Patient Classification and Automatic Configuration of an Intelligent Wheelchair

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Abstract. The access to instruments that allow higher autonomy to people is increasing and the scientific community is giving special attention on designing and developing such systems. Intelligent Wheelchairs (IW) are an example of how the knowledge on robotics and artificial intelligence may be applied to this field. IWs can have different interfaces and multimodal interfaces enabling several inputs such as head movements, joystick, facial expressions and voice commands. This paper describes the foundations for creating a simple procedure for extracting user profiles, which can be used to adequately select the best IW command mode for each user. The methodology consists on an interactive wizard composed by a flexible set of simple tasks presented to the user, and a method for extracting and analyzing the user's execution of those tasks. The results showed that it is possible to extract simple user profiles, using the proposed method.

Keywords: Classification, Patient, Intelligent Wheelchair, Knowledge Discovery.

1 Introduction

The population with physical disabilities has earned more relevance and has attracted the attention of international health care organizations, universities and companies interested in developing and adapting new products. The current tendency reflects the demand for an increase on health and rehabilitation services, in a way that senior and handicapped individuals might become more and more independent when performing quotidian tasks.

Regardless the age, mobility is a fundamental characteristic for every human being. Children with disabilities are very often deprived of important opportunities and face

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serious disadvantages compared to other children. Adults who lose their independent means of locomotion become less self-sufficient, raising a negative attitude towards themselves. The loss of mobility originates obstacles that reduce the personal and vocational objectives [1]. Therefore it is necessary to develop technologies that can aid this population group, in a way to assure the comfort and independence of the elderly and handicapped people. Wheelchairs are important locomotion devices for those individuals. There is a growing demand for safer and more comfortable wheelchairs, and therefore, a new Intelligent Wheelchair (IW) concept was introduced. However, most of the Intelligent Wheelchairs developed by distinct research laboratories [1] have hardware and software architectures very specific for the used wheelchair model/developed project and are typically very difficult to configure in order for the user to start using them.

The paper is organized as follows: Section 2 presents the state of art on intelligent wheelchairs and the IntellWheels project. Section 3 contains a description of the methodology for automatically extracting the users' profiles in order to give the best interface. The implementation of the system is presented in section 4 and the experiments and results achieved are presented in section 5. Finally some conclusions and future work are described in the last section.

2 Intelligent Wheelchairs

In the last years several prototypes of Intelligent Wheelchairs have been developed and many scientific work has been published [2] [3] in this area. Simpson [1] provides a comprehensive review of IW projects with several descriptions of intelligent wheelchairs. The main characteristics of an IW are [2] [4]: autonomous navigation with safety, flexibility and obstacle avoidance capabilities; communication with others devices such automatic doors and other wheelchairs and interaction with the user using distinct types of devices such as joysticks, voice interaction, vision and other sensor based controls like pressure sensors.

2.1 Intelligent Wheelchairs' Projects

The first project of an autonomous wheelchair for physical handicapped was proposed by Madarasz in 1986 [5]. It was planned as a wheelchair with a micro-computer, a digital camera and an ultra-sound scanner with the objective of developing a vehicle that could move around in populated environments without human intervention. Hoyer and Holper [6] presented a modular control architecture for an omni-directional wheelchair. The characteristics of NavChair [7], such as the capacity of following walls and avoid obstacles by deviation are described in [7-9]. Miller and Slak [10] [11] proposed the system Tin Man I with three operation modes: one individual driving a wheelchair with automatic obstacles deviation; moving through-out a track and moving to a point (x,y). This kind of chair evolved to Tin Man II which included advanced characteristics such as storing travel information, return to the starting point, follow walls, pass through doors and recharge battery. Wellman [12] proposed a hybrid wheelchair equipped with two extra legs in addition to its four wheels, to allow stair climbing and movement on rough terrain. FRIEND is a robot for rehabilitation which consists of a motorized wheelchair and a MANUS manipulator [13] [14]. In this case, both the vehicle and the manipulator are controlled by voice commands. Some projects present solutions for quadriplegic individuals, where facial expressions recognition is used to control the wheelchair [4] [15] [16]. In 2002, Pruski presented VAHM, a user adapted intelligent wheelchair [17].

