IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received October 12, 2017, accepted November 19, 2017, date of publication November 27, 2017, date of current version December 22, 2017.

Digital Object Identifier 10.1109/ACCESS.2017.2777823

Enhancing User Satisfaction by Adapting Robot's Perception of Uncertain Information Based on Environment and User Feedback

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This work was supported by the University of Moratuwa under Senate Research Grant SRC/CAP/16/03.

ABSTRACT Assistive robots have been developed to improve the living standards of older people. These assistive robots are intended to be operated by non-expert users. Hence, they should have the ability to interact with humans in a human-friendly manner. Humans prefer to use voice instructions, responses, and suggestions in their daily interactions. Such voice instructions and responses often include uncertain terms and lexical symbols rather than precise quantitative values. Therefore, the ability of robots to understand uncertain information is a crucial factor in the implementation of human-friendly interactive features in robots. This paper proposes a novel method of adapting the perception of the uncertain spatial information contents of navigational commands, such as "far" and "little", based on environmental factors and user feedback. The proposed uncertain information understanding module has been implemented using fuzzy neural networks in such a way that the system can concurrently adapt to environmental factors while learning from user feedback. The proposed method has been implemented on the MIRob platform, and experiments have been conducted in an artificially created domestic environment to evaluate the performance and behaviors of the proposed concept. The experimental results validate the improvement of user satisfaction related to the understanding of uncertain information.

INDEX TERMS Uncertain information understanding, robot learning, human-robot interaction, human-friendly robot, assistive robots, human-centered robotics.

I. INTRODUCTION

The older population is growing considerably in every region of the world [1]. Most older people are incapable of performing their daily routines by themselves and require physical and cognitive assistance from caregivers. However, there is a shortage of such caregivers, and the gap between caregiver demand and supply is widening [2], [3]. This situation has profound implications for human socio-economic wellbeing.

Assistive robots are being developed to improve people's standards of living [4]–[7]. The attitudes and preferences of older adults regarding robot assistance with everyday tasks in domestic environments have been studied [8]–[10]. Older adults are generally open to robot assistance but show differences in their acceptance of assistance for different tasks. Nevertheless, robots can be used to provide both physical support and cognitive assistance to some extent [10], [11].

Assistive robots are intended to be operated in human working environments by non-expert users, and the assistive tasks for elderly/disabled persons include direct interaction between robot and user. Therefore, human-friendly robots that can engage in natural interaction with human peers are preferred for providing assistive services [12]–[14]. The ability to realize the idea of a perfect assistive robot obviously depends on the ability to achieve human-human-like interaction capabilities in human-robot interactions. In this context, intelligent service robots with some complex, human-like features have been developed to perform assistive tasks [15]–[19]. However, the present systems have some limitations, and the abilities of the existing robots are not sufficient to allow them to provide perfectly equivalent assistance to that which would be provided by a human caregiver.

Voice instructions are often used to convey information between peers in human-human interactions. Accordingly, the capability for human-like voice communication between robots and humans would enhance the overall interaction quality between robots and their users [20]. Systems equipped with human-like voice communication would be able to assist older/disabled people in a friendlier manner [21]. Typically, precise quantitative information is not conveyed through voice instructions, and such voice instructions tend to involuntarily contain imprecise and uncertain terms, lexical symbols and notions, which must be interpreted correctly for a command to be understood. As an example, humans tend to issue commands such as "move a little bit toward the TV" instead of "move 0.5 meters toward the TV". The actual quantitative meanings of uncertain terms such as "close", "near", "little", "far", "small", "large" and "few" are related to spatial information such as the size /length of an item and depend on the environment, the overall context and the perception of the user. Therefore, the ability of a robot assistant to interpret such uncertain information in voice commands and respond appropriately to those commands is crucial.

Various methods of controlling robots using natural language voice instructions with fuzzy implications have been developed [22]–[24]. However, these methods mainly focus on the handling of natural language commands rather than the effective interpretation of fuzzy implications, and the quantitative outputs for given fuzzy implications are predetermined. Some concepts have been introduced to enable the interpretation of fuzzy linguistic information in user commands based on the previous movements of a robot [25], [26]. Knowledge of the robot's previous movements is very useful for understanding the fuzzy linguistic information contained in user commands in a context-dependent manner. However, in these methods, the robot adapts its perception according to its own experience, and it does not obtain corrective measures from the user or the environment. Methods of adapting the perception of fuzzy linguistic information by evaluating feedback from the user have also been developed [27], [28]. However, when performing assistive tasks, robotic assistants need to operate in dynamically changing heterogeneous environments. Examples of such dynamic situations include moving from the living room to the kitchen and the user changing the arrangement of the objects on a table. The systems mentioned above do not acquire sensory inputs from the surrounding environment and cannot adapt their perception of uncertain information based on environmental factors. The previously developed concepts do not consider the operation of a robot in a dynamically changing environment, and the previous studies have been limited to the adaptation of the perception of fuzzy linguistic information based on user feedback. Moreover, the meanings of specific pieces of uncertain information are fixed after the end of the learning process. Therefore, these methods are not suitable for a mobile robot whose working environment is dynamic with respect to the robot itself.

The meaning of an uncertain term depends on the environment, and therefore, a robot needs to perceive its environment for effective interpretation. In this context, a method has been introduced in [29] for evaluating the crisp distance values corresponding to fuzzy implications in user commands based on the average distances to surrounding objects in the visual field. A method of qualitative spatial reasoning about positional information in a domestic environment has been introduced in [30]. It introduced the concept of scaling positional fuzzy sets based on a frame size, such as the size of a room. In the methods mentioned above, the perception of uncertain terms is adapted merely with respect to a single environmental factor. According to [31], the effectiveness of the interpretation of uncertain information can be improved by considering multiple environmental factors rather than a single factor. This concept has been implemented using a fuzzy inference system, which evaluates the spatial arrangement of a robot's surroundings by examining the available free space, the size of the room and the possible movement restrictions in the environment. Further improvements in interpretation capability have been achieved by introducing a Robot Experience Model (REM) to organize a robot's knowledge about its environment, actions and context [32]. Notably, the perception of uncertain terms varies from person to person. In real-world situations, peers mutually adapt to align with each other's perceptions. Therefore, robots must also be capable of this behavior to increase user satisfaction. However, the methods discussed above lack a means of adapting a robot's perception toward user expectations based on corrective measures received from the user.

This paper proposes a novel method of interpreting uncertain terms contained in navigational user commands based on the environment and prior experience. The main advantage of the proposed method over the existing systems is that the proposed system is capable of concurrently adapting to the environment while learning from user feedback. Section II presents a functional overview of the system. The user command understanding system is explained in section III. The details of the experiment and the corresponding results are discussed in section IV. Finally, a conclusion is presented in section V.

