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A new multi-criteria optimization strategy for shared control in wheelchair assisted navigation

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Abstract In nowadays aging society, many people require mobility assistance, that can be provided by robotized assistive wheelchairs with a certain degree of autonomy when manual control is unfeasible due to disability.

Robot wheelchairs, though, are not supposed to be completely in control because lack of human intervention may lead to loss of residual capabilities and frustration. Most these systems rely on shared control, which typically consists of swapping control from human to robot when needed. However, this means that persons never deal with situations they find difficult. We propose a new shared control approach to allow constant cooperation between humans and robots, so that assistance may be adapted to the user's skills. Our proposal is based on the reactive navigation paradigm, where robot and human commands become different goals in a Potential Field. Our main novelty is that human and robot attractors are weighted by their respective local efficiencies at each time instan. This produces an emergent behavior that combines both inputs in an efficient, safe and smooth way and is dynamically adapted to the user's needs. The proposed control schema has been successfully tested at hospital Fondazione Santa Lucia (FSL) in Rome with several volunteers presenting different disabilities.

Keywords Shared control · autonomous navigation · wheelchair · reactive behaviours

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1 Introduction

Autonomy in an agent can be defined as the ability to make activities independently [27, 41]. It has been reported that mobility is of key importance for a person to be autonomous [54]. However, a physically and/or cognitive challenged person may require some assistance to achieve autonomous navigation, either from a machine or from other persons. Chronic diseases may frequently lead to disability. It is estimated that the costs of health care could rise from 1.3 trillion to over 4 trillion dollars for these reasons [8]. Furthermore, lack of human resources to assist elder people leads naturally to create systems to do it in an autonomous way (eg. [57] [66]).

Studies on the use of assistive devices in a general population in Swedish descriptive cross-sectional cohort studies [30] reported that one-fifth at the age of 70 and almost half the population at the age of 76 had assistive devices, usually in connection with bathing and mobility. Another study of 85-year-old patients in a general elderly population found that 77% of them had one or more assistive devices, also more frequently for bathing and mobility. The same pattern has been found in other general population studies, although the prevalence rates vary from 23 to 75% according to studied population, age group and type of assistive devices. To sum up, prevalence rates vary, but the use of assistive devices is very common among the elderly, particularly bathing and mobility devices, and their use increases with age [69].

Specifically, it is stated by health professionals that mastering of mobility assistive device skills enhances a person's autonomy and participation in activities of daily living (ADL) [12]. When a person can walk with some assistance, walkers are used. Otherwise, persons rely on wheelchairs and, if they can not manipulate a traditional one, power wheelchairs are employed. In some cases, though, persons can not exert full control over a power wheelchair due to lack of practice, skills with technology or specific disabilities. To this respect, wheelchairs may be robotized to assist persons in control. However, it has been reported that excessive assistance may lead to loss of residual capabilities [12] [43], so it is important to provide the right amount of help: no more, no less.

1.1 Autonomous robot motion

Robotics has traditionally offered an alternative to human controlled wheelchairs. A robot is considered to be autonomous when it can perform a task in a dynamic environment without continuous human guidance. Traditionally, navigation was solved either deliberatively or reactively. The so called sense-plan-act scheme (SPA) (e.g. [2] [29] [46] [49]), uses a model of the environment to calculate a safe path to the goal. SPA control presents some basic drawbacks: i) all modules had to be fully functional to perform a basic task; ii) a single failure provokes a collapse in global functioning; iii) it has poor flexibility; and iv) it can not act rapidly because information is linearly processed by every module. In order to solve the SPA drawbacks, the subsumption architecture [6] is based on a bottom-up behavioral approach: i) simple behaviors are the result of coupling sensor readings and actions; and ii) the combination of several basic behaviors running concurrently produces a complex one. Reactive behaviors are fast, quite robust against sensor errors and noise and can easily adapt to changes in hardware or tasks [63]. Unfortunately, emergent behaviors are unpredictable [16], not necessarily efficient and prone to fall into local traps.

Hybrid schemes solve the aforementioned problems by combining both reactive and deliberative paradigms to achieve the best possible performance. The hybrid style facilitates the design of efficient low level control connected to high level reasoning and it is the most usual scheme in wheelchair autonomous navigation. One of the best known reactive schemes is the 3T system [3], which basically consists of a set of basic behaviors whose combination may produce complex ones. These behaviors must be fast, robust and not depend on any environment representation. The control system supervises behavior triggering and cooperation to achieve a higher level plan, which is provided by the deliberative System. This plan provides global guidelines or partial goals to the reactive system, which is supposed to follow the plan as much as possible while avoiding unexpected obstacles at the same time. Most current hybrid architectures are derived from a 3T scheme (*e.g.*[56] [64]).

Unfortunately, if a wheelchair is fully controlled by a navigation system, the recommended action might go against the user's wishes and cause him/her stress and, as commented, excessive assistance may lead to loss of residual capabilities, as no effort is required on the user's part. Furthermore, participation and feedback is reported to enhance rehabilitation. Consequently, many approaches to wheelchair navigation focus on cooperation between person and machine.

1.2 Collaborative control

Situations where machines and persons cooperate to achieve a common goal fall within the field of collaborative control. Agents involved in collaborative control need to dynamically adjust their own level of autonomy depending on the situation, by transferring decision making from one to another in an adaptable, smart way [59]. *Adjustable autonomy* (AA) focuses on performing this task without overly burdening humans.

AA can be applied to different fields. In the most general case, agents embedded in large organization do not only interact with one or several persons, but also with other agents as well (teamworking). Most works in this complex scenario are related to *software* agents associated to different persons and have mostly focused on coordination [12] [59], but there are also works with teams of robots [25], which are easier to handle than persons and, hence, a particular case of the general problem. It has also been traditionally simplified to interaction between a single agent and a single person, where research is usually related to cost based decision theory [19]. This field includes interaction between a *physical* agent and a person, which is typical in situations where a robot in a hazardous environment needs to be remotely controlled, like space or rescue missions [7] [18] [48]. Under these circumstances, robots need to have a certain degree of autonomy because communication can not be taken for granted and, in some cases, persons can not keep attention focused on so many minor, yet key details for prolonged time spans.

There are many studies on the level of autonomy a robot might have when interacting with a human and viceversa [1] [7] [28] [37]. Depending on the amount of autonomy given to the machine, collaborative approaches for human/machine control can be roughly categorized into i) safeguarded operation; and ii) shared control. An extreme case, where humans only point the machine to the target and let it drive alone, would be equivalent to autonomous deliberate robot control and is commented afterwards. In the first case vehicles can be totally controlled by humans, but in some cases the robot makes some decisions to avoid imminent danger when communication interruption and delays are frequent [38] [47] or when human control is not adequate[45] [53] [52].

This work focuses on human-robot interaction, but specifically in the field of wheelchair navigation. It is important to note that wheelchair navigation strongly differs from other human-robot shared control approaches, in the sense that persons are actually riding the robot and, hence, have first-hand feedback on resulting actions, and also because a high collaborative profile is desirable to avoid loss of residual skills, whereas in other situations it is usually better to reduce the number of interactions with the robot to reduce the cognitive burden of driving the machine. In the next sections, we focus on wheelchair collaborative control and present related work is presented in order of increased robotic assistance.

