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An Assisted Navigation Training Framework Based on Judgment Theory Using Sparse and Discrete Human-Machine Interfaces

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Abstract— **This paper aims to present a new framework to train people with severe motor disabilities steering an assisted mobile robot (AMR), such as a powered wheelchair. Users with high level of motor disabilities are not able to use standard HMIs, which provide a continuous command signal (e. g. standard joystick). For this reason HMIs providing a small set of simple commands, which are sparse and discrete in time must be used (e. g. scanning interface, or brain computer interface), making very difficult to steer the AMR. In this sense, the assisted navigation training framework (ANTF) is designed to train users driving the AMR, in indoor structured environments, using this type of HMIs. Additionally it provides user characterization on steering the robot, which will later be used to adapt the AMR navigation system to human competence steering the AMR. A rule-based lens (RBL) model is used to characterize users on driving the AMR. Individual judgment performance choosing the best manoeuvres is modeled using a genetic-based policy capturing (GBPC) technique characterized to infer non-compensatory judgment strategies from human decision data. Three user models, at three different learning stages, using the RBL paradigm, are presented.**

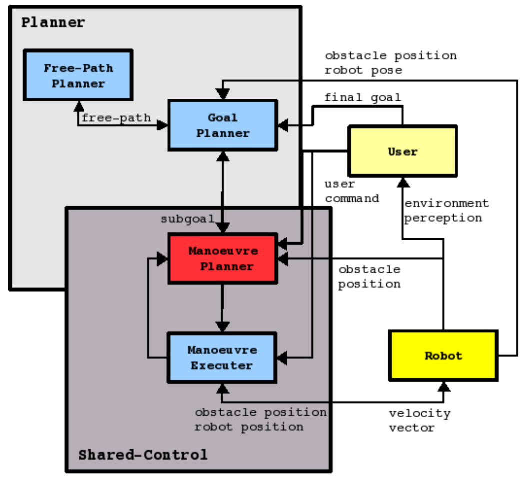

Fig. 1. Navigation system architecture

I. INTRODUCTION

Increasing mobility of people with severe motor disabilities is one of the most important goals of this work. Cerebral Palsy is a broad term used to describe a group of chronic movement or posture disorders. It is not caused by problems with the muscles or nerves, but rather with the brain's ability to adequately control the body. Cerebral palsy symptoms vary significantly among patients, since they can go from simple difficulty to walk to lower cognitive capabilities. Due to this fact, designing interfaces for ambient assisted living technologies for such specific users may become a very difficult task.

This work is being developed with the Portuguese Association for Cerebral Palsy (APPC), and the first task consisted in analyzing several patients, to decide about the most appropriate HMI to steer a powered wheelchair. For users able to control at least one of their arms or legs, a joystick is a suitable choice, since it provides a continuous command signal over time. However, for users that are not able to control neither arms or legs, choosing a sparse discrete interface may be the only possible solution. An HMI of this type only provides the system with a small set of sparse and discrete commands, such as: go forward, turn right, etc. There are some different HMIs of this type that could be used for this task, namely commands from: switch/multiple-switch with scanning interface, non-invasive brain computer interface (BCI), head-trackers, or eye-trackers.

This type of HMI requires the use of a shared-control system able to predict and execute user navigation goals with minimum commands. Given all the limitations imposed to the system, it is of major importance that users provide the system with the most accurate information as possible. This is the key motivation to develop the assisted navigation training framework, whose purpose is twofold: to train users to carry out navigation tasks, and to characterize user models on steering a powered wheelchair. In this sense, the ANTF is intended to train users to decide the best set of manoeuvres to reach a predefined final goal, as well as to train them to use a graphic scanning interface (e. g. scanning times can be adapted to the user ability operating the HMI). Figure 1 shows the overall navigation system architecture. Moreover, the training framework also provides a user characterization that will later be used to adapt the navigation system to the user competence. This approach may benefit users in the rehabilitation process to achieve a greater level of autonomy, even during training sessions. The ANTF may also be adapted to other navigation systems requiring other types of interfaces.