II. SYSTEM OVERVIEW

The overall structure of the proposed system is illustrated in Fig. 1. The system is capable of interacting with the user through voice communication and the actions of the robot. Voice commands are recognized and analyzed by the Voice Recognition and Understanding Module. Voice recognition is implemented using the Speech Recognition 3.1 library. Voice responses are generated by the Voice Response Generation Module, which is a text-to-speech converter implemented using the Microsoft Speech API. Basic dialogue and grammar patterns, keywords and lexical symbols are stored in the language memory. The interactions between the robot and the user are managed by the Interaction Management Module (IMM) in accordance with information retrieved from the Robot Experience Model (REM). The required set of actions for a particular interaction is determined by the IMM. Then, this required set of actions is executed by the Action Planning Module with the aid of the Action Knowledge Base and the Navigation Controller. The REM is a layered architecture that organizes the knowledge of the robot about its environment, actions, and context. In addition, the Action

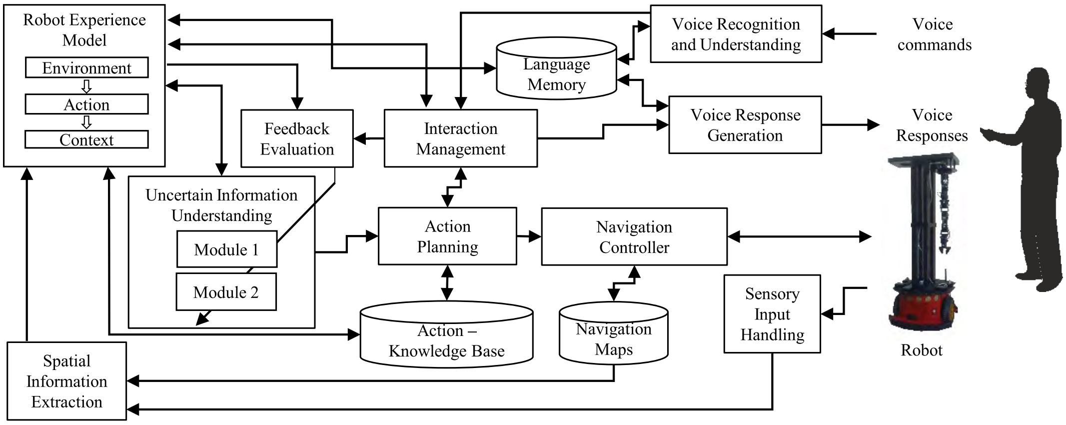

FIGURE 1. System overview.

Knowledge Base and the Language Memory are managed by the REM.

Quantitative distance values are assigned to uncertain terms contained in user commands through interpretation by the Uncertain Information Understanding Module (UIUM). This module consists of two independent submodules, which are used to interpret uncertainties related to motional and positional information separately; the required submodule is selected based on the robot's action. These submodules are capable of interpreting uncertain information based on the knowledge of the REM. These submodules are implemented using fuzzy neural networks to enable the learning ability of the UIUM based on error evaluations from user feedback. User feedback is identified by the IMM. The Feedback Evaluation Module (FEM) is deployed to generate a quantitative error value for a particular instance of user feedback following a robot action based on the knowledge of the REM.

The low-level control functionalities of the robot are handled by the Navigation Controller. It is capable of navigating and path planning from an initial position to a goal position while avoiding obstacles in the environment. The required navigation maps are created using the Mapper3Basic software application. The Sensory Input Handling Module (SIHM) is used to retrieve information from the robot's built-in sensors, such as sonar sensors. The Spatial Information Extraction Module (SIEM) perceives spatial information about the environment by extracting information from the navigational maps and from the information retrieved by the SIHM. Then, the perceived spatial information is sent to the REM.

III. USER COMMAND EVALUATION

A. COMMAND AND ROBOT ACTION IDENTIFICATION

Navigational user commands can be classified into two main categories [32]: motional commands and positional commands. A motional command is used to move a robot in a desired direction, without mention of a reference position. A positional command is used to move the robot to a desired position. "Move a little toward the table" and "Move near to the table" can be regarded as examples of a motional command and a positional command, respectively.

TABLE 1. Example user commands and corresponding robot actions.

User Command	Command Description	Required Robot Action(s)
1. Move a little forward 2. Go far to the right	Motional	Type I
3. Move a little toward the TV 4. Move a little in the direction of the table	Motional	Type II
5. Go near to the TV 6. Move near to the table in the kitchen	Positional	If same room, Type III; Otherwise, Types IV & III
7. Go to the office	Positional	Type IV
8. Go near to the bed in the office (no bed in the office)	Erroneous or Ambiguous	Type V (voice response)
9. Too little (after action I or II) 10. Too far (after action III)	Feedback	Type VI (learning)

The motion direction of a motional navigation command can be given directly with respect to the robot or with respect to a reference point in the surroundings. For simplicity of the implementation of the command identification process, it is assumed that motional commands can be classified into two types based on the manner in which the direction is given. If the direction is given directly with respect to the robot, the possible directions are assumed to be "left", "right", "forward" and "backward". Commands 1 and 2 in Table 1 are examples of such commands. In commands of this type, the distance that must be traveled by the robot is expressed by means of an uncertain term such as "little" or "far". The robot needs to assign a quantitative value to this uncertain term and then move the corresponding quantitative distance in the given direction. Robot action type I is defined for the execution of commands of this kind. For a direction that is given with respect to a reference point, such as the location of an object in the surrounding environment, it is assumed that such commands will contain direction-related keywords such as "toward" and "direction of". Commands 3 and 4 in Table 1 are examples of such commands. To satisfy a command of this type, the robot first needs to identify the reference object. The environmental knowledge layer of the REM is used to identify the reference object and its location (see section III-B). Subsequently, the robot needs to assign a quantitative distance to the uncertain term in the command and then move the corresponding distance. Robot action type II is defined for the execution of such tasks.

When executing a positional command, the robot first needs to identify the reference object and its location. Commands 5 and 6 in Table 1 are examples of commands of this kind. In this scenario, the robot needs to move to a position that is uncertain because of the uncertainty in interpreting terms such as "near" and "close". Therefore, the robot needs to assign a reasonable quantitative value to the uncertain term and then move to a position at the corresponding distance from the reference point. Robot action type III is defined for executing such tasks. However, there are situations in which the reference object is in another room and the robot needs to move from the current room to that of the reference object. Robot action type IV is defined for room-to-room navigation. Thus, the robot needs to first perform a type IV action to move to the room where the reference object is located and then perform a type III action. Positional commands also encompass room-to-room navigation commands (e.g., command 7), in which case it is assumed that there are no uncertain terms to interpret; the robot simply moves from the current room to the stated room. Robot action type IV is used for this task.

A user command may be erroneous or ambiguous depending on the arrangement of the environment or the situation. In such a case, the robot uses voice responses to ask for further information or notify the user about the situation. Robot action type V is defined for actions in which only voice interactions are involved. The learning action is defined as robot action Type VI. User responses such as "too little", "too far" and "too close" are treated as feedback; if such feedback is received, then the robot performs a type VI action to adapt its perception (see section III-D). Examples of user commands and the corresponding robot actions for the possible cases are given in Table 1.