1.2.1 Safeguarded navigation

The field of wheelchair navigation is particularly concerned with shared control, where control may be handed from user to machine depending on the situation at hand. A first group of approaches leaves control mostly to the person, and automatic navigation is only triggered when a given situation is detected, like imminent collision. Under these circumstances, a reactive algorithm, most frequently a Dynamic Window Approach [22] based algorithm [23] [40] [44], is used to avoid obstacles.

1.2.2 Behavior-based shared control

A second group of approaches [10] [28] [44] [58] [62] rely on using a basic set of primitives like *AvoidObstacle*, *FollowWall* and *PassDoorway* to assist the person in difficult maneuvers, either by manual selection or automatic triggering. Hence, the operator may guide the robot directly, or switch among various autonomous behaviors to deal with complex situations. Many of these wheelchairs rely on a subsumption-like scheme [6], where detected events trigger one or several behaviours -chosen either automatically or by the user- and merged into an emergent one that is finally executed. MAID [57], NavChair [62], TinMan [44], Smartchair [58], Wheelesley [70], VAHM [5] Rolland III [40] follow this approach for assisted navigation. The main difference among them is how behaviours are implemented. For example, NavChair relies on a Vector Field Histogram (VFH) method to avoid obstacles, that simply models the obstacle distribution around the robot, whereas Rolland III uses a Dynamic Window Approach (DWA) where wheelchair kinematics are taken into account. Both implementations are well known in autonomous navigation and fully described in [4] [22].

1.2.3 Deliberative shared control

In an extreme case, the human operator might only point the target and the machine would be in charge of motion planning and path tracking on its own [5] [14] [23] [24] [50] [61]. These systems work like a conventional autonomous robot: the user simply provides a destination and the wheelchair is totally in charge of getting there via a hybrid navigation scheme. At any point, the user may override automatic control and take over. SENARIO [33], for example, uses a local navigation layer controlled by a high level planner based on a topological representation of the environment. TAO [24] uses two CCD cameras to detect the depth and size of free space in front of the robot but also to detect visual landmarks. This is also combined into a topological map for deliberative navigation. Rolland III [40] uses a Dynamic Window Approach (DWA) for local navigation, whereas deliberative navigation relies on a laser based evidence grid to extract Voronoi diagram. SIAMO [42] models the environment by means of Visibility Graphs processed by an A* algorithm and relies on a Potential Fields Approach (PFA) for local navigation. More cooperative systems rely on dialogue via prompting to take some decisions, so that the robot is assured about the ongoing plan [20].

1.3 Proposed scheme

Most commented approaches to shared control usually rely on swapping control from human to machine either by human request, hazard detection or according to more or less complex algorithms to detect specific situations. However, control swapping provokes curvature changes and discontinuity from the wheelchair point of view. Sharp control changes are not positive for humans either. If control swap is automatic, they would not know when they could lose control and, hence, not feel in charge. If it is persons who decide when to give up, they would not make efforts to overcome certain situations and, consequently, lose residual capabilities. Also, interfaces in these cases become more complicated and less intuitive for people.

In this paper, we propose a new shared control approach to assisted navigation based on a reactive algorithm. Its main novelty is that machine and human cooperate in a continuous way to achieve a better combined result in situations where one or the other perform better. Also, the person always contributes to navigation. Our approach relies on locally evaluating the performance of human and robot for each given situation. Then, both their motion commands are weighted according to those efficiencies and combined in a reactive way. This approach benefits from the advantages of typical reactive behaviors to combine different sources of information in a simple, seamless way into an emergent trajectory. The collaboration scheme is presented in section 2. The proposed system has been evaluated in a rehabilitation hospital by users presenting different disabilities and their performance has been evaluated both from an analytical and subjective point of view by doctors, engineers and the users themselves. Experiments are deployed in section 3. Finally, conclusions and future work are presented in section 4.

2 Collaborative navigation system

In order to collaborate through a trajectory, humans may provide motion commands through any human-computer interface (HCI), depending on their physical and/or cognitive condition. Wheelchairs have typically been controlled by joysticks, pads, voice and specific devices for people with severe mobility problems [17] [31] [60] [61]. In case of cognitive disabilities, complex devices -e.g. multiplexed buttons- or controllers requiring a high attentional profile -e.g. most Brain Computer Interfaces (BCI)- are feasible as well. There are also specific studies for collaborative interfaces for motion control [21] [20]. In any case, though, motion commands coming from a human can be reduced to a motion vector. Wheelchairs need to provide their own motion commands as well, based on their on-board sensors. In most cases, these sensors return range measurement, indicating how far the system is from nearby obstacles. Data that is available on the robot (position with respect to goal and obstacles) can be translated into appropriate motor commands via a navigation architecture.

In our work, reactive navigation schemes are particularly interesting because they may deal with several sensors and goals in a simple way, so they can be used to combine human and wheelchair commands and goals. The resulting system, though, is not completely reactive, as humans tend to have a deliberative agenda that is propagated down to joystick commands. Human influence on a reactive layer may be of help to gain global efficiency via prediction and to avoid local traps. Should the person present a cognitive disability that prevents him/her to make deliberative plans, a deliberative layer could be also added to the robot in a hybrid way, as commented in next subsection.

2.1 Wheelchair autonomous motion

Our reactive layer is based on a pure Potential Fields Approach (PFA) [34]. PFA basically relies on modelling obstacles as repulsors and goals as attractors to create a vector field that returns a motion vector at each point. PFA provides a simple and efficient tool for autonomous motion that, in its simplest version, has been reported to present some problems due to their reactive nature: i) oscillations when obstacles are too close; ii) incapacity to move safely through narrow corridors; and iii) local traps. Many of these problems may be solved by empowered versions of the purely reactive algorithm if the application domain is somewhat restricted. For example, our experiments have been conducted indoors in a rehabilitation hospital, where persons are expected to navigate through hospital corridors and cross doorways. Without a major loss of generality, we can set the PFA to keep obstacles on the sides of the wheelchair at the same distance by adding three forces (Fig.1.a): $f_{CFparal}$ tries to move the robot parallel to a wall. f_{CFdist} takes into account the wall on the other side, should there be any. Finally, $f_{CFavoid}$ avoids obstacles that may appear in the way of the chair. Let $k_{CFparal}$, k_{CFdist} and $k_{CFavoid}$ be three factors that weigh $f_{WFparal}$, f_{WFdist} and $f_{WFavoid}$, respectively. If d_C tends to the distance to the obstacle, robot rotational velocity (v_{rR}) and robot translational velocity (v_{tR}) are calculated as:

$$
\begin{aligned}
v_{rR} &= f_{CFparal} + f_{CFdist} + f_{CFavoid} = \\
&= k_{CFparal} \cdot \alpha_W + \\
&+ k_{CFdist} \cdot (d_C - d_W) + \\
&+ k_{CFavoid} \cdot (d_{CFSEC} - d_F) \\
v_{tR} &= f_{CFavoid} = k_{CFavoid} \cdot (d_{CFSEC} - d_F)
\end{aligned}
\tag{1}
$$

α_W being the angle to the nearest right wall, d_W being the current distance to the right wall and d_F being the distance to obstacles in front of the robot. d_{CFSEC} is a threshold distance to consider that an obstacle is too close to the robot. It can be noted that in absence of walls, this equation tends to be equal to a purely reactive PFA.

