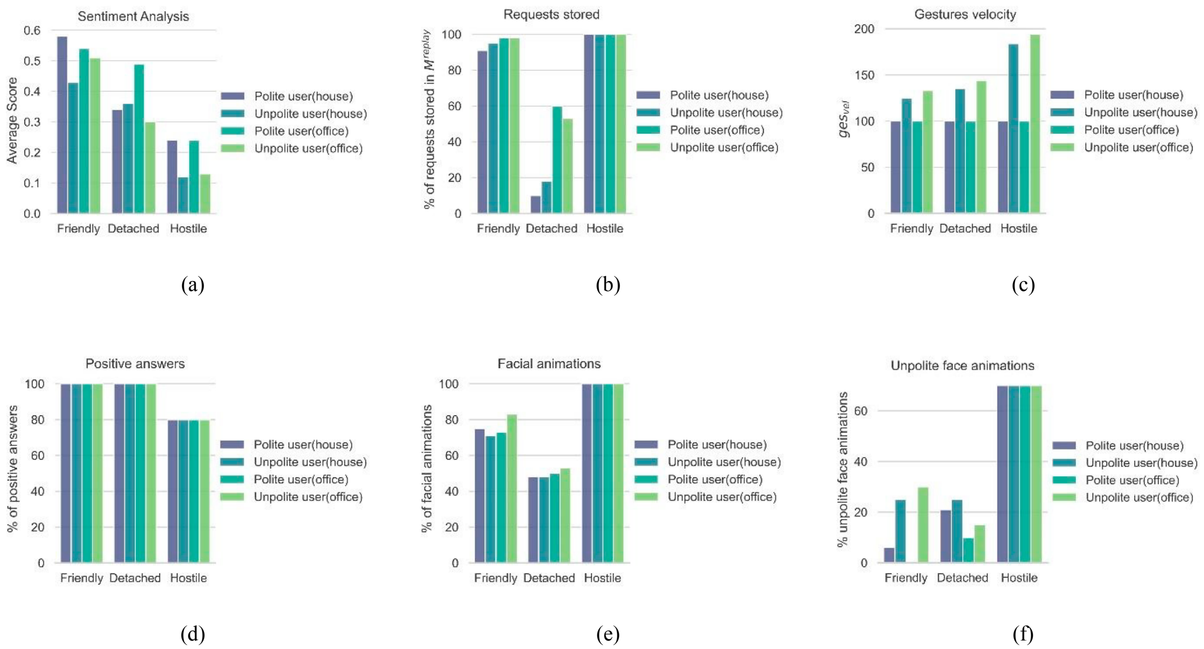


Fig. 2. All the subfigures show the results of different measurement parameters for three Care-O-Bot 4 behaviors: friendly, detached, and hostile. (a) shows the sentiment analysis results from flair regarding the answers of the robot. (b) shows the quantity of requests remembered by the robot, (c) shows the gesture velocity. (d) shows the quantity of positive answers. (e) shows the percentage of face animations compared to the total number of requests. (f) shows the percentage of unpolite face animations from the robot.

Figure 2.b shows the ratio of questions per stored *RequestReturn* request, which depends on consciousness. The higher the ratio, the more requests and answers the robot stored in its memory. Friendly behavior was shown to be coherent with its consciousness value, since during this experiment, the robot paid attention to a high percentage of the requests and stored them. The detached behavior results showed that the robot was not focusing enough and forgot most of the requests. Moreover, the detached personality was also shown to improve its consciousness when the environment was the office. The hostile behavior was also coherent with its consciousness and stored all the transitions.

Figure 2.c shows the increment of the gesture velocity according to the user connotation of the requests, as well as the environment. The gesture velocity value is 100 when the robot is relaxed and can increase till 200 when the robot is upset. For friendly behavior, the robot was shown to be neutral for polite users, but the interaction with an unpolite user made the robot increase the velocity of its gestures. Detached behavior was shown to cause the robot to avoid paying attention to the context, and the changes in velocity were less pronounced than in friendly behavior. Hostile behavior was shown to be the most sensitive to unpolite users. Since the level of neuroticism for hostile behavior is higher, its patience is lower, and the robot is more reactive to user unpoliteness. Figure 2.d shows the percentage of positive answers from the robot with respect to the requests of the user. Consequently, the higher the percentage, the more requests the robot accepted to perform. Friendly and detached behaviors responded positively to all the requests of the user, while hostile behavior answered positively to 80% of them. The hostile behavior is shown to be less patient and is also coherent with its level of neuroticism. The robot changed its behavior according to its own synthetic genome and the context of the two scenarios. All the behaviors tended to increase the score of sentiment analysis and

memory length when the environment was the office, and the robot tended to relax when the environment was the house. Moreover, the connotation of the human requests also changed the behavior of the robot and affected different measures in the responses of the robot. Friendly behavior was more patient and polite with the user, but still reacted to the unpoliteness of the human. Detached behavior was shown to be more attentive to its own synthetic genome than to the environment, and it increased its level of consciousness in an office environment. Hostile behavior tended to react conclusively and refused to answer positively to the user. Extraversion $\boldsymbol{\epsilon}$ is also an important characteristic that displays a clear message about the emotions of the robot. Figure 2.d shows that the frequency with which the Care-O-Bot displayed a facial animation is consistent with the value of the extraversion parameter $\boldsymbol{\epsilon}$ of every behavior. Figure 2.f shows the frequency with which Care-O-Bot exhibited more negative facial expressions. When the user was unpolite and when the value of $\boldsymbol{n}$ was high (hostile behavior), Care-O-Bot displayed more negative facial animations than friendly and detached behaviors. During the implementation of the scenarios, there were issues with speech recognition. Specifically, when the user tried to ask a question, the text output did not coincide with the speech input. Moreover, the presence of multiple speakers confuses the robot. Further improvements are also required to find similarities among a set of phrases with the same meaning. Finally, a larger data set is required to extend the knowledge of the robot and its capability to respond to a wide variety of situations (all these challenges will be further investigated in future developments).

Conclusions

This paper introduced a method to represent and dynamically change the behavior of robots based on the context of the location and mood of the user and the five traits of personality (OCEAN). Context-sensitive behaviors for robots offer significant research challenges and have the potential to enhance HRI. Our method showed the capacity to change the behavior of the robot according to the context of the situation and its own synthetic genome, which have significant contributions. CSBR is relevant for HRI since it allows robots to communicate and interact with people in a more human-friendly manner. In this work, we provided locational context with a house scenario and an office scenario, a set of questions with their contextual information attached (e.g., formal, informal), and three different behaviors (friendly, detached, and hostile). All the behaviors managed to adjust according to the context and the user mood, this is particularly relevant in the field of affective computing since we showed that CSBR can produce changes in the mood of the robot. In the future, we aim to develop methods to automatically extract contextual information from the users (e.g., mood, sentiment analysis, and gestures) and make it suitable for use with our method. We will explore more algorithms to classify information compatible to the structure of the Q&A data set utilized by CBRS. Since CBSR scalability relies in the content of the dataset, the implementation of algorithms to find similarities between a request and the content of the Q&A data set is also required.

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