The implemented method of identifying user commands and actions is similar to the method used in [32], with modifications for identifying user feedback and performing the learning action. User commands are identified by analyzing the received voice commands using the keywords, basic grammar components and lexical symbols that are available in the language memory. Subsequently, the required actions for a particular command are identified based on the knowledge of the REM. This approach allows the user to issue commands that are not bounded by a strict grammar model. However, assumptions have been made in implementing the command identification process; this usage of assumptions is considered to be valid since the main contribution of the research is the development of a novel method of interpreting uncertain information.

B. ROBOT EXPERIENCE MODEL (REM)

The Robot Experience Model (REM) [32], [33] is used to organize the robot's knowledge of its environment, actions and context. It is separated into three layers for knowledge representation, namely, the environment layer, the robot action layer and the context layer. The context layer of the REM is intended for future developments; it is currently inactive.

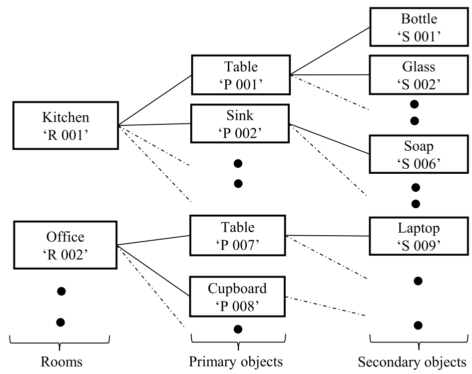

FIGURE 2. **Hierarchical tree structure of the environment layer of the REM.**

The knowledge of the robot about its working environment is stored in the environment layer in a hierarchical tree structure, as shown in Fig. 2. This enables the robot to organize its knowledge about heterogeneous domestic domains in a constructive manner such that it can be utilized for high-level decision-making. Knowledge about the rooms in the domestic environment is represented in the top sublayer. The next sublayer contains knowledge about the primary objects located inside the rooms represented in the top layer. The bottom sublayer contains knowledge about secondary objects that are often located on top of primary objects. The knowledge stored in the environment layer is used to identify the object of interest referenced in a particular user command. The characteristics of the object of interest and the room of interest can be retrieved from this layer to interpret uncertain information. In addition, this enables the IMM module to detect inaccurate user commands that do not comply with the environment and to subsequently generate responses to them. The environment layer of the REM is updated in accordance with navigational maps, sensory inputs and knowledge acquired through interactive discussions in a manner similar to that described in [33].

The robot action layer represents the robot's knowledge of its actions. The action layer has been improved to better organize parameters related to the previous actions of the robot. Consequently, the improved action layer can be used to retrieve information on previously performed actions during execution of an interaction with a user. In addition, the knowledge stored in the robot action layer is used to identify the required set of actions for satisfying a particular user command based on the information in the environment layer.

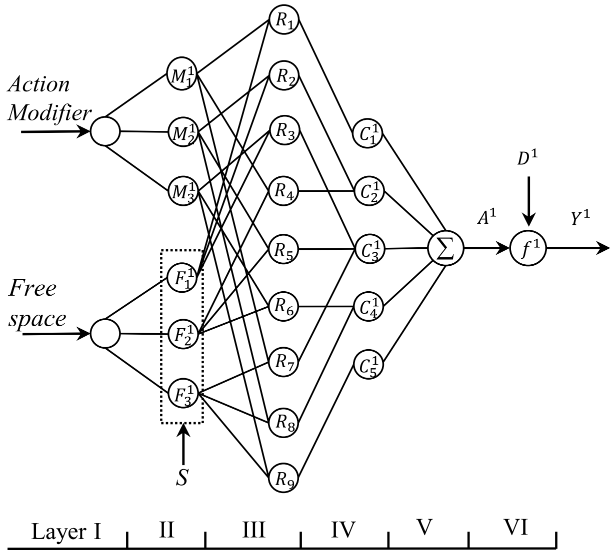

FIGURE 3. Structure of submodule 1 of the UIUM. The fuzzy neural network consists of 6 layers. The action modifier and the available free space are the inputs to the network. The membership functions for the free space are adjusted according to the room size (S). Therefore, the nodes that represent the free-space membership functions, which are bounded by a dotted line, take S as an input. The activation transfer function f^1 depends on the perceptive distance D^1.

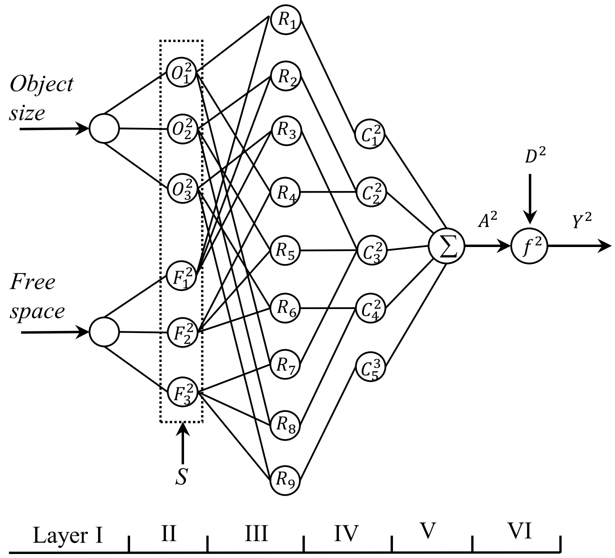

FIGURE 4. Structure of submodule 2 of the UIUM. The fuzzy neural network consists of 6 layers. The size of the object of interest and the available free space are the inputs to the network. The membership functions for the size of the object of interest and the free space are both adjusted according to the room size (S). Therefore, the nodes that represent the input membership functions, which are bounded by a dotted line, take S as an input. The activation transfer function f^2 is adjusted according to the perceptive distance D^2.

C. UNCERTAIN INFORMATION UNDERSTANDING MODULE (UIUM)

The Uncertain Information Understanding Module (UIUM) is used to assign quantitative values to uncertain terms such as "far", "close" and "little" in user commands. The perception of uncertain terms strongly depends on the spatial information of the surrounding environment. In addition, the perception of uncertain terms varies with the expectations of the user. Therefore, the UIUM must be implemented such that it can learn from user feedback to adjust its perception to match the expectations of the user in addition to adapting to knowledge about the environment. Systems based on fuzzy logic and fuzzy neural networks are often used to understand the meaning of natural language user commands [34]. However, the existing systems cannot concurrently adapt to both the spatial information about the environment perceived from sensory information and the corrective feedback received from the user. Therefore, the UIUM is implemented with fuzzy neural networks that can perceive the environment by means of spatial information inputs while concurrently learning from user feedback. Two independent fuzzy neural networks have been developed for the separate interpretation of uncertain terms related to motional and positional information. Submodule 1 is used to interpret distance-related uncertain terms in motional commands, i.e., when executing a robot action of type I or II. Submodule 2 is used to interpret uncertainties related to positional information in user commands; therefore, it is used when executing type III robot actions. The structures of submodules 1 and 2 are shown in Fig. 3 and Fig. 4, respectively.