In order to also avoid oscillations and incapacity to cross doorways, when a door is detected in front of the wheelchair (as a wall opening), a door crossing behavior, also based on PFA, is triggered to move through. It affects only to the rotational component of the robot velocity, whereas the translational component remains unchanged. This behaviour is based on two forces (Fig.1.b): f_{DCort} allows the robot to stay orthogonal to the doorframe; and $f_{DCavoid}$ avoids the doorframe, preventing the robot from colliding with it. Let

Fig. 1 PFA forces for: a) corridor path; and b) door crossing.

k_{DCort} be a constant that weighs f_{DCort} and $k_{DCavoid}$ be another constant that weighs $f_{DCavoid}$. Let also be d_L and d_R the distance to the left and right part of the door, respectively. If d_F is the distance to obstacles in front of the robot, v_{rR} is:

$$\begin{aligned} v_{rR} &= f_{DCort} + f_{DCavoid} = \\ &\quad + k_{DCort} \cdot (d_L - d_R) + \\ &\quad + k_{DCavoid} \cdot (d_{DCSEC} - d_F) \\ v_{tR} &= f_{CFavoid} = k_{CFavoid} \cdot (d_{CFSEC} - d_F) \end{aligned} \tag{2}$$

being d_{DFSEC} a threshold distance to consider that an obstacle is close enough to the robot to be of interest. In order to simplify notation, we will denote speed as a vector formed by translational and rotational components $\mathbf{v}_R = [v_{tR} \quad v_{rR}]$.

There are two important things to be noted at this point. First, PFA are fairly common in navigation, both for autonomous robots [34] and assistive wheelchairs [24] [42]. In fact, many asssitive wheelchairs rely for collision avoidance in algorithms derived from PFA, most usually the Vector Field Histogram (VFH) [33][62], which cope with traditional problems in PFA (oscillations, refusal to move into narrow corridors...). The proposed adaptation of PFA to corridors and doors is not novel either. There are PFA versions that propose similar solutions to deal with such environments. However, it needs to be noted that our PFA implementation is not the novelty of our proposal. The main feature of our architecture is a local efficiency based weighting method to combine human input and robot commands in an adaptive, continuous way, as explained in next subsection. It could also be argued that, rather than implementing a variation of PFA, we could have used VFH or even a Dynamic Window Approach (DWA) as in [40], that would have been more efficient. However, we do not want the robot to be too efficient, just enough to help the user a bit when needed. If the robot is too efficient, our efficiency weighted vector combination would mostly favor it and the wheelchair would behave like an autonomous robot. With our implemented PFA, user and robot may cooperate in more equal terms.

Any PFA based algorithm allows an almost seamless combination of human and robot commands by definition. PFA return a motion vector that may be combined with the joystick vector. This approach has the side effect of avoiding local minima, as humans provide an uncorrelated force to the vector combination, as explained in next section.

2.2 Shared control

The proposed approach to collaborative control is quite simple: basically, human and robot produce a motion command together. Wheelchair control will be higher or lower depending on the user's general condition and their respective efficiencies at the time.

$$\mathbf{v}_S = (1 - k_H) \cdot \eta_R \cdot \mathbf{v}_R + k_H \cdot \eta_H \cdot \mathbf{v}_H \tag{3}$$

Fig. 2.a shows how human and robot commands ($\mathbf{v}_H$ and $\mathbf{v}_R$) are combined into an emerging shared control command ($\mathbf{v}_S$) at location q. $\mathbf{v}_S$ is not just the average of $\mathbf{v}_H$ and $\mathbf{v}_R$. These commands are weighted by their respective efficiencies: η_H and η_R. There is also another factor, K_H that allows a global increase/decrease of human contribution to the equation if advised by caregivers (e.g. an user in good physical and cognitive condition, has a k_H equal to 0.75). Unless stated otherwise, K_H is equal to 0.5 in all our experiments. Yet, it must be noted that k_H is just an amplification factor, so the amount of control exerted by human and machine would still fluctuate otherwise. Efficiencies range from 0 to 1, but no extreme case has been observed in our experiments, specially because the safeguard layer forces a minimun efficiency in terms of safety all the time.

The key in equation 3 is how to locally estimate motion efficiency, because, due to the purely reactive nature of the approach, global factors like trajectory length or completion time can not be used. Indeed, efficiency (η) has to be measure in a punctual way. We have identified three factors with an impact on η: *smoothness* (η_{sf}), *directness* (η_{tl}) and *safety* (η_{sc}), each of them ranging from 0 to 1. Global efficiency η is the average of these three efficiencies. It needs to be noted that human, robot and shared commands are usually different, so their respective efficiencies are different as well and calculated separately for each. Fig. 2.b shows how these factors are calculated at location q. Smoothness reflects how sharp direction changes are undesirable for driving. Safety reflects that it is better to keep away from obstacles. directness tries to reflect that keeping directions in average leads to shorter paths.

Fig. 2 a) Vectors involved in motion command calculation; and b) local efficiency factors for an agent i.

Smoothness (η_{sf}) is locally evaluated as the angle between the current direction of the wheelchair and the new motion vector. This factor is included because non-holonomic mobiles may can not change directions abruptly due to their kinematics. Hence, it is better to change heading as little as possible to avoid slippage and oscillations (Fig. 2.b). Given C_{sf}, a constant to fix how efficiency is affected by direction changes, and α_{dif}, the angle between the current direction and the command vector, η_{sf} will be:

$$\eta_{sf} = e^{-C_{sf} \cdot |\alpha_{dif}|} \tag{4}$$

directness (η_{tl}) is locally measured in terms of the angle formed by the input command and the direction towards the next target, should there be any. Partial targets come from a deliberative planner, as presented in [55], and correspond to the points of maximum curvature of the path it returns, meaning that a robot could move between partial goals safely and with minor curvature changes if no unexpected obstacles appear in the way. From the wheelchair's point of view, a partial goal would be the place of choice to change directions if there is a global plan. Otherwise, the target is calculated by averaging the wheelchair heading within a shifting time window whose size is inverse to the average curvature of the path within the window. This means that if the user is turning consistently, the window becomes small and directness may be high even though heading is changing. However, if we sway the wheelchair with no clear purpose, heading becomes inconsistent and directness decreases. In this sense, when there are no deliberative goals to reach, we just reward the skill of keeping directions.