Satoh and Sakaue [18] presented an omni-directional stereo vision-based IW which detects both the potential hazards in a moving environment and the postures and gestures of a user, using a stereo omni-directional system, which is capable of acquiring omni-directional color image sequences and range data simultaneously in real time. In 2008 John Spletzer studied the performance of LIDAR based localization for docking an IW system [19] and in 2009 Horn and Kreutner [20] showed how the odometric, ultrasound, and vision sensors are used in a complementary way in order to locate the wheelchair in a known environment. In fact, the research on IW has suffered a lot of developments in the last few years. Some IW prototypes may be even controlled using "thoughts". This type of technology uses sensors that pick up electromagnetic waves of the brain [21-23] and are able to detect patterns on the brain waves that may be associated with the users' desired commands.

2.2 IntellWheels Project

This section presents a brief overview of the Intelligent Wheelchair project that is being developed at the University of Porto in collaboration with INESC-P, University of Aveiro, University of Minho, IPP and APPC in Portugal. The main objective of the IntellWheels Project is to develop an intelligent wheelchair platform that may be easily adapted to any commercial wheelchair and aid any person with special mobility needs. Initially, an evaluation of distinct motorized commercial wheelchair platforms was carried out and a first prototype was developed in order to test the concept. The first prototype was focused on the development of the modules that provide the interface with the motorized wheelchair electronics using a portable computer and other sensors. Several different modules have been developed in order to allow different ways of conveying commands to the IW. These include, for example, joystick control with USB, voice commands, control with head movements and gestures, and facial expressions recognition. Fig. 1 shows the input devices already available in the IntellWheels IW.

Fig. 1. Joystick, headset with microphone, Nintendo Wii Remote and Emotiv Brain Computer Interface [24]

The project research team considered the difficulty that some patients have while controlling a wheelchair using traditional input devices such as the traditional joystick. Therefore, new ways of interaction between the wheelchair and the user have been integrated, creating a system of multiple entries based on a multimodal interface. The system allows users to choose which type of command best fits their needs, increasing the level of comfort and safety.

A simulated environment was developed that models the intelligent wheelchair and its environment. In this environment it is possible to test in a safe manner the different ways of driving the intelligent wheelchair, since the behavior of the simulated intelligent wheelchair is very identical to the behavior of the real intelligent wheelchair.

3 Methodology for Automatic Extraction of User Interfaces/Profiles

The potential users of the Intelligent Wheelchair have particular characteristics and constraints. Therefore it is very important to adjust and adapt the way of driving the intelligent wheelchair to the specific patient. The data acquired when the users are performing a test drive using a multimodal interface and an intelligent wheelchair will allow improving the adaptability.

This section presents the features and the global architecture developed of the IntellWheels Multimodal Interface.

3.1 IntellWheels Multimodal Interface

There are several publications in the literature of projects related to the issue of adapting and designing specific interfaces for individuals with severe physical disabilities [25-27]. Nevertheless, most of these projects present restricted solutions concerning the accessibility to the user to drive a particular wheelchair. It is common to find just one solution such as voice recognition, while other focus merely on facial expressions recognition [27]. Since the physical disability is very wide and specific to each individual, it becomes important to provide the greatest possible number of recognition methods to try to cover the largest possible number of individuals with different characteristics.

The IntellWheels Multimodal Interface offers five basic input devices: joystick, speech recognition, recognition of head movements and gestures, the use of a generic gamepad and facial expressions. In addition, IntellWheels project proposes an architecture that makes the interface extensible enabling the addition of new devices and recognition methods in an easy way. It also presents a flexible paradigm that allows the user to define the sequences of inputs to assign to each action, allowing for an easy and optimized configuration for each user. For example an action of following the right wall can be triggered by blinking the left eye followed by the expression "go".