A. Literature Review

Increasing mobility of people with motor disabilities has motivated researchers to develop assisted navigation technologies to give, otherwise motor impaired people, a higher freedom of movement. In this sense, several research works

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related to the development of intelligent wheelchairs have been performed in past recent years [1], [2], and [3]. The development of user modeling is a relevant research topic when dealing with human-machine shared-control systems. In [4] a user modeling with Gaussian processes for Bayesian plan recognition during powered wheelchair steering, is presented. Sawaragi et al. [5] modeled an ecological expert that was able to compare human skills steering a robot with a fuzzy controller.

Judgment theory is often used to model the judgment of a human selecting a criterion value based on a set of probabilistic cues. Brunswik's Lens Model (BLM) and its extensions [6], [7] are examples of the application of linear models to describe judgment behavior. The BLM provides dual, and symmetric models of the human judge and the environment. Since those models are based on the same environmental information (the cues), the fit between the model of the human judge and the environmental structure can be formally measured. Rothrock and Kirlik [8] proposed a technique called genetic-based policy capturing (GBPC) to infer non-compensatory judgment strategies from human decision data, which explores rule-based modeling using propositional logic. They focused on the development of an inductive inference technique to capture judgment policies. Jin and Rothrock [9] developed a rule-based analytical model of the conceptual BLM, designated by rule-based lens model (RBL). The role of the GBPC within the RBL is to generate environment and human models.

II. Human Modeling based on Rule-Based Lens Paradigm

Figure 2 shows the RBL framework proposed for the ANTF. Achievement, *ra*, represents the correspondence between human judgments and the actual value of the environmental criterion. The environmental predictability, *Re*, measures how well the non-compensatory environmental model can be used to predict the criterion value while, *Rs*, labeled as human control, indicates how well the non-compensatory judgment model captures actual human judgments. Parameter *G* represents how well the non-compensatory model of the environment maps onto the non-compensatory model of the human judgments strategy. Parameter *C* captures systematic regularities between the errors of the non-compensatory environmental and judgment models. In the RBL, the range of parameters *ra*, *Re*, *Rs*, and *G* is $[0,1]$. The closer these values are to 1, the better the achievement, environmental predictability, human control and modeled knowledge, respectively. For *C*, a high value reveals a high degree of unmodeled knowledge [9].

A. Environmental and Human Models based on GBPC Methodology

Performers in time-stressed, information-rich environments, develop heuristic task-simplification strategies for coping with the time-pressure and often severe information processing demands of judgment and decision making tasks.

TABLE I

String Bit Position and Representation

Bit	Representation	1	0
#1	X1 $E_\theta = 0$	Yes	No
#2	X2 $E_\theta = \pi$	Yes	No
#3	X3 $E_\theta > 3\pi/2$	Yes	No
#4	X4 $E_\theta < 2\pi$	Yes	No
#5	X5 $E_\theta > \pi/2$	Yes	No
#6	X6 $E_\theta < \pi$	Yes	No
#7	X7 $E_\theta < \pi/2$	Yes	No
#8	X8 $E_\theta > 0$	Yes	No
#9	X9 $E_\theta > \pi$	Yes	No
#10	X10 $E_\theta > \pi/2$	Yes	No
#11	Y1 - Go Forward	Yes	No
#12	Y2 - Go Backwards	Yes	No
#13	Y3 - Rotate Left and Go Forward	Yes	No
#14	Y4 - Rotate Left and Go Backwards	Yes	No
#15	Y5 - Rotate Right and Go Forward	Yes	No
#16	Y6 - Rotate Right and Go Backwards	Yes	No