Layer I of each submodule is the input layer, and it contains two types of nodes for acquiring inputs: for the 1st submodule, these nodes correspond to the action modifier in the user command and the free space available in the environment, and for the 2nd submodule, they correspond to the size of the object of interest and the available free space. The neurons in this layer transmit external input signals directly to layer II, which is the fuzzification layer. The neurons in this layer represent fuzzy sets used in the antecedents of fuzzy rules for the action modifier and the free space. The membership functions for the free space and size of the object of interest are adjusted according to the size of the occupied room (S). The size of the room, the available free space and the size of the object of interest can all be retrieved from the knowledge contained in the environment layer of the REM. Layer III is the fuzzy rule layer. Each neuron in this layer corresponds to a single fuzzy rule. A fuzzy rule neuron receives inputs from the fuzzification neurons that represent the fuzzy sets in the antecedents of the corresponding rule. The algebraic product operator is used as the T-norm fuzzy operator; hence, the output of a neuron in this layer is the algebraic product of the incoming signals. Layer IV is the output membership layer. The neurons in this layer represent the fuzzy sets used in the consequents of the fuzzy rules, and an output membership neuron combines all of its inputs using the fuzzy union operator. Any node C_i^k in the k^{th} submodule, where $i = 1, \ldots, 5$, represents a triangular membership function with a center of $a_i^k \epsilon [(a_i^k)_L, (a_i^k)_H]$ and a width of $b_i^k \epsilon [(b_i^k)_L, (b_i^k)_H]$.

Layer V is the defuzzification layer. It takes the output fuzzy sets clipped by the respective integrated firing strengths

FIGURE 5. D_r **and** D_{obj} **are explained in this figure. The robot is to move in the direction indicated by the white arrow. The distance from the robot to the nearest obstacle or the object of interest is denoted by** D_r**. The distance between the object of interest and the closest nearby object in the approach direction is denoted by** D_{obj}**.**

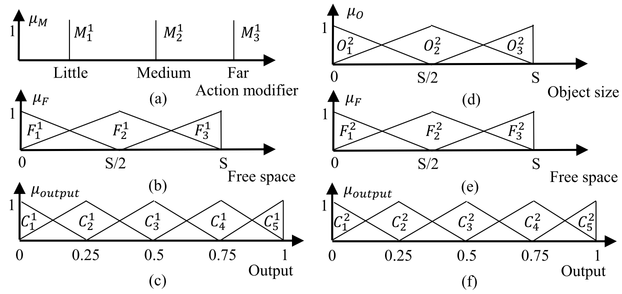

FIGURE 6. (a) represents the input membership functions for the action modifiers. It has singleton membership functions labeled as M_1^1**,** M_2^1 **and** M_3^1 **for the action modifiers "little", "medium" and "far", respectively. (b) represents the input membership functions for the free space. It has triangular membership functions labeled as** F_1^1**,** F_2^1 **and** F_3^1**, which are adjusted according to the size of the room (**S**). (c) represents the initial membership functions for the output of submodule 1. (d) represents the input membership functions for the size of the object of interest. It has triangular membership functions labeled as** O_1^2**,** O_2^2 **and** O_3^2**. (e) represents the input membership functions for the free space. It has triangular membership functions labeled as** F_1^2**,** F_2^2 **and** F_3^2**. These input membership functions are adjusted according to the size of the room (**S**). (f) represents the initial membership functions for the output of submodule 2.**

and combines them into a single fuzzy set. The sum-product composition method can be used to simulate the center-of-area method of defuzzification for a Mamdani fuzzy system [35], and the defuzzification output is obtained from (1), where A^k is the output of layer V of the k^{th} submodule and μ_i^k is the integrated firing strength of the i^{th} output fuzzy set of the k^{th} submodule.

$$A^k = \frac{\sum_{i=1}^{5} a_i^k b_i^k \mu_i^k}{\sum_{i=1}^{5} b_i^k \mu_i^k} \tag{1}$$

Layer VI of each submodule consists of an activation transfer function that is used to scale the output. The transfer functions are given in (2), where Y^k is the output distance of the system, d_0 is the clearance of the robot, and the perceptive distance D^k is given in (3), where D_r is the distance from the robot to the object of interest or the nearest obstacle in the direction of its motion and D_{obj} is the distance between the object of interest and any other nearby object in the approach direction of the robot (as illustrated in Fig. 5). The free space, the size of the object of interest, the room size, D_r and D_{obj} are all obtained from the environment layer of the REM based on sonar sensor readings and navigation maps.

$$Y^k = \begin{cases} (D^k - d_0)A^k & \text{if } k = 1 \\ (D^k - d_0)A^k + d_0 & \text{if } k = 2 \end{cases} \tag{2}$$

$$D^k = \begin{cases} D_r & \text{if } k = 1 \\ \frac{1}{2}[min(D_r, D_{obj})] & \text{if } k = 2 \end{cases} \tag{3}$$

The initial membership functions for submodules 1 and 2 are defined similarly to the membership functions for the system proposed in [32] and are shown in Fig. 6. The initial membership functions for the output distance determine the initial connection weights of layer V, which are then adjusted based on user feedback using a backpropagation algorithm. The Feedback Evaluation Module (FEM) is used to evaluate the normalized distance error ($\hat{e}$) of a particular movement by evaluating the user feedback given immediately after the robot performs an action of type I, II or III. The submodule that needs to be adjusted is chosen based on the robot action executed immediately before the feedback is received. If the previous action is an action of type I or II, then submodule 1 will be adjusted; if the previous action is a type III action, then submodule 2 will be adjusted. The robot action layer of the REM is used to identify the previous action. Then, membership parameter training (corresponding to network weight training) is performed for the i^{th} node of the k^{th} submodule with the execution of the $(t+1)^{\text{th}}$ action, as given in (4) and (5), where the $(t+1)^{\text{th}}$ action is a learning action, i.e., a type VI robot action. Here, η^k is the learning rate, and δ_a^k and δ_b^k are scalar constants that are used to maintain the variations of the parameters within the desirable ranges during the learning phase. If no feedback is given, then the weights are not adjusted.

$$a_i^k(t+1) = \begin{cases} a_i^k(t) + \eta^k \delta_a^k \hat{e} \mu_i^k & \text{if } a_i^k(t+1) \\ & \quad \epsilon[(a_i^k)_L, (a_i^k)_H] \\ a_i^k(t) & \text{otherwise} \end{cases} \tag{4}$$

$$b_i^k(t+1) = \begin{cases} b_i^k(t) + \eta^k \delta_b^k \hat{e} \mu_i^k & \text{if } b_i^k(t+1) \\ & \quad \epsilon[(b_i^k)_L, (b_i^k)_H] \\ b_i^k(t) & \text{otherwise} \end{cases} \tag{5}$$

D. FEEDBACK EVALUATION

Voice feedback includes directives from the user to modify the perception of the robot concerning uncertain terms. As an example, suppose that immediately after the robot has executed a type I action in response to a particular user command, the user issues a feedback statement of "too little". The user feedback "too little" indicates that the distance moved by the robot in response to the corresponding user command is less than the user expected. Furthermore, it conveys the intent of the user to adapt the system to generate a greater output distance on similar occasions in the future. Therefore, the robot should be able to extract the required degree of adjustment to adapt its perception to the user's expectation. However, such feedback statements do not contain precise quantitative values. Therefore, the quantitative meaning of a particular feedback statement must be evaluated to judge the required adjustment.