Fig. 2 shows the IntellWheels Multimodal Interface where all the input devices are connected.

Fig. 2. IntellWheels Multimodal Interface

3.2 Multimodal Data Gathering System

Based on the IntellWheels prototype and using the real and simulated environments, this work is focused on devising appropriate data gathering and data analysis systems that enable the construction of patient and environment models using knowledge discovery methodologies. The constructed models will be used together with a simple interface library in the context of an interface selector application that will also use knowledge discovery methodologies in order to select and configure the most appropriate multimodal interface for each patient in each specific situation.

The multimodal data gathering system enables the collection of real-time input information from patients with distinct disabilities. The system also enables the collection of environmental information and more high-level information concerning the wheelchair localization and orientation, task in execution, among other information.

Considering the concept of flexibility and multimodality of the IntellWheels project, the required data to collect from the platform may come from many sources: input devices, sensors (both real and virtual) and the Simulator. The Fig. 3 presents the software architecture.

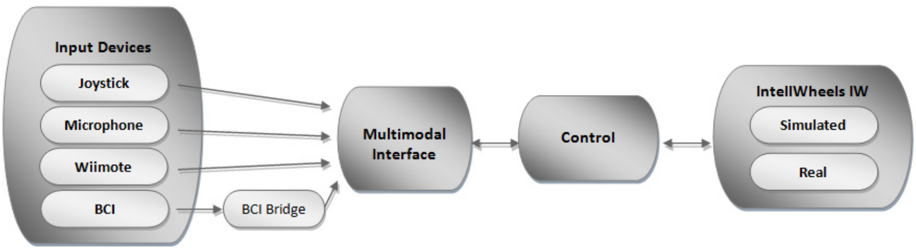

Fig. 3. IntellWheels' software architecture

The control application can connect to both the real IW or the Simulator, gathering and processing data from their sensors. The control works as the server side regarding data communication with the Multimodal Interface. The Multimodal Interface, in turn, acts as the server side concerning the input devices connections, since the Multimodal Interface manages all the input devices.

The data acquisition system is distributed among the Control application, the Multimodal Interface and the input devices bridge applications. As such, one file with captured data is created by each application.

Data Synchronization. In order to synchronize the files, a timestamp is attached to all information acquired. The information required for the synchronization concerns the IntellWheels platform uptime. For this reason and since the applications are not executed at the same time, a flow to set the same uptime for all applications was created: the Control application, the first one to be executed, sends its uptime to the Multimodal Interface, which in turn sends this value to all input devices' bridge applications. Each application has a time delta variable which stores the difference between its own uptime and the Control's uptime. The time delta variable is updated several times throughout the acquisition process. After a certain amount of inputs is received from the Multimodal Interface by the Control application, it again sends a message with its current uptime, which once more is distributed to all applications by the flow previously explained.

Data File Format. To save the data, an extensible markup language (XML) type file format was chosen to be used because of its flexibility.

The header of the file contains the description of each type of data the application gathers. An example of an input data collected file can be seen next:

```
<MMI_LOG>
 <INPUTS>
  <item>
   <id> wiimote </id>
   <label> VelX; VelY; VelZ; Button N;Battery Level %;Error
</label>
  </item>
 </INPUTS>
 <DATA>
  <item>
   <timestamp> 579.6243 </timestamp>
   <input> wiimote </input>
   <values> -10; -15; 0; ; 78; </values>
  </item>
 </DATA>
</MMI_LOG>
```

3.3 Data Gathering Process

The sample of individuals includes patients with distinct disabilities (Thrombosis, Stroke, Cerebral Palsy, Parkinson, Alzheimer and Multiple Sclerosis, among others).

The data collecting process was divided into two parts. In each of the parts, the patients are asked to perform distinct inputs:

- Perform obligatory inputs, including a complete set of a previously specified protocol: voice commands; facial expressions; head, arm and hand movements. The objective of this protocol is to make a profile of the users.
- Perform free inputs, which enable the patient to perform some given tasks but using its own and completely free preferred process.