Judgment strategies in these environments may have a non-compensatory nature, which may be adaptive to the time stressed nature of these tasks, since such heuristics typically make lower demands for information search and integration than do corresponding, linear-additive, compensatory strategies as proposed by standard representation of the BLM. As a result, linear regression may be inappropriate for inferring the judgment strategies used by users in time-stressed environments. The technique, genetic-based policy capturing (GBPC), infers non-compensatory judgment strategies under the assumption that these strategies can be described as a disjunctive collection of conjunctive rules. For modeling the use of information, cues and user judgments were encoded in GBPC as a 16-bit string. The meaning of each string position is shown in Table I. To quantify the progress of the user's improving controlling skills using the training platform, a criterion definition that is a normative judgment with which the user's judgment is compared must be performed. In our case this is defined as a set of decisions provided by

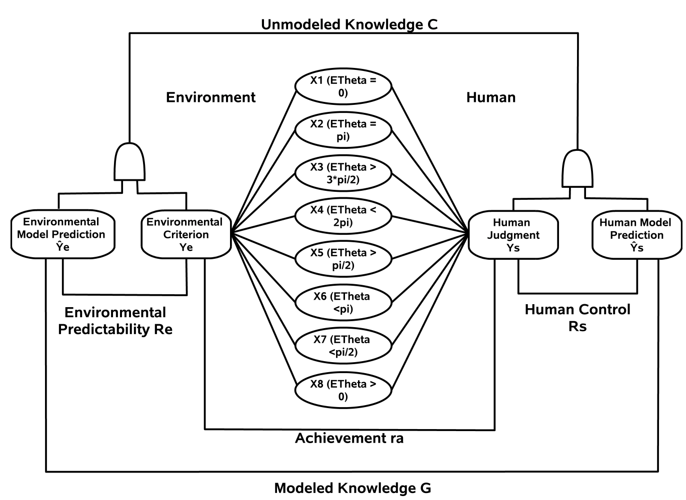

Fig. 2. Rule-Based Lens Model based on [9]

TABLE II

EXEMPLAR REPRESENTATION

Ex.	Characteristics Represented	16-Bit String
1	$(E_\theta = 0) \cap (Y = Y1)$	1000000000100000
2	$(E_\theta = \pi) \cap (Y = Y2)$	0100000000010000
3	$(E_\theta > 3\pi/2) \cap (E_\theta < 2\pi) \cap (Y = Y3)$	0011000000001000
4	$(E_\theta > \pi/2) \cap (E_\theta < \pi) \cap (Y = Y4)$	0000110000000100
5	$(E_\theta < \pi/2) \cap (E_\theta > 0) \cap (Y = Y5)$	0000001100000010
6	$(E_\theta > \pi) \cap (E_\theta > 3\pi/2) \cap (Y = Y6)$	0000000011000001

the assisted robot autonomous system. For this purpose, *a maneuvering system was developed, in which, control rules are defined as association rules whose antecedent parts consist of heading errors, and steering commands as a consequent part*. Whenever a user makes a maneuvering judgment, the autonomous system also outputs a manoeuvre decision (environmental criterion) based on the cues associated to the heading error. The autonomous system decision rules were developed in order to minimize the turning effort. Further research is required on the development of more efficient manoeuvre planners, with other cues being used (e. g. distance to obstacles, etc.), and other rules for using the heading error cue. In this manner system environmental criterion (Y_e) was obtained to be compared with the user judgment (Y_s), allowing to classify the human user achievement in steering the assisted navigation robot. The environmental criterion was established based on a set of disjunctive and conjunctive rules that are in accordance with the encoded data presented in Table I. An example of such rules is as follows:

if $(E_\theta > \frac{3\pi}{2}) \cap (E_\theta < 2\pi) \cap (Y = Y3) \cup$

The exemplar set and the set of rules were established according to the GBPC method described in [8]. Table II shows the exemplar set defined for the environmental model. Users at three learning stages were considered for the development of human models:

- Beginner: has no practice (is afraid) on steering the assisted robot backwards;
- Average: has practice on steering the assisted robot in all directions, but is not skilled to minimize the turning effort;
- Expert: has practice on steering the assisted robot in all directions, and is skilled to minimize the turning effort;

Based on the previous assumptions three human user models ($\hat{Y}_s$) were developed also based on a set of disjunctive and conjunctive rules that are in accordance with the encoded data presented in Table I.