Let C_{tl} be a constant and α_{dest} the angle between the robot heading and the direction towards the next partial goal (Fig. 2.b). We presented α_{dif} in equation 4, as the difference between current direction and command vector. The difference between α_{dest} and α_{dif} is the same as between command vector and next partial goal. Hence, η_{tl} is calculated as:

$$\eta_{tl} = e^{-C_{tl} \cdot |\alpha_{dest} - \alpha_{dif}|} \tag{5}$$

The third factor, *Safety* (η_{sc}), depends on the distribution of the closest obstacles at each instant with respect to the proposed command. The closer the wheelchair gets to obstacles, the less safe the trajectory is. In our implementation, the PFA repulsion forces are obtained from obstacle distribution at the evaluated location. Assuming that C_{sc} is a constant and that α_{min} is the complement angle conformed by the input command and the resulting PFA repulsion force ($\bar{\nabla} U_o(q)$) - meaning that we want the robot to keep away from all obstacles around- (Fig. 2.b). The difference between α_{min} and α_{dif} is proportional to the angle difference between user command vector and PFA repulsion force. The safest situation is when both vectors are equal, so we defined η_{sc} as:

$$\eta_{sc} = 1 - e^{-C_{sc} \cdot |\alpha_{min} - \alpha_{dif}|} \tag{6}$$

Finally, efficiency η is obtained by averaging the three aforementioned factors. Since each of the factors ranges from 0 to 1, they have equal weight in the global efficiency calculation. However, due to the commented safeguard layer, safety efficiency is usually higher than the rest.

It needs to be noted that a local efficiency equal to 1 is not always the best choice. Some efficiency factors may be opposite in presence of obstacles, like keeping far from them and trying to turn as little as possible. Also, the layout of the environment may make it necessary not to head towards the goal all the time. Finally, in order to move through narrow places like doors, safety efficiency might be low sometimes.

The proposed approach has several advantages: i) it tends to preserve curvature and to grant safety, as most PFA-based algorithms; ii) humans are in control all the time and they do not perceive sharp control swaps; and iii) humans provide deliberation to avoid local traps. Furthermore, the proposed reactive scheme is fully compatible with higher level navigation layers to achieve a hybrid shared navigation system, if necessary.

3 Metrics and performance evaluation for shared control

Regarding evaluation, there are well established metrics for manual wheelchair driving through obstacle courses (e.g. [67]). However, there are not so many standards for power wheelchair navigation, especially when shared control is concerned. There seems to be an agreement, though, to distinguish between task metrics and psycho metrics [11]. The first ones refer to goal achievement features, like error rate with respect to an unique, prefixed trajectory. The second ones try to measure parameters like fatigue and attention from the user point of view.

Regarding *Task Metrics*, some researchers focus on drawing a trajectory on the floor and asking persons to follow it as close as possible. This is usual when persons perform in pre-established environments to check their skills in various tasks like negotiating kerbs, ascending slopes, etc [36]. However, in general performance cannot be measured in terms of error with respect to a fixed trajectory, as there is no unique, prefixed choice to move through a corridor in an everyday dynamic situation. We have performed this kind of experiments before, by painting a line in the floor and measuring how much the users derivated from this line and we found out that users were too worried about tracking the line to really care about general driving guidelines [13]. Hence, in current experiments we decided to simply characterize the efficiencies of human, machine and shared control at each point via local parameters, as specified in previous sections: ***safety***, ***directness*** and ***smoothness***. Thus, following a fixed path is not as important as driving well. It needs to be noted that our approach aims at optimizing those three efficiencies, but, as commented, most of the time it is not possible to keep them all well balanced in mildly complex indoor environments. Also, human contribution to control may decrease these efficiencies. Hence, they are good choices to evaluate global performance, plus they have a clear qualitative meaning.

All these parameters are locally evaluated, so we use a graphical shortcut to easily represent them all locally at the same time over the trajectory. Graphically, each one of the local efficiency factors is assigned to an RGB color channel: red for smoothness, η_{sc}, green for directness, η_{tl}, and blue for safety, η_{sc}. Then, a 3D representation is employed, where the XY plane represents the floor where the chair moves, and the Z axis is assigned to combined efficiency η at each point. When the trajectory is deployed on the XY plane, it is possible to know how good each control parameter rated at each trajectory point depending on its color. If projected onto XZ, the height of the point may represent at the same time the combined efficiency at the point. This representation proved to be useful, as it could be recognized from a simple look at their colors how trajectories behaved at certain areas.

We also use some global parameters to measure the emergent trajectory in absence of a path traced on the floor. A simple parameter of this kind is the maximum/minimum of the aforementioned local parameters or their statistical averages and deviations. In our case, we have also chosen ***trajectory curvature*** (Curv), a parameter that measures how much a curve r bends at each point (Eq. 3), estimated as proposed by the authors in [65]

$$Curv(t) = \frac{(r' \cdot r'') \cdot r''}{||r' \cdot r''||^2} \tag{7}$$

A common parameter in this type of experiments that can also be measured in our case is the well known ***Time to destination*** and/or *Travelled distance*. We are not so interested in measuring how fast a given user may guide his/her wheelchair as to check if this time is reduced through use, meaning that the person actually learns to drive the wheelchair through practise. In our experience, persons who drive the wheelchair well tend to minimize their time to destination and travelled length, mostly because they drive more fluidly, reduce manoeuvre times and oscillations and perform more precise movements. Naturally, these reductions are noticeable when we compare a user's performance to his/her earlier tries, not to other people, because each person achieves different results depending on his/her condition and skills.

Psycho metrics in absence of biometrics sensors can only be indirectly measured. ***Intervention level*** is defined as the portion of time that the user moves a joystick [11]. It must be noted that in our approach to shared control, a high intervention level is desired, meaning that the system is highly cooperative. In other cases, though, it is desirable to keep this parameter as low as possible, meaning that the user mostly agrees with the machine [11]. In our case, we have chosen to evaluate this agreement via a parameter named ***Disagreement***, which represents the difference between the human output and the robot output. Since both outputs are vectors, we measure Disagreement in terms of angles. A 0 Disagreement means that the robot and the human totally agree. A high Disagreement is expected to be related with effort and frustration. Given the target population, it is also important to take into account ***Inconsistency***, defined as the variation of the user output when facing similar situations. A low Inconsistency is expected to be related to users with good cognitive capabilities, whereas a high one is related to random joystick motion. A second parameter related to user control is ***Joystick Variation***, which measures a change of more than 10% in the position of the stick. This information has been used as an indirect measure of workload [9] [35]. It is important to note, though, that it may be also related to spasmodic joystick movements.

Finally, all users were asked to fill the *PIADS (Psychosocial Impact of Assistive Devices Scale)*[1] [32] questionnaire proposed by doctors for usability. PIADS can be filled in 5 to 10 minutes and includes ratings for self-esteem, well-being, quality of life, embarrassment, eagerness to try new things and up to 26 other subjective factors scoring from **-3** to **3**.

All metrics are briefed in table 1

[1] *http://www.piads.ca/*

Table 1 Metrics in the experiment

Metric	Type	Relates to
Smoothness	Task	Sharp direction changes
Safety	Task	Closeness to obstacles
directness	Task	Keeping the goal ahead
Curvature	Task	Global trajectory smoothness
Time to destination	Task	Total time to complete the path
Travelled distance	Task	Total path length
Intervention level	Psycho	Collaboration with machine
Disagreement	Psycho	Effort and frustration
Inconsistency	Psycho	Cognitive capabilities
Joystick variation	Psycho	Workload
PIADS	Usability	User's opinion

4 Experiments and results

In order to test the proposed shared control algorithm, we used CARMEN[2], a Runner Meyra wheelchair, donated by Sauer Medica S.L., adding odometry and a frontal Hokuyo laser URG04-RX for localization and obstacle detection (Fig. 3.a).