The inputs are performed in distinct environmental conditions: noise and lighting variations; distinct pavement and wheelchair movements; tasks performed in parallel (such as maintaining a conversation). Tracing a user diagnostic can be very useful to adjust certain settings allowing for an optimized configuration and improved interaction between the user and the multimodal interface.

Accordingly, the Intellwheels Multimodal Interface contains a module capable of performing series of training sessions, composed of small tests for each input modality. These tests may consist, for example, of asking the user to press a certain sequence of buttons on the gamepad, or to move one of the gamepads' joysticks to a certain position. Another test may consist in asking the user to pronounce a set of voice commands, or to perform a specific head movement.

The tests should be performed sequentially and should have an increasing difficulty. Additionally, the tests should be reconfigurable and extensible. Finally, the tests sets and theirs results should be saved on a database, accessible by the Intellwheels Multimodal Interface. Therefore, the following user characteristics should be extracted and these characteristics can be separated in two different types: quantitative and qualitative. The quantitative measures consist of: the time taken to perform a full button sequence; the average time between pressing two buttons; the average time to place a gamepad analogical switch on a certain position; the average time to position the head on a certain position; the trust level of speech recognition; maximum amplitude achieved with the gamepad analogical switches in different directions; maximum amplitude achieved with the head in different directions and number of errors made using the gamepad. Using the quantitative measures, the following qualitative measures should be estimated: user ability to use the gamepad buttons; user ability to perform head movements and user ability to pronounce voice commands.

At the end of the training session, the tracked user information should be saved to an external database, containing the users' profile. The user profile can be used to improve security, by defining, for each user, a global trust level for each input modality. The trust level can be used to advice the user of which modality to use, at the creation of a new association. Also, it could be useful to activate confirmation events whenever a user requests a certain output action using an input level with a low trust level.

Another functionality of the user´s profile is capturing the EEG signals using a brain computer interface [27] for using as input facial expressions and thoughts.

The users will be asked to fill a complete questionnaire about the experiment and their preferences regarding each control method for each task in each environmental condition.

Also, a simple library of wheelchair interfaces is being developed together with an application that enables fast generation and configuration of these interfaces. The interface selection application will be based on the use of machine learning algorithms that will use the available patient and environment models to select the most appropriate interfaces from the interface library.

4 Implementation

This section presents the implementation for the proposed User Profile feature. Firstly, it explains the approach followed to specify which test sets are going to be loaded by the module responsible for tracking the users' profile. Secondly, we show the simple profiling methods that were implemented to create the future user classification. Next, we will present how the extracted information was used to adjust certain settings of the interface. Finally, a demonstration of how the profile is stored to enable future use is also made.

4.1 Definition of the Sets

To perform the measures previously described, a simple XML grammar was defined. It implements four configurable distinct test types: sequences of gamepad buttons; voice commands; positions for both joysticks and positions for head.

Example of XML containing user profile test set:

```
<INTELLWHEELS_PROFILER>
 <BINARY_JOYSTICK>
  <item>
   <sequence> joystick.1
      joystick.2 </sequence>
   <difficulty> easy </difficulty>
  </item>
 </BINARY_JOYSTICK>
 <ANALOG_JOYSTICK>
 (…)
 <ANALOG_WIIMOTE>
  <item> <x>100</x> <y>0</y></item>
 </ANALOG_WIIMOTE>
 <SPEECH>
  <item> go forward </item>
  <item> turn right </item>
  <item> create new sequen </item>
  <item> stop </item>
 </SPEECH>
</INTELLWHEELS_PROFILER>
```

The proposed XML grammar makes it possible for an external operator to configure the test set that they find most appropriate for a specific context or user. When a user starts the training session, the four different types of tests are iterated. In order to attain a consistent classification of the user, the defined grammar should be sufficiently extensive. The test set specified on the XML file is iteratively presented to the user. It starts by asking the user to perform the gamepad button sequence as can be observed in Fig. 4.