B. Results

To evaluate the achievement of human users a set of indicator functions (1)-(5) were determined according to the work described in [9], in order to calculate the RBL relationships, as defined in Fig. 2.

$$Re = \frac{\sum_{i=1}^{n} Ie_i}{n} \quad where \quad Ie_i = \left\{ \begin{array}{l} 1 \ if \ Ye_i = \hat{Y}e_i, \\ 0 \ otherwise \end{array} \right\} \quad (1)$$

$$Rs = \frac{\sum_{i=1}^{n} Is_i}{n} \quad where \quad Is_i = \left\{ \begin{array}{l} 1 \ if \ Ys_i = \hat{Y}s_i, \\ 0 \ otherwise \end{array} \right\} \quad (2)$$

$$ra = \frac{\sum_{i=1}^{n} Ir_i}{n} \quad where \quad Ir_i = \left\{ \begin{array}{l} 1 \ if \ Ye_i = Ys_i, \\ 0 \ otherwise \end{array} \right\} \quad (3)$$

$$G = \frac{\sum_{i=1}^{n} IG_i}{n} \quad where \quad IG_i = \left\{ \begin{array}{l} 1 \ if \ \hat{Y}e_i = \hat{Y}s_i, \\ 0 \ otherwise \end{array} \right\} \quad (4)$$

$$C = \frac{\sum_{i=1}^{n} IC_i}{n} \quad where \quad IC_i = \left\{ \begin{array}{l} 1 \ if \ Ye_i = Ys_i = 0, \\ 0 \ otherwise \end{array} \right\} \quad (5)$$

A training platform simulator using the player/stage [10] environment was developed (see Fig. 3). A graphic scanning interface with a switch device is used as the system HMI. The graphic interface only provides sparse and a small set of commands to the system, namely: go forward, go backwards, go left, and go right, which makes very difficult to steer the AMR. To overcome the limitations originated by this type of HMIs, the navigation system includes a manoeuvre executer (see Fig. 1) that receives the desired manoeuvre, and the next subgoal to be reached, and performs the most appropriate trajectory. In this sense, the ANTF is intended to train users to decide the best set of manoeuvres to reach a predefined final goal, as well as to train them to use the graphic scanning interface. Moreover, the training framework also provides a user characterization that will later be used to adapt the navigation system to the user capacity. Three kind of human behaviors (beginner, average, and expert) were tested, in the simulator, in steering the AMR in a kind of passing-door manoeuvre, as depicted in Fig. 3 b). Every time a subgoal (denoted by A, B, C, D in Fig. 3 b)) is reached the user issue a command to reach the next subgoal. For example, if the user issue a "rotate left" command, the robot rotates left till the heading error is 0 or π, and then goes forward or backwards, respectively. The next subgoal and the global path were defined by the system goal planner (see Fig. 1). The user indicates his/her desired manoeuvre using the graphic scanning interface (see Fig. 3 a)) operated by a switch device. To evaluate the user capacity in deciding the best set of manoeuvres, the autonomous system (manoeuvre planner) also decides, in parallel, the best manoeuvre to reach the desired subgoal, according to the decision rules defined previously, which were designed to minimize the turning effort. The autonomous system decisions correspond to the environment part of the RBL model (environment criterion), as shown in Fig. 2. The comparison between user (human judge) and autonomous system manoeuvre decisions, using the RBL model allow us to obtain the user characterization steering the AMR. Some preliminary results are presented

TABLE III

SIMULATION RESULTS FOR BEGINNER, AVERAGE, AND EXPERT USERS

Human Operator	*Re*	*Rs*	*ra*	*G*	*C*
Beginner	1	0.59	0.37	0.25	0
Average	1	0.75	0.56	0.5	0
Expert	1	0.87	0.87	1	0