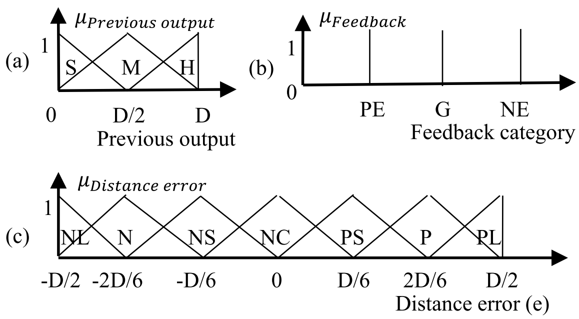

FIGURE 7. (a) represents the input membership functions for the previous output. It has 3 triangular fuzzy sets, labeled as S: Small, M: Medium and H: High. (b) represents the input membership functions for feedback terms. It has 3 singleton fuzzy sets, labeled as PE: Positive Error, G: Good and NE: Negative Error. (c) represents the output membership functions for the distance error. It has 7 triangular membership functions, labeled as NL: Negative Large, N: Negative, NS: Negative Small, NC: No Change, PS: Positive Small, P: Positive and PL: Positive Large. The membership functions for the previous output and the distance error are adjusted according to *D*.

TABLE 2. Rule base of the fuzzy inference system for feedback evaluation.

Input Memberships		Previous output		
		S	M	H
Feedback term	PE	PS	P	PL
	G	NC	NC	NC
	NE	NS	N	NL

The Feedback Evaluation Module (FEM) is implemented using a fuzzy inference system to assign a quantitative distance error (e) to a particular instance of feedback. It is assumed that the quantitative meaning of a feedback term depends on the user's observation, i.e., the immediately preceding action of the robot. Therefore, the previous output and the user feedback term are used as the inputs to the system. The output of the system is the evaluated distance error (e) corresponding to an instance of feedback on a particular robot action. The input and output membership functions of the system are shown in Fig. 7. The rule base of the system is shown in Table 2. Three singleton fuzzy sets, namely, Positive Error (PE), Negative Error (NE) and Good (G), are defined as the membership functions for the feedback term. It is assumed that the user feedback will take different forms when feedback is given for different types of robot actions. For robot action types I and II, the possible feedback statements are assumed to be "too little", "too much" and "good", and for robot action type III, the possible feedback statements are assumed to be "too close", "too far" and "good". The mapping between the actual voice feedback statements and the feedback terms in the input membership functions is given in Table 3. The membership functions for the previous output and the distance error are adjusted according to D, where D is the maximum possible output for the particular robot action corresponding to the feedback. D is given in (6). The previous output ($Y^k(t)$) and the corresponding $D^k(t)$ are obtained from the knowledge stored in the action layer of the REM when the $(t+1)^{\text{th}}$ action is the corresponding learning action (i.e., a robot action of type VI). The normalized distance error ($\hat{e}$) can be obtained from (7).

TABLE 3. Mapping of user feedback terms.

User feedback		Mapped feedback term
For a type I or II robot action	For a type III robot action	
Too little	Too close	PE
Good	Good	G
Too much	Too far	NE

$$D = \begin{cases} D^k(t) - d_0 \mid k = 1 & \text{when the } t^{\text{th}} \text{ action is} \\ & \quad \text{a type I or II robot action} \\ D^k(t) \mid k = 2 & \text{when the } t^{\text{th}} \text{ action is} \\ & \quad \text{a type III robot action} \end{cases} \tag{6}$$

$$\hat{e} = \frac{e}{D} \tag{7}$$

IV. RESULTS AND DISCUSSION

A. EXPERIMENTAL SETUP

The proposed concept has been implemented on the MIRob platform [33], and a user study has been conducted in an artificially created domestic environment inside the research facility to validate the performance gain of the proposed method over the existing systems. The experimental environment consisted of three rooms, namely "Kitchen", "Corridor" and "Office". These three rooms differed in their characteristics, such as room size, free space and object arrangement. The room names and the objects present during the experiment are annotated on the map shown in Fig. 8.

To evaluate the performance of the system, a parameter called the "satisfactory level" [28] is used; the definition of the "satisfactory level" (SL_{N_A}) is given in (8), where N_{FG} is the number of feedback instances of "good" type received following the execution of N_A previous movement-related user instructions. It should be noted that if feedback is not given for a particular action, it is assumed to be "good".

$$SL_{N_A} = \frac{N_{FG}}{N_A} \tag{8}$$

During the experiment, the parameters related to learning were chosen to be $\eta^k = 0.1$, $\delta_a^k = 5$ and $\delta_b^k = 3$ for $k = 1$ and 2. The definitions of the lower and upper bounds on the centers $((a_i^k)_L, (a_i^k)_H)$ and widths $((b_i^k)_L, (b_i^k)_H)$ of the output

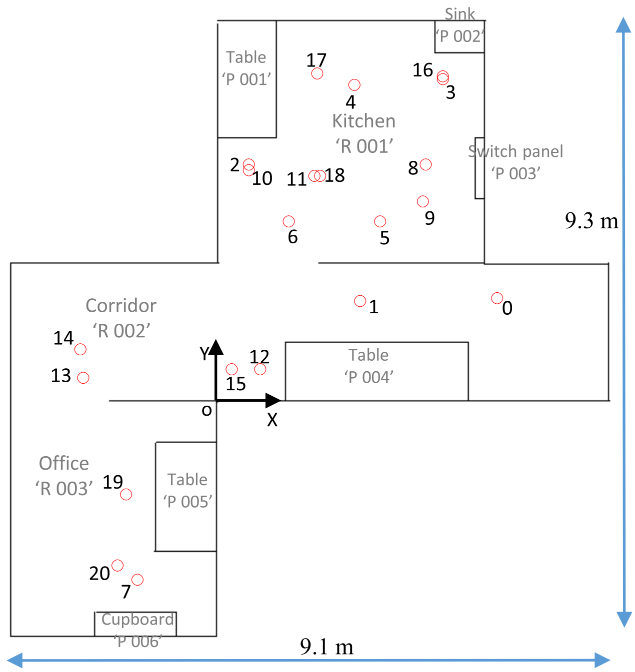

FIGURE 8. **The positions of the robot after executing the user instructions listed in Table IV are marked on the map with the corresponding command numbers. The map is drawn to scale. However, it should be noted that the markers are not drawn to scale and do not reflect the actual size of the robot.**

membership functions are given in (9), (10), (11) and (12), respectively.

$$(a_i^k)_L = \begin{cases} 0 & \text{if } i = 1 \\ a_{i-1}^k(0) & \text{otherwise} \end{cases} \tag{9}$$

$$(a_i^k)_H = \begin{cases} a_{i+1}^k(0) & \text{if } i = 1, 2, 3, 4 \\ 1.0 & \text{otherwise} \end{cases} \tag{10}$$

$$(b_i^k)_L = \frac{b_i^k(0)}{2} \tag{11}$$

$$(b_i^k)_H = \frac{3b_i^k(0)}{2} \tag{12}$$

B. EXPERIMENT AND RESULTS

Since user studies are highly subjective in nature, the user study performed to validate the performance of the proposed method was designed and conducted with due attention to the recommendations given in [36] for designing, planning and executing human studies of human-robot interaction.