The goal of these experiments is to check: i) if assistance is adapted to user's needs; if this is the case, different patients should have similar efficiencies despite their condition; ii) if users keep a high cooperative profile to avoid losing residual abilities, even in situations they find hard to solve; iii) if they are not too aware that they are receiving assistance or accept it willingly; iv) if the proposed control type eases drive learning. To this purpose we use metrics in the previous section and also measure the amount of help provided to the user at each point of every trajectory, his/her stand-alone efficiency when possible, time required to finish each trajectory and the subjective degree of satisfaction of each user.

All 30 volunteers in our experiments were hospital in-patients selected by doctors to have different physical and cognitive skills. Persons supervising the experiments were allowed to move freely in the proposed environment, but the place was closed to other patients, visitors or staff for security reasons.

Our main experiment was to move through a door (around 90 cms wide) from a room to a corridor and viceversa, which was stated by doctors as the most typical situation in hospital navigation that users have problems with. However, doctors also estimated that many of our volunteers would probably not be able to do this operation in standalone mode, so these tests were performed only in shared control more. However, since we wanted an estimation on how users drive on their own for comparison, doctors suggested that corridor navigation would be adequate for safe standalone navigation. Hence, all volunteers did corridor following experiments in standalone and shared control mode as well. The door crosing experiment was repeated at least 2 times per patient in each direction, plus they followed the corridor in both directions at least once in standalone and once in shared control mode. In brief, each used made no less than 8 trajectories with CARMEN. Fig.3.b shows an example of these trajectories. All inpatients involved in the experiments -30 volunteers- successfully finished them in shared control mode.

According to Yanco et al in HRI evaluations [71], the major shortcomings in this kind of experiments are that: i) system designers are often enlisted as test users; ii) HRI evaluations are commonly informal and rarely provide controlled, objective assessment; iii) there is a very limited number of users. We took this into account in the present experiments. There is and assessment section (section 3) and next subsection covers the specifics of users in the experiment.

[2] Collaborative Autonomous Robot for Mobility ENhancement

Fig. 3 a) Modified wheelchair; b) Experiment goal paths

4.1 Target population

Our wheelchair was extensively used during July, 2007 in FSL[3], a rehabilitation hospital in Rome. All experiments were approved by the hospital Ethical Committee and performed by volunteering in-patients, always in presence of at least one authorized medical supervisor and one engineer. All volunteers signed an agreement to do the experiment and also agreed to fill a PIADS questionnaire afterwards. Our target community were people who have difficulties to guide a power wheelchair via a joystick due to various difficulties ranging from physical to cognitive. Also, they lacked experience with power wheelchairs.

Following the doctors' advice, several disability scales were used to evaluate the state and condition of the inpatients, namely the Mini-Mental State Examination (MMSE), Geriatric Depression Scale (GDS), Apraxia and Barthel.

The mini-mental state examination (MMSE) or Folstein test [15] is a brief 30-point questionnaire test that is used to assess cognition. It is commonly used in medicine to screen for dementia. In the time span of about 10 minutes, it samples various functions, including arithmetic, memory and orientation. Even though results

[3] *http://www.hsantalucia.it/*

Fig. 4 Standalone efficiencies following a straight line for humans: a) usual performance; b) erratic case

may change slightly depending on the number of questions applicable to the in-patient, **24** is usually the accepted threshold for dementia.

The Geriatric Depression Scale (GDS), first created by Yesavage et al. [72], has been tested and used extensively with the older population. It is a brief questionnaire in which participants are asked to respond to the 30 questions by answering yes or no in reference to how they felt on the day of administration. Scores of **0 - 9** are considered normal, **10 - 19** indicate mild depression and **20 - 30** indicate severe depression.

Apraxia is a neurological disorder characterized by loss of the ability to execute or carry out learned purposeful movements, despite having the desire to and the physical ability to perform the movements. It scores from 0 (worse result) to **10**.

The Barthel Index [39] consists of 10 items that measure a person's daily functioning specifically the activities of daily living and mobility. Items include feeding, moving from wheelchair to bed and return, grooming, transferring to and from a toilet, bathing, walking on level surface, going up and down stairs, dressing, continence of bowels and bladder. Over a maximum score of **100**, less than 20 means total dependency, over 60 is slight dependency and from 40 to 55 is a mild one. Average indexes are briefed in table 2. Cognitively, our volunteers are under the threshold of dementia, but deviation in MMSE shows that some presented severe cognitive disabilities, whereas others had none. Apraxia is generally unremarkable except in a few cases, so users' commands should correspond to what they want to do. The average Barthel index is 64.2, corresponding to a mild dependency. Its variation, however, goes up to almost 30, meaning that some volunteers may present severe physical disabilities. All in all, it is important to note that each person's skills depend largely on his/her condition. This suits well our proposal to provide assistance on a need basis: we will not assist actions the user can achieve on his/her own, but we will provide as much help as needed when necessary.

Table 2 Disability indexes in the test population

Index	Average	Deviation
MMSE	23.47	8.57
GDS	5.02	3.70
Apraxia	8.94	2.47
Barthel	64.20	29.66

4.2 Human standalone and robot autonomous performances

Table 3 briefs the performance of the robot in both corridor and door situations, and human corridor standalone performance, as standalone door crossing was forbidden by doctors. The robot is very efficient in the corridor tests, but doors are hard for the purely reactive PFA, as expected. Minor variations in robot performance are due to small shiftings in the departing position, people moving around and minor sensor errors.

Table 3 Statistical results of stand-alone performances for robot and human.

Test	Corridor	Door
Robot Average Efficiency (%)	91.90	58.84
Robot Variance Efficiency (%)	2.79	9.01
Robot Sum Curvature Function (°)	1.68	92.64
Robot Variance Curvature Function (°)	0.56	7.02
Human Average Efficiency (%)	73.63	N/A
Human Variance Efficiency (%)	27.52	N/A
Human Sum Curvature Function (°)	0.86	N/A
Human Variance Curvature Function (°)	19.04	N/A

Unlike robots, persons found it harder to drive in a straight way and drifted towards the walls, so their directness was not very good, as reflected in Fig. 4.a. Although efficiency is initially high, efficiency steadily decreases and goes pink, meaning that *directness* (green) is lower than *safety* and *smoothness*. Also, efficiency deviation for humans is quite larger than for robots because each person drives differently. Fig. 4.b shows a particularly bad run for one of the in-patient. Although local efficiencies are balanced (grey-black plot), global efficiency is lower than in the previous case: instead of improving directness, this user reduced safety and smoothness in her second try. It is interesting to note that low average curvature values along with high absolute curvature ones mean that in-patients are not able to correctly follow a straight line, but are capable of correcting their trajectories.

After evaluating these results, it would be interesting to check if shared control can: i) improve directness; ii) reduce efficiency variation; iii) enhance efficiency average; iv) empower door crossing; and v) reduce mental load. At the same time, it is important to: i) keep a high intervention level to avoid loss of residual capacities; and ii) keep disagreement between the person and emerging motion as low as possible.