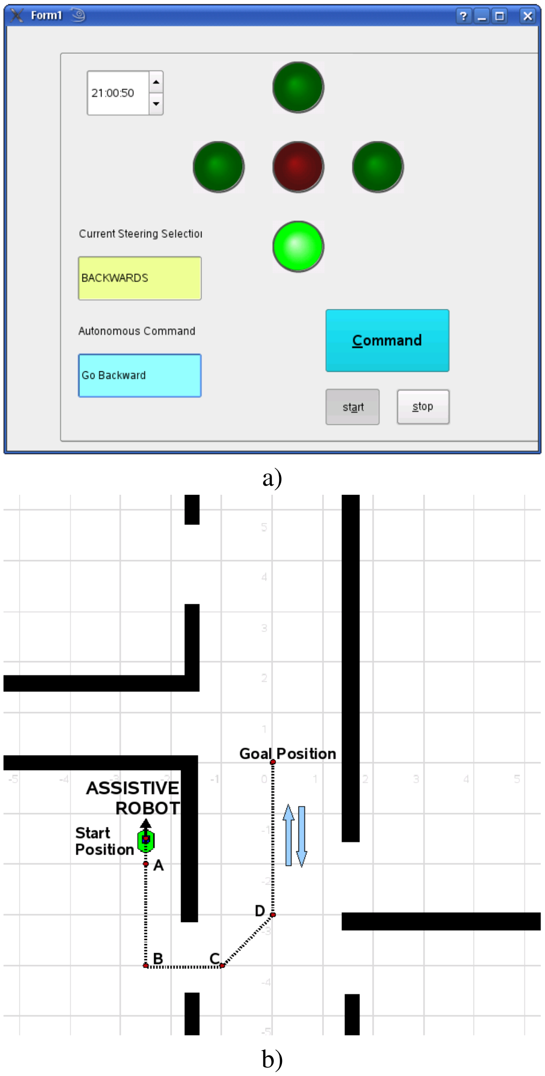

Fig. 3. Assisted navigation training platform simulator: a) scanning interface; b) simulation indoor environment, including a path with one goal position and 4 subgoals (A,B,C,D).

in Table III. One can observe that the beginner user had an achievement rate (ra) of 0.37, which is quite low. This result is related to his/her low level of knowledge (G), disabling him/her to perform some types of manoeuvres such as moving backwards. The cognitive control (Rs) value shows that some judges did not match the human model for the beginner user. This can be related to difficulties using the HMI device. For the expert user, the achievement rate has a high value, which is related with his/her high level of knowledge, meaning that the human model for expert users matches the environmental criterion designed for the autonomous system. It was considered that the environmental criterion exactly matched the environmental model, since the autonomous system always behaves in the same manner. For that reason Re is equal to one for all cases.

III. CONCLUSIONS AND FUTURE WORKS

A. Conclusions

This paper presents an assisted navigation training framework intended not only to train users' ability in steering a powered wheelchair in an appropriate manner, given the restrictions imposed by their limited motor capacities, but also to characterize the user navigation model that will later be used in the shared-control manoeuvre planner. In this manner, it is possible to tailor the navigation autonomous system to the capacity of the user, increasing the overall navigation task efficiency. A RBL model was used as the paradigm to establish the human judgment model, as well as the environment criterion model. An evaluation performance of human users steering the wheelchair, based on five parameters, was obtained. The achievement rate *ra*, and the human control *Rs* parameters will have a drastic impact in the design of the shared-control manoeuvre planner, since they give us a clear information about the overall user performance, and its current level of knowledge.

B. Future Works

Further experimental analysis is required to better characterize the performance of the proposed ANTF. A detailed comparison of the application of different modeling strategies is to be analyzed. Further research is required on the development of more efficient manoeuvre planners, with other cues being used (e. g. distance to obstacles, etc.), and other rules for using the heading error cue.

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