The user study was conducted with 24 participants (male = 15, female = 9) between 22 and 67 years of age (mean = 34.6, SD = 15.4). At the start of the experiment, the subjects were instructed on the possible structures of the navigation commands that could be understood by the robot. Subsequently, they were asked to freely navigate the robot such that the robot's movements would cover the entire environment. This decision was made since asking users to navigate a robot using a predefined set of commands or along a predefined path is highly restrictive for users, and consequently, the resulting behavior may not reflect actual user desires. Furthermore, this approach ensures that the intentions of the users are solely related to navigation, without any intent to perform any other task (e.g., placing/picking up an object on a table), which may influence the characteristics of the desired movement. The initial position of the robot was not fixed; instead, the initial position was selected randomly for each run. The users were also asked to follow the robot such that they could visually observe the movements of the robot and the environment. A few snapshots taken during the experiment are shown in Fig. 9. The users were advised to issue voice feedback about the movements of the robot (considering only the quantitative distances corresponding to the uncertain terms in the user commands) when it was necessary. To increase the voice recognition accuracy, a wireless headset with a microphone was provided to each user for issuing voice commands.

FIGURE 9. **Snapshots of MIRob taken during the experiment are shown here.**

Humans have great adaptive capabilities, and during experiments, users may adapt to the behavior of robots. Therefore, to rectify the bias due to this adaptation, the participants were divided into two groups, each comprising 12 participants. In the first part of the experiment, the concept proposed in this paper was implemented in the robot. Each user in the first group was taken individually to conduct the experiment. Subsequently, the learning ability of the system was disabled, and the abilities of the system were modified to be similar to those of the system explained in [32]. Then, the users in the second group were taken in for the study. Afterward, the users in the first group were taken in to conduct the study again

TABLE 4. Example results for the system with the learning ability.

	User command	k	AM or OS (m^2)	Room size (m^2)	Free space (m^2)	D^k (cm)	Y^k (cm)	Destination position X	Y	θ	Feedback	e (cm)	SL_{10}
1	Move a little forward	1	little	18.85	16.33	500	204	217	146	-178	too much	-143	-
2	Move near to the table in the kitchen	2	1.62	15.08	12.95	65	46	46	355	90	-	-	-
3	Move near to the sink	2	0.379	15.08	12.95	65	44	341	486	90	too far	-22	-
4	Move a medium distance toward the table	1	medium	15.08	12.95	250	145	205	479	-179	-	-	-
5	Move far to the left	1	far	15.08	12.95	294	223	245	268	-78	-	-	-
6	Move right	1	medium	15.08	12.95	236	136	106	270	-175	too much	-70	-
7	Move near to the cupboard	2	0.652	11.5	9.27	47	36	-122	-279	-90	too close	17	-
8	Move near to the switch panel	2	0.138	15.08	12.95	165	79	315	357	0	too far	-53	-
9	Move a medium distance to the right	1	medium	15.08	12.95	163	73	310	299	-93	-	-	-
10	Move near to the table	2	1.62	15.08	12.95	97	56	46	345	90	-	-	0.5
11	Move a little right	1	little	15.08	12.95	347	95	146	337	-1	too much	-83	0.5
12	Move near to the table in the corridor	2	2.52	18.85	16.33	58	42	63	45	0	-	-	0.5
13	Move far backward	1	far	18.85	16.33	370	274	-207	32	-177	too little	124	0.5
14	Move a little right	1	little	18.85	16.33	175	42	-212	76	92	-	-	0.5
15	Move near to the table	2	2.52	18.85	16.33	160	87	18	45	0	too far	-53	0.4
16	Move near to the sink	2	0.379	15.08	12.95	65	41	341	489	90	too far	-22	0.4
17	Move near to the table	2	1.62	15.08	12.95	120	60	150	494	180	-	-	0.5
18	Move a medium distance to the left	1	medium	15.08	12.95	284	152	156	340	-89	-	-	0.6
19	Move near to the office table	2	1.56	11.5	9.27	85	48	-142	-148	0	too far	-28	0.5
20	Move far to the right	1	far	11.5	9.27	158	103	-153	-256	-97	-	-	0.5

using the system with no learning ability, since there was a considerable time gap that should have allowed the adaptation of the users toward the robot to fade. Finally, the users in the second group were taken in to conduct the study again using the system with the learning ability.

The number of interactions with the robot (navigation commands only) was limited to 50 per user. This value was chosen because the satisfactory level reaches saturation before that point. The robot's movements and the parameters related to the UIUM for the first 20 commands issued by a randomly chosen user when interacting with the system with the learning ability are given in Table 4. The corresponding positions of the robot after executing each user command are annotated with the corresponding command numbers on the map shown in Fig. 8.

In this run, the robot was initially placed at location '0' on the map ($X = 421$, $Y = 154$, $\theta = -178$). Then, the robot was commanded to "move a little forward" by the user. This is a motional command, and the quantitative distance value for the uncertain term "little" was interpreted to be 204 cm by submodule 1 of the UIUM. Therefore, the robot moved to location '1' by performing a type I robot action to fulfill the user command. However, the distance moved (i.e., the interpreted quantitative value for the term "little") was larger than the distance expected by the user, and therefore, the user gave the feedback "too much" to the system. Therefore, the robot performed a type VI robot action to learn from this feedback, and the FEM evaluated a quantitative error value for the feedback term (i.e., e). As a result of this user critique, the parameters of the output membership functions of submodule 1 of the UIUM were modified to the values given in the 2^{nd} row (command no. 1) of Table V. Then, as the 2^{nd} user command, the robot was commanded to "move near to the table in the kitchen". This is a positional command, and the quantitative distance value for the uncertain term "near" was interpreted to be 46 cm by submodule 2 of the UIUM. Therefore, the robot moved to location '2', at the corresponding distance from the table in the kitchen ('P 001'), by performing a type IV action (to move to the kitchen, 'R 001') followed by a type III action. In this case, the distance interpreted by the robot was accepted by the user, and therefore, no feedback was given to modify the robot's perception. Then, the robot was commanded to "move near to the sink". In this case, the distance assigned to the term "near" by the robot was 44 cm, and the robot moved to location '3'. The position reached by the robot was deemed to be "too far" from the sink ('P 002') according to the user's expectation. Therefore, the parameters of the output membership functions of submodule 2 of the UIUM were modified to the values given in the 3^{rd} row (command no. 3) of Table V by means of a type VI robot action. Similarly, a total of 50 navigation commands were issued by the user, and the variations in the parameters of the UIUM corresponding to the commands listed in Table IV are given in Table V. The observed modification of the parameters of the output membership functions of the UIUM confirms that the system

TABLE 5. Variations in the parameters of the output membership functions with the user instructions given in Table IV.