Fig. 5 Efficiencies following a straight line for: a) robot alone; b) human alone; and c) shared control

4.3 Shared control performance

Next experiments were performed using shared control. It must be noted that emergent trajectories can not be directly compared to the ones achieved by the wheelchair alone or by any human driver on his/her own, as their commands are merged at all times and, hence, it is not possible to know what each agent would have done on their own from the emerging trajectories. Nevertheless, local efficiencies were compared to input human and robot control commands at each time instant for local comparison between performances.

4.3.1 ***Corridor experiments***

Fig. 5.a-c shows local efficiencies at each point of the corridor in a run of an average user (MMSE=23, Barthel=68) for robot, human and shared control, respectively. Robot efficiency decreases a bit along the way due to human influence, but, still, it remains close to 1 (white) (Fig. 5.a). Our volunteer, however, does not have a good directness and, hence, gets a lower, pink efficiency (Fig. 5.b) and, in the end, even smoothness is reduced. Shared control efficiency (Fig. 5.c) also goes pink at the end of the path, but it is clearly higher than human's and smoothness is preserved all the way.

Efficiency differences in the commented experiments throw similar conclusions. Figs. 6.a and b represent the difference between the global efficiencies of robot E_{rob} and human E_{joys} for a new volunteer in standalone (tests 0 and 4) and shared control mode (tests 1 and 5), respectively. In standalone mode, shared and human efficiency are practically the same except for some minor peaks, where a safeguard layer is triggered to avoid inminent collisions. It can be observed that the robot is typically better than the human, especially at the beginning of test 0, because this particular volunteer learnt to use the system quite fast. Shared control efficiency is closer to human performance but, still, better (Fig. 6.b). Also, it is interesting to note that there are fewer peaks in this second case, meaning that the user should feel more in control in shared control mode because emergent motion is closer to his/her commands.

In brief, corridor experiments point out that humans are less efficient than the robot and shared control due to loss of directness. Nevertheless, they performed well in terms of safety and acceptably -with variations depending on the user condition- regarding smoothness. Most remarkable variations were related to people with major cognitive disabilities, that tended to drift towards the wall very often. Collisions were prevented by the safeguard layer even in standalone mode. People with severe physical disabilities often found it harder to control the wheelchair, but managed to kept directions on their own. In fact, all volunteers managed to finish the task on standalone mode no further than $1m$ from the goal, but all of them improved in efficiency in shared control mode.

Assistance was particularly noticeable at the beginning of each test, when they had to start moving the wheelchair, due to inertia. Errors at this point seemed to make them nervous and provoked heavy oscillations in standalone mode that were mostly filtered by shared control.

Fig. 7 Average efficiencies and deviations for all users in the tests.

4.3.2 ***Door experiments***

As commented, we had no standalone reference for door crossing experiments, so we compare shared control to input human and robot commands instead. Fig.7 shows statistics for all users in these experiments. Robots' commands in average are better than humans'. However, shared control is better in average than the robot in terms of smoothness and safety, proving that humans contribute positively to the emergent behavior. As usual, humans' worst feature is directness. This can be due to the non-existence of visual marks in the experiment -only general guidelines were provided to the persons-, plus the lower precision of humans with respect to machines at metric level. It is also interesting to note that human deviation is the largest, meaning that there is much variation in performance in this more complex test from one person to the next. Shared control presents less deviation: it tends to equalize human performance despite the users' condition.

Fig. 8 presents efficiencies for human, robot and shared control for a random user (MMSE=26, Barthel= 76) in a room to corridor test. It can be observed that the robot is not adept for door crossing due to PFA oscillations (Fig. 8.a). This volunteer does not perform so well, either, especially when she needs to turn right to position herself in the corridor. However, she was better than the robot at door crossing, as she kept moving in an almost straight way. In this case, the full potential of shared control can be observed in the white efficiency plot in Fig. 8.c, as it clearly improves not only user's performance but also robot's door crossing skills.

Fig. 6 Corridor following: robot-human/shared-human efficiency difference for: a) standalone mode; b) shared control

Fig. 8 Local efficiencies for door crossing for: a) robot; b) human; and b) shared control.

Fig. 9 Tracks to move from corridor to room.

In our tests, room to corridor paths are not symmetrical with corridor to room ones. The second task is usually harder because it is necessary to choose when to turn to face the door with a comfortable heading. We can appreciate this effect particularly in persons with severe disabilities, who find it harder to maneouver the wheelchair. This is the case, for example, of in-patient 28 (tables 4 and 5 (MMSE=20, GDS=10, Apraxia=10 and Barthel=41). This person takes 49,74s to get out of the room and 62.87s to go in, due to a major smoothness loss in a try to head the door in a straight way. Despite this problem, shared control provides similar average efficiencies in both cases. Psycho metrics are significantly different, though. Intervention level is high in both cases, but quite below the group average. Disagreement in the corridor to room test, on the other hand, is almost twice disagrement in the room to corridor test and presents a large variance, basically centred in the door area. This means that the emergent behavior of the wheelchair does not match the user's commands. This would not be a good feature, but if we we observe the user's consistency, we can see that he is not so sure about his actions either, basically because he does not know how to solve th situation at hand. Thus, shared control fills this gap. Nevertheless, joystick variation is not that large, meaning that this disagreement is not related to frequent sharp joystick changes that typically indicate that the user is stressed.

Table 4 Metrics for in-patient 28 (room to corridor)

Metric	Type	Average (%)	Deviation
Smoothness	Task	80.35	22.64
Safety	Task	95.44	17.75
directness	Task	62.76	25.59
Curvature	Task	0.11	0.34
Time to destination	Task	49,74	10.06
Intervention level	Psycho	80,87	
Disagreement	Psycho	19.46	13.26
Inconsistency	Psycho	8.71	8.20
Joystick variation	Psycho	2.39	6.77

In general, most users in the corridor to room experiments perform similarly except those with severe disabilities, either cognitive, physical or both. Fig. 9 shows the paths of every volunteer in this text. Initially paths are very similar, but they change significantly when they turn to cross the door, depending on how soon the user starts to steer. According to their opinion, this was the hardest experiment for most volunteers and, in fact, many of them stopped at the turning point and spent some time there trying to figure out a way in. This is specially the case for people who delayed too much their decision to turn, as appreciated in the detail in Fig. 9. Nevertheless, all of them suceeded. Users' statistics in this test support that: i) shared control is smoother than robot and human control; ii) in terms of directness, the robot system is still the best, but shared control deviation is clearly lower than both human and robot, i.e. emerging trajectories are more homogeneous in terms of directness; iii) regarding safety, both robot and shared control are better than human control. Finally, it can be observed that shared efficiency is slightly better than robot efficiency, but this happens only because pure PFA are not good at door crossing, so it is not significant. However, deviations in shared mode are smaller in every case, meaning that shared control equalizes performance for all users despite their condition.