Fig. 4. User profiler gamepad and voice tests

When the user ends the first component of the user profiler module, the navigation assistant asks the user to pronounce the voice commands stored in the XML. Also, the quantitative results for the gamepad buttons test are presented.

The last part of the user profiler test is shown in Fig. 5. The user is invited to place the gamepad's joystick into certain positions. A similar approach is used for the head movements test.

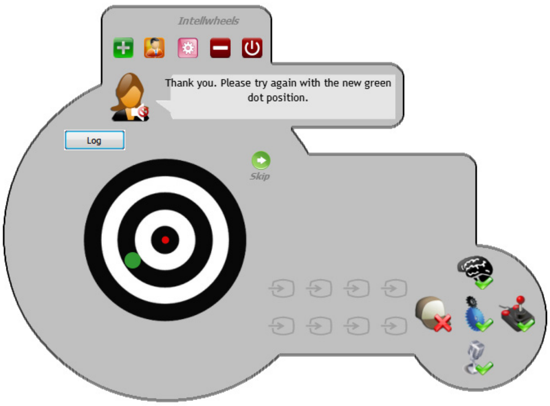

Fig. 5. User profiler joystick test

To define the user proficiency in using the gamepad buttons, a simple method was implemented. Each sequence defined on the grammar should have an associated difficulty level (easy, medium or hard). The difficulty type of a sequence may be related to its size, and to the physical distance between the buttons on the gamepad. Since the layout of a generic gamepad may change depending on the model, defining whether or not a sequence is of easy, medium or difficulty level is left to the operator.

When the user completes the gamepad sequences training part, an error rate is calculated for each of the difficulty levels. If these rates are higher than a minimum acceptable configurable value, the user classification in this item is immediately defined. This classification is then used to turn on the security feature, which is characterized by a confirmation event performed by the navigation assistant. For a grammar with 5 sequences of difficulty type easy, the maximum number of accepted errors would be 1. If the user fails more than one sequence, the confirmation event is triggered for any input sequence, of any difficulty type, and the gamepad training session is terminated. If the error rate for the easy type is less than 20% (=1/5) the training with the sub-set composed by the sequences of medium difficulty is initiated. At the end, a similar method is applied. If the error rate for the medium level is higher than 30%, the confirmation is triggered for the medium and hard levels of difficulty, and the training session is terminated. Finally, if the user makes it to the last level of difficulty, the training for the hard sequences sub-set is started. If the error rate is higher than 50%, the confirmation event is triggered only for sequences with a hard difficulty level. The best scenario takes place when the user is able to surpass the maximum accepted error rates for all the difficulty levels. In this situation, the confirmation event is turned off, and an output request is immediately triggered for any kind of input sequence composed only by gamepad buttons.

Defining the ideal maximum acceptable error rates is not easy. With this in mind, we made it possible to also configure these values in the XML grammar.

The joystick phase of the training session can be used to calculate the maximum amplitude achieved by the user. This value can then be used to parameterize the maximum speed value. Imagining a user who can only push the joystick to 50% of its maximum amplitude, the speed can be calculated by multiplying the axis value by two. This feature was not implemented. However, all the background preparation to implement it was set for future work.

The speech component of the training session was used to define the recognition trust level for each of the voice commands. The trust level is a percentage value retrieved by the speech recognition engine. This value is used to set the minimum recognition level for the recognition module.

Finally, the head movement phase of the training session has a similar purpose to the joystick's phase. Additionally, the maximum amplitude for each direction can be used to determine the range that will trigger each one of the leaning inputs of the head gestures recognition.

An extension of this profiling is related to the facial expressions and thoughts. A brain computer interface (BCI) was incorporated which can recognize the facial expressions and thoughts. However several patients suffering of cerebral palsy for example, are not able to produce all the facial expressions. For that reason it is also implemented a component in the profiling for testing the facial expressions (and even the thoughts) and where all the brain activity is recorded using the 14 sensors in the BCI for posterior analysis.