Command number	k (submodule)	a_1^k	a_2^k	a_3^k	a_4^k	a_5^k	b_1^k	b_2^k	b_3^k	b_4^k	b_5^k
Initial	1 and 2	0.0833	0.2500	0.5000	0.7500	0.9167	0.2500	0.5000	0.5000	0.5000	0.2500
1	1	0.0833	0.2093	0.3885	0.7500	0.9167	0.2500	0.4756	0.4331	0.5000	0.2500
3	2	0.0833	0.2017	0.3773	0.7414	0.9167	0.2500	0.4710	0.4264	0.4948	0.2500
6	1	0.0833	0.2093	0.3403	0.6277	0.9167	0.2500	0.4756	0.4042	0.4266	0.2500
7	2	0.0833	0.2702	0.4854	0.7614	0.9167	0.2500	0.5121	0.4912	0.5069	0.2500
8	2	0.0833	0.2247	0.3698	0.7585	0.9167	0.2500	0.4848	0.4219	0.5051	0.2500
11	1	0.0833	0.1722	0.3403	0.6277	0.9167	0.2500	0.4533	0.3476	0.4266	0.2500
13	1	0.0833	0.1722	0.3403	0.6763	0.9167	0.2500	0.4533	0.3476	0.4558	0.3299
15	2	0.0833	0.1801	0.3698	0.7139	0.9167	0.2500	0.4580	0.3486	0.4783	0.2500
16	2	0.0833	0.1324	0.3698	0.7054	0.9167	0.2500	0.4294	0.2759	0.4732	0.2500
19	2	0.0833	0.1324	0.2674	0.6600	0.9167	0.2500	0.3905	0.2759	0.4460	0.2500

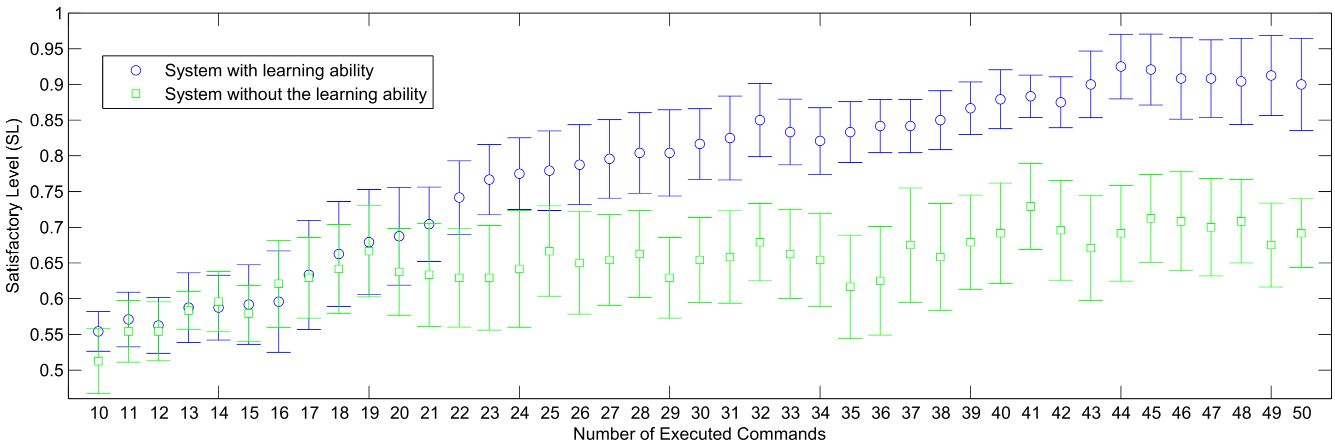

FIGURE 10. This plot shows the variations in the SL_{10} values of the system with the learning ability and the system with no learning ability. The markers represent the mean values, and the error bars represent the 95% confidence intervals (CIs) for the means based on a t-distribution.

is capable of modifying its perception of uncertain information based on user feedback. The satisfactory level (SL) was calculated based on the 10 previous states, and the variation in the SL_{10} value is given for the 10$^{\text{th}}$ user command onward in Table IV. Another similar experimental run was performed by the same user after the learning ability of the system had been disabled (i.e., the system was similar to that described in [32]). In this case, the parameters of the output membership functions of the UIUM were not modified in response to the feedback from the user and instead remained constant at their initial values.

Similar experimental runs were conducted using the system with the learning ability (i.e., the system proposed in this paper) and the system with no learning ability (i.e., similar to the system proposed in [32]) by all 24 participants. The variations in the SL_{10} values with the number of executed commands for both systems were calculated for all users. The variations in the mean SL_{10} values with error bars are shown in Fig. 10. The error bars represent the 95% confidence intervals (CIs) with respect to the mean values. The variations in SL_{10} for all users are also shown as box plots in Fig. 11 for better visualization of the results.

In the initial stage (after execution of the 10$^{\text{th}}$ user command), both systems exhibit rather low mean satisfactory levels (0.5542 for the system with the learning ability and 0.5125 for the system with no learning ability), and up to the 22$^{\text{nd}}$ user command, the difference between the two means is not statistically significant ($P \geq 0.05$) according to the t-test. Furthermore, the differences between the means for the two systems are very small, and in some situations, they overlap. The variations of the medians also exhibit similar characteristics. Therefore, it can be concluded that there was no initial prejudice in the users' evaluations of the two systems due to their adaptation toward the system in earlier runs.

The satisfactory level of the system proposed in this paper (i.e., the system with the learning ability) increased gradually over time, and finally, the mean of SL_{10} settled at approximately 0.9 (after the 46$^{\text{th}}$ command, $SL_{10} = 0.9083$; after the 47$^{\text{th}}$, $SL_{10} = 0.9083$; after the 48$^{\text{th}}$, $SL_{10} = 0.9042$; after the 49$^{\text{th}}$, $SL_{10} = 0.9125$; and after the 50$^{\text{th}}$, $SL_{10} = 0.9000$). Therefore, the learning ability of the system facilitates the adaptation of its perception of uncertain information to match the perception of the user. Hence, in this experiment, user satisfaction increased with successive interactions. Meanwhile, the satisfactory level of the system with no learning ability was also increased at the end of the experiment compared with the initial stage (initially, after the 10$^{\text{th}}$ user command, $SL_{10} = 0.5125$; after the 50$^{\text{th}}$ command, $SL_{10} = 0.6917$).