Table 5 Metrics for in-patient 28 (corridor to room)

Metric	Type	Average (%)	Deviation
Smoothness	Task	75.32	26.81
Safety	Task	95.28	15.80
directness	Task	60.88	28.78
Curvature	Task	-0.65	8.43
Time to destination	Task	62.87	8.77
Intervention level	Psycho	80.26	
Disagreement	Psycho	36.36	34.23
Inconsistency	Psycho	13.06	13.40
Joystick variation	Psycho	2.14	7.29

Fig. 10 shows results for the room to corridor experiment. This test is easier because user start facing the door, and most variations depend on when they decide to turn and face the corridor (see detail in the figure). However, in this case the turning point is not so critical, because they are already out of the narrow area (door). Global efficiency is larger in all cases than in the previous experiment. Regarding smoothness, shared control still behaves better than robot and human and, again, deviations are smaller for shared control. All in all, we can extract the same conclusions than in the previous case, only this time differences between persons with severe disabilities and the rest were not so large.

Fig. 10 Tracks to move from room to corridor.

Fig.11 illustrates the effect of shared control in detail in a room to corridor experiment for a random user (volunteer 18). It can be observed in Fig.11.b that shortly after he leaves the room and turns to head the corridor, the overturns and moves towards the wall. This is clearly reflected in the efficiencies in Fig.11.a. Volunteer 18 has a very poor performance at the area, but PFA behave correctly, even though they yield some efficiency loss due to oscillations close to the wall. Shared control presents an efficiency almost as high as PFA, but noisier, as it preserves a filtered version of what the user is doing with the joystick. Fig.11.b shows how the user steadily recovers from this error and faces correctly the corridor in parallel with the wall.

4.4 General Metric evaluation

Table 6 shows the metrics of all in-patients in all experiments to wrap up results in general.

Table 6 Metrics for all experiments

Metric	Type	Average	Deviation
Smoothness	Task	78.72	25.50
Safety	Task	95.48	16.13
directness	Task	57.15	27.13
Curvature	Task	-0.11	3.78
Intervention level	Psycho	84.07	
Disagreement	Psycho	25.13	19.94
Inconsistency	Psycho	13.37	13.94
Joystick variation	Psycho	2.19	7.31

4.4.1 Safety, smoothness and directness

This system mostly preserves safety over all. Since it is derived from PFA, it also tends to return a smooth emergent behavior (average curvature = -0.11). Average efficiency in all our trials was over 80% and, in most cases, over 95%, despite the users' different cognitive and physical skills. Our worst feature is, by far, directness, because it was extremely low for some users. Nevertheless, all in-patients eventually reached the goal in shared control mode. Variation in these features in shared control mode is lower than in standalone or human performance in shared mode. From this point of view, shared control tends to equalize users' performance.

4.4.2 Collaboration

Our shared control scheme requires the user to provide commands, so Intervention levels is always higher than 70 %. Inertia takes care of the rest. Fortunately, this intensive collaboration does not seem to imply a too high workload on users according to Joystick Variation [9] [35]. This active profile avoids loss of residual skills. Intervention Level does not seem to be correlated with efficiency, but with it is correlated with Disagreement. Usually, a high Intervention Level implies a high Disagreement (15-20) as well, meaning that in-patients tend to intervene more when the wheelchair is not doing what they want. This was to be expected. Nevertheless, Disagreement is never over 25, because emergent behavior always takes into account the user's commands. It needs to be noted that even in standalone mode Disagreement is never lower than a 7% approximately, which seems to be related to the wheelchair usability as a vehicle.

4.4.3 Disagreement

High Disagreement and low consistency are related to persons with poor cognitive skills that tend to manipulate the joystick randomly. In these cases, emergent efficiency is not too affected because the robot corrects them most times. High Disagreement and good consistency are usually linked to poor performance. It usually means that the in-patient is prone to systematic errors that the robot may correct. However, the user fights correction (Disagreement) and this provokes an efficiency reduction. For example in-patient 4 and 5 (48.55/4.1 and 54.93/4.15 respectively) have emerging directness around a 45%. These cases are related to severe functional physical disabilities, but high cognitive profiles -these in-patients had MMSE close to 28-. Users seem to realize that the wheelchair is correcting them and, even though they need help, they fight it. In order to solve this problem, the robot control algorithm should be closer to human driving than PFA, so they would not notice so much that they are receiving assistance.

A high Inconsistency is not necessarily related to high Disagreement. For example, in-patient 3 in door experiments has a Disagreement equal to 17.3 in average along with an average Inconsistency equal to 16.4. This means that users make different decisions for similar situations, but do not oppose shared control either. In these cases, emerging efficiency is not so affected.

Fig. 11 Efficiencies for room to corridor for: a) robot, human and shared control; and b) resulting path

4.4.4 Learning

In general, we appreciated that volunteers learnt quite fast to control the wheelchair in. This effect was far more evident in persons who lacked experience with power wheelchairs or presented a mild functional disability. For example, in-patient 5 (MMSE=28, GDS=8, Apraxia=10, Barthel=69) reduced trajectory time in the room to corridor tests from 110.56s (10.8 meters) to 56.01s (10.60 meters). In corridor to room tests, he went from 195.90 s. (24.66 meters) to 53.81s (11.01 meters). Reduction in travelled distance also indicates that this run was far more efficient that the first. Disagreement and Joystick variation decreased as well. If we check volunteers as a whole, it takes them 6.9s less in average, with a variation of 21.1s, to reach their target after the first try. This average is not too meaningful, as time required for different trajectories is different as well, but it indicates that users do learn fast from experience with shared control.

4.4.5 Workload

If workload is measured in terms of Joystick Variations, it can be concluded that it was not too heavy for our users, because this variation was lower than 3% in average. However, as our emergent behavior is quite influenced by the driver and sharp variations are punished, this was to be expected except for spasmodic movements, which are filtered out of the system due to its random nature. We believe that in this case another parameter is required to measure workload. Probably, Disagreement is the closest metric we have to this purpose, but, yet, it does not reflect well the reality of in-patients with high functional disabilities. Further studies would be required to this respect.

5 Conclusion and future work

This paper has presented a new approach to shared control for collaborative wheelchair navigation. The key idea of this work is to locally measure the efficiency of both human and robot at each time instant. These efficiencies are used to weight human and robot commands and linearly combine them into an emergent motory command in an almost seamless way.

We have tested the system with 30 volunteers presenting different disabilities profiles at FSL (Rome). All of them succeeded in the proposed trajectories in shared control mode. In almost every case, shared control performance improved human performance and in many cases, it also improved robot performance, especially in situations where PFA has been reported to fail, like doors or close obstacles. In corridor navigation, shared control helped users to keep a straight trajectory, parallel to the walls. Assistance in turns tended to help people decide when to start turning to cross a door as easy as possible.

Safety in our tests was always high, specially because there was always a safeguard layer operating at the lowest level of the architecture to prevent collisions. Some volunteers had specific problems to move smoothly, that shared control reduced up to a point. However, directness yielded the lowest efficiencies, as evidenced by efficiency plots going pink or violet. This was expected because there were no physical references, further than the door, to follow one path or another, so each person drove at will. Shared control also compensated directness, but it was harder than to compensate smoothness.