5 Experiments and Results

The main objective of the experimental work was to make a preliminary study of the tasks that can be implemented and the responses of the individuals in order of get information for the user profiling. The experiments involved 33 voluntaries, with a mean age of 24, a standard deviation of 4.2 and without any movements' restrictions.

The first experiment consisted in performing the sequence tasks with several levels of difficulty. In the first sequence the users needed to push the gamepad buttons GP1 - GP2 (easy level of difficulty); the second sequence was GP3 - GP8 (easy level of difficulty); the third sequence was GP5 - GP8 - GP9 (medium level of difficulty) and the last sequence was GP6 - GP1 - GP7 - GP4 - GP2 (hard level of difficulty). For the experiments with voice commands the individuals had to pronounce the sentences: "Go forward"; "Go back"; "Turn right"; "Turn left"; "Right spin"; Left Spin" and "Stop" to get the information about the recognition trust level for each voice command.

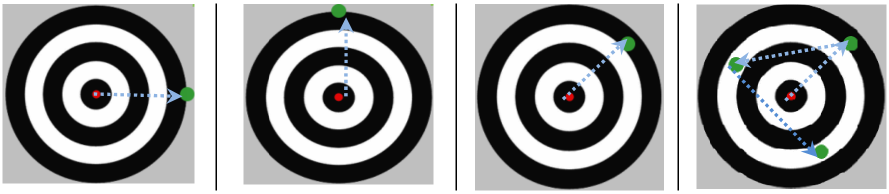

Fig. 6. User profiler joystick tests

The last two experiments involved the precision of the gamepad's joystick and the head movements. The voluntaries should move the small dot into the bigger one with the gamepad's joystick and with the wiimote controller. Fig. 6 shows some of the tasks that were asked. The positions were moving right; up; down; northeast; northwest; southeast and a sequence northeast - northwest - southeast without going back to the initial position in the center of the target.

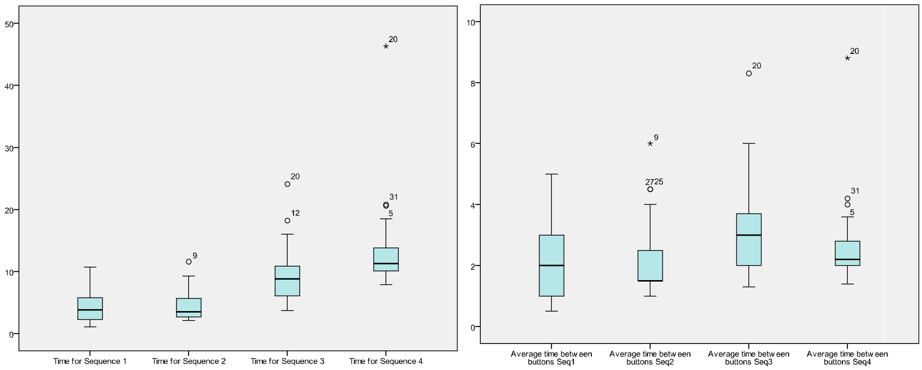

Fig. 7. Time for performing the sequences and average time between gamepad buttons

In general, the achieved results show the good performance of the individuals using gamepad and voice commands. The behaviour with head movements reflects more asymmetry and heterogeneous results, since several moderate and severe outliers exist in the time results. The time consumed to perform the sequences confirmed the complexity of the tasks as can be seen in Fig. 7. In terms of average time between buttons (Fig. 7) it is interesting to notice the results for the last sequence. Although it is more complex and longer it has a positive asymmetry distribution. This probably reveals that training may improve the user's performance.

In terms of errors, the third sequence presents a higher result with at least one fail. The last sequence presented a case where 12 errors were committed.

Table 1. Contingency table with the errors of sequences using gamepad

	Number of Errors							
Seq	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**12**
1	30	1	2	0	0	0	0	0
2	31	2	0	0	0	0	0	0
3	20	7	3	1	1	0	1	0
4	27	1	1	1	0	2	0	1

Table 2 presents several descriptive statistics, such as central tendency (mean, median) and dispersion (standard deviation, minimum and maximum), for the trust level of speech recognition.