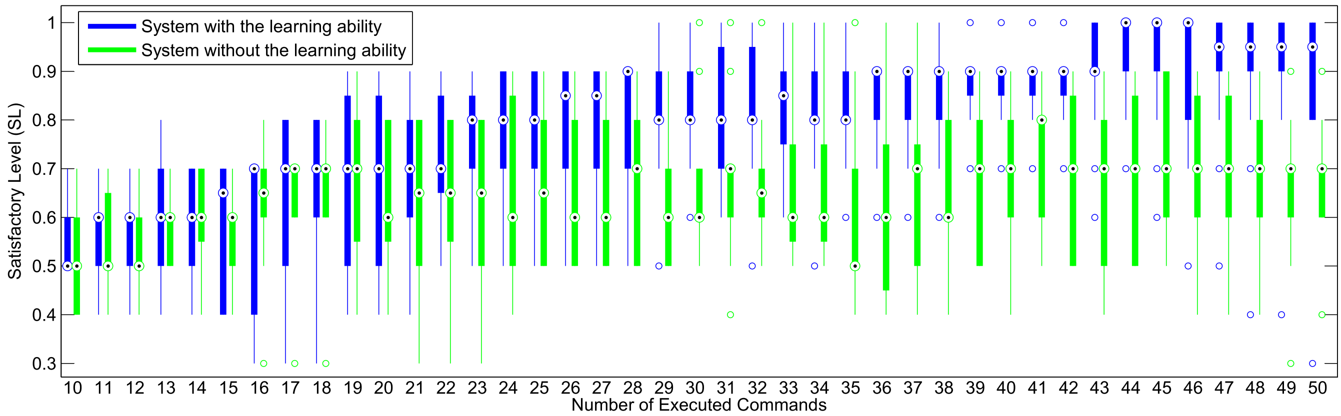

FIGURE 11. This figure shows box plots of the variations of the SL_{10} values with the number of executed commands for all users. The results for the system with the learning ability are shown in blue, and the results for the system with no learning ability are shown in green. The black dots in white circles represent the medians, and the boxes represent the interquartile ranges. The whiskers represent the maximum and minimum values of each distribution. However, the maximum length of the whiskers is limited to 2.7σ; any outliers are marked with circles in the color of the corresponding data set.

This occurred because humans have a great cognitive ability to adapt their perceptions in accordance with the actions of their peers. Hence, the users adapted to the perception of the robot during the experimental runs. Therefore, user satisfaction increased with successive interactions even though the system did not adapt to their perceptions. However, the SL of the system with no learning ability was lower than that of the system with the learning ability; from the 22nd command onward, the differences between the means are statistically significant at the 95% confidence level ($P < 0.05$). When the power values of the statistical analysis are considered, from the 22nd command onward, the power values are also greater than 0.8 (according to Cohen's four-to-one weighting of the beta-to-alpha risk criterion [37], power values greater than or equal to 0.8 can be considered as good). Therefore, it can be concluded that the experimental results correctly indicate rejection of the null hypothesis (i.e., H_0: the mean SL values of the two systems are the same) when the alternative hypothesis (i.e., H_1: the mean SL value of the system with the learning ability is greater than that of the system with no learning ability) is true (from the 22nd command onward). Furthermore, from the 26th command onward, Cohen's d values of greater than 0.8 can be observed. This implies that there is a large effect (values above 0.8 are considered to be large [37]). Therefore, it can be concluded that there is a definite, noticeable effect on the SL due to the addition of the learning ability. Based on these statistical observations regarding user satisfaction, it can be concluded that the experimental results confirm that the performance enhancement of the system with the learning ability (i.e., the system proposed in this paper) over the system with no learning ability is significant and reliable. Ultimately, with regard to user satisfaction, the system with the learning ability (i.e., the system proposed in this paper) surpasses the system with no learning ability (i.e., similar to the system explained in [32]).

The medians of the SL scores also exhibit a phenomenon similar to that of the means of SL, as seen from the box plots shown in Fig. 11. According to these box plots, there are both positive and negative outliers for both systems. The existence of outliers for a user study of this kind is natural, since there may be users whose expectations and perceptions are significantly different from those of others. Except for a single user, the individual variations in the SL outliers are similar to the variations of the majority of the data, although the absolute SL scores are above or below the others. Furthermore, the variations for the older users were separately analyzed and were found to exhibit characteristics similar to those of the overall results. Therefore, even though not all participants were older or challenged users, this aspect of the study population showed no significant effect on the evaluation of the performance of the system. Furthermore, assistive robots can be used indirectly for assisting elderly/disabled people by using them as support agents for human caregivers in care facilities such as nursing homes [38], and hence, not all users of such systems will be older people.

The proposed method enables a robot to learn from user feedback while concurrently adapting its perception of uncertain information according to the spatial information of its current working environmental. Moreover, the proposed system is capable of modifying the parameters of the output membership functions of the system proposed in [32]. Therefore, the key characteristics of the scheme for perception adaptation based on environmental factors that is presented in [32] are clearly well preserved in the method proposed in this paper. By contrast, the methods proposed in [27] and [28] are capable of perception learning based only on user feedback, and after the learning process is complete, the meanings of uncertain terms are fixed. Systems that assign such fixed meanings to uncertain information are suitable for use only in a fixed working environment and cannot be used in dynamic working environments. The experiment performed in this study was conducted in an environment that was static with respect to the global frame. However, this environment was dynamic with respect to the robot's frame since the environmental parameters perceived by the robot varied with its current position in the globally fixed environment.

Therefore, the environment perceived by the system was not a static one. Moreover, the working environment was also dynamic due to the changing position of the robot during navigation. Therefore, the proposed system is capable of adapting the perception of a robot toward that of its user based on user feedback while concurrently adapting its perception in accordance with its current environment. This is the major improvement of the proposed method over existing methods.

V. CONCLUSION

This paper proposes a method of effectively interpreting uncertain information related to navigation commands by adapting a robot's perception of uncertain information based on both the environment and user critiques. The main improvement of the proposed concept over existing systems is that the proposed system is capable of concurrently adapting its perception based on the spatial information of the environment while learning from user feedback.

The Uncertain Information Understanding Module (UIUM) is implemented using fuzzy neural networks. These fuzzy neural networks enable the system to learn from user feedback while simultaneously adapting its perception based on sensory information related to the environment. The Feedback Evaluation Module (FEM) evaluates the quantitative meanings of feedback terms.

Experiments were conducted to validate the performance enhancement achieved by the system due to its learning ability. An index called the user "satisfactory level" was used for the performance analysis. The experimental results confirm the performance improvement of the proposed method over the existing methods. The performance of the system with the learning ability surpasses that of a system with no learning ability. Therefore, the proposed concept is capable of enhancing user satisfaction by adapting a robot's perception of uncertain information based on the environment and user feedback.

The meaning of uncertain information may depend on the specific awareness about a particular task. As an example, the quantified meaning of the term "near" in a situation where a plastic bottle is moved near to a lighted candle will be different from moving the same bottle near to a glass on top of a dinner table. Since it involves the specific knowledge of the human that the closing the plastic near to a flame is unsafe. However, the system proposed in this paper is not capable of adapting the perception based on such specific awareness in relation to different objects or tasks. The main intention of the work was to develop a system that is capable of concurrently adapting its perception of uncertain information contained in navigational command based on the spatial information of the environment while adapting toward users. The effects caused to the perception due to such specific knowledge about different contexts are minor for navigation. Therefore, further improvement for adaptation of the perception according to such specific knowledge of different tasks is proposed for the future work.

ACKNOWLEDGMENT

The authors acknowledge the commitment of the volunteers, who have participated in the user study.

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