Table 2. Descriptive Statistics for the trust level of speech recognition

Sentence	Mean	Median	S. Dev	Min	Max
"Go Forward"	**95.36**	**95.50**	0.51	93.9	95.9
"Go Back"	94.37	95.00	2.44	82.2	95.9
"Turn Right"	95.31	95.40	**0.42**	94.4	95.9
"Turn Left"	94.76	95.20	1.42	88.4	95.8
"Left Spin"	93.69	94.90	2.88	83.1	95.8
"Right Spin"	94.82	95.00	1.25	89.7	97.2
"Stop"	**92.67**	94.30	**3.85**	82.2	95.8
Total Sentences	94.43	94.99	1.08	92.24	95.93

The speech recognition has very good results. In fact, the minimum of minimums was 82.2 for the sentences "Go Back" and "Stop". The expression "Go Forward" has the highest mean and median. The sentence "Stop" is more heterogeneous since it has the higher standard deviation (3.85).

The paired samples t test was applied with a significance level of 0.05 to compare the means of time using joystick and head movements. The null hypothesis was established: the means of time to perform the target tasks with joystick and head movements were equal. The alternative hypothesis is: the means of time to perform the target tasks with joystick and head movements were different. The achieved power was of 0.80 with an effect size of 0.5. Table 3 contains the p values of the paired sample t tests and the 95% confidence interval of the difference. Observing the results for the positions Down and Northwest, it is valid to claim there are statistical evidences to affirm that the mean of time with joystick and head movements is different. This reveals the different performance by using in the same experience the joystick and the head movements.

Table 3. Confidence intervals of the difference and p values

	95% Confidence Interval of the difference		
Move the red dot to:	**Lower**	**Upper**	**P value**
Right	-2.29	0.67	0.273
Up	-1.38	0.08	0.080
Down	-9.67	-1.87	0.005*
Northeast	-2.89	0.66	0.211
Northwest	-2.74	-0.17	0.028*
Southeast	-6.26	1.00	0.150
Northeast - Northwest - Southeast	-5.32	0.37	0.085

Clustering analysis is a technique that can be used to obtain the information about similar groups. In the future, this can be used to extract characteristics for classification and users' profiling.

The results obtained by hierarchical clustering, using the nearest neighbour method and squared Euclidean distance, show the similar performance of subjects except one individual. In this case, using the R-square criteria, the number of necessary clusters to achieve 80% of the total variability retain by the clusters is 12. Since the sample of volunteers was from the same population, this kind of conclusions are very natural. So the next step will consist in obtain information about handicapped people. In fact, if the clusters of subjects could be defined then it should be interesting to work with supervised classification in which the best command mode would be the class.

6 Conclusions and Future Work

Although many Intelligent Wheelchair prototypes are being developed in several research projects around the world, the adaptation of user interfaces to each specific patient is an often neglected research topic. Typically, the interfaces are very rigid and adapted to a single user or user group. The Intellwheels project is aiming at developing a new concept of Intelligent Wheelchair controlled using high-level commands processed by a multimodal interface. However, in order to fully control the wheelchair, users must have a wheelchair interface adapted to their characteristics. In order to collect the characteristics of individuals it is important to have variables that can produce a user profile. The first stage must be a statistical analysis to extract knowledge of user and the surrounding.

The second stage must be a supervised classification to use Machine Learning algorithms in order to construct a model for automatic classification of new cases.

This paper mainly refers to the proposal of a set of tasks for extracting the required information for generating user profiles. A preliminary study has been done with several voluntaries, enabling to test the proposed methodology before going to the field and acquiring information with disabled individuals. In fact, this will be the next step of future work. The test set presented in this paper will be tested by a group of disabled individuals, and the results of both experiments will be compared to check if the performances of both populations are similar. Also, in order to collect feedback regarding the system usability, disabled users will be invited to drive the wheelchair in a number of real and simulated scenarios.

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