Our most important conclusion, though, was that shared control tends to equalize performance among persons presenting very different disabilities. This means that, indeed, assistance is provided on a need basis, filling what each person needs at each situation. It was also very interesting to note that time and trajectory length required by persons to do same tests decreased significantly even after their first try, even though none had previous experience with power wheelchairs. Doctors in our team had reported that, in their experience, most people has trouble to get used to power wheelchairs even if they drive a conventional one. However, users commented that they found it easy to drive CARMEN in shared control mode. PIADS questionnaires pointed in the same direction. Thus, we conclude that shared control may be beneficial for learning to use power wheelchairs steadily.

Future work will focus on extending this study to persons presenting more severe disabilities and also to more complex scenarios, specially home-like ones. In these cases, development of higher level layers will most likely be necessary. Doctors are also interested in correlating our results with the functional disability degree of each in-patient.

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References

1. Aigner P, McCarragher BJ (2000) Modeling and constraining human interactions in shared control utilizing a discrete event framework. IEEE Transactions on Systems, Man and Cybernetics - Part A: Systems and Humans 30(3):369–379
2. Albus JS (1991) Outline for a theory of intelligence. IEEE Transactions on Systems, Man, and Cybernetics 21(3):473–509
3. Bonasso, R. P. Integrating reaction plans and layered competences through syncronous control (1991). In Proceedings of the International Joint Conference on Artificial Intelligence, p. 1225-1233, 1991
4. Borenstein J, Everett B, Feng L (1996) Navigating mobile robots: Sensors and techniques. A.K. Peters Ltd., Wellesley, Massachusetts
5. Bourhis G, Agostini Y (1998) The vahm robotized wheelchair: System architecture and human-machine interaction. Journal of Intelligent Robotic Systems 22(1):39–50
6. Brooks RA (1986) A robust layered control system for a mobile robot. IEEE Journal of Robotics and Automation 2(1):14–23
7. Bruemmer DJ, Few DA, Boring RL, Marble JL, Walton MC, Nielsen CW (2005) Shared understanding for collaborative control. IEEE Transactions on Systems, Man and Cybernetics - Part A: Systems and Humans 25(4):494–504
8. Ciole R, Trusko B (1999) HealthCare 2020: Challenges for the. Millennium, pp 34–38
9. Clarke D, Yen S, Kondraske GV, Khoury GJ, Maxwelle KJ (1991) Telerobotic network workstation for system performance and operator workload monitoring. NASA JSC, Houston, TX, Tech Rep 91-013R
10. Connell JH, Viola P (1990) Cooperative control of a semi-autonomous mobile robot. In: Proc. of the IEEE Conference on Robotics and Automation, Cincinnati, USA, pp 1118–1121
11. Cooperstock J, Pineau J, Precup D, Atrash A, Jaulmes R, Kaplow R, Lin N, Prahacs C, Villemure J, Yamani H (2007) Smartwheeler: A robotic wheelchair test-bed for investigating new models of human-robot interaction. In: Proc. of the IEEE Conference on Intell. Robots and Systems (IROS), San Diego, USA
12. Cortés U, Annicchiarico R, Campana F, Vázquez-Salceda J, Urdiales C, Cañamero L, López M, Sánchez-Marré M, Vincenzo SD, Caltagirone C (2004) Intelligenza artificiale in medicina: progetto di una piattaforma mobile inserita in un ambiente intelligente per li assistenza ai disabili e agli anziani. Recenti Progressi in Medicina 95(4):190–195
13. Cortés U, Urdiales C, Annicchiarico R, Barrue C, Martinez AB, Caltagirone C (2007) Assistive Wheelchair Navigation: A Cognitive View, Springer Berlin / Heidelberg, pp 165–187
14. Crisman J, Cleary M (1998) Progress on the deictic controlled whellchair, Springer-Verlag, pp 137–149
15. Crum R, Anthony J, Bassett S, Folstein M (1993) Population-based norms for the mini-mental state examination by age and educational level. Journal of the American Medical Association 269(18):2386–239
16. Darley, V.(1994) Emergent Phenomena and Complexity. Artificial Life IV. Proceedings of the Fourth International Workshop on the Synthesis and Simulation of Living Systems. MIT Press, pp. 411–416.
17. Detriche J, Lesigne B (1990) Robotic system master. In: European Conf. on the Avancenient of rehabilitation technology, Maastricht, Pays-Bas, pp 12–15
18. Dorais GA, Bonasso RP, Kortenkamp D, Pell B, Schreckenghost D (1998) Adjustable autonomy for human-centered autonomous systems on mars. In: First Int. Conf. of the Mars Society
19. Ferguson G, Allen J, Miller B (1996) Trains-95 : towards a mixed initiative planning assistant. Proc of the Third Conf on Artificial Intelligence Planning Systems pp 70–77
20. Fong T, Thorpe C, Baur C (2003) Multi-robot remote driving with collaborative control. IEEE Trans on Industrial Electronics 50(4):699–704
21. Fong T, Thorpe C, Baur C (2003) Robot, asker of questions. Robotics and Autonomous Systems 42:235–243
22. Fox D, Burgard W, Thrun S, Cremers A (1998) A hybrid collision avoidance method for mobile robots. Proc of IEEE Int Conf on Robotics and Automation pp 1238–1243
23. Frese U, Larsson P, Duckett T (2005) A multigrid algorithm for simultaneous localization and mapping. IEEE Transactions on Robotics 21(2):1–12
24. Gomi T, Griffith A (1998) Developing Intelligent Wheelchairs for the Handicapped, Springer-Verlag, pp 150–178
25. Gunderson JP, Martin WN (1999) Effects of uncertainty on variable autonomy in maintenence robots. In: Proc. of Agents'99, Workshop on Autonomy

Control Software
26. Guralnik JM, Simonsick EM (1993) Physical disability in older americans. Journal of Gerontology (48):3–10
27. Hexmoor, H.; Castelfranchi, C.; Falcone, R. (Eds.). Agent Autonomy. Series: Multiagent Systems, Artificial Societies, and Simulated Organizations, Vol. 7
28. Horiguchi Y, Sawaragi T (2005) Effects of probing to adapt machine autonomy in shared control systems. In: Proc. International Conference on Systems, Man and Cybernetics, Hawaii, USA, vol 1, pp 317–323
29. Hu H, Brady M (1996) A parallel processing architecture for sensor based control of intelligent mobile robots. Robotics and Autonomous Systems 17:235–257
30. Ivanoff S, Sonn U (2005) Changes in the use of assistive devices among 90-year-old person. Aging Clin Exp Res 17(3):246–251
31. Jaffe D (1990) A case study: The ultrasonic head controlled wheelchair and interface. OnCenter - Technology Transfer News 1(2)
32. Jutai J, Bortolussi J (2003) Psychosocial impact of assistive technology: development of a measure for children, IOS Press, Amsterdam, pp 936–940
33. Katevas NL, Sgouros NM, Tzafestas SG, Papakonstantinou G, Beattie P, Bishop JM, Tsanakas P, Koutsouris D (1997) The autonomous mobile robot senario: A sensor-aided intelligent navigation system for powered wheelchairs. IEEE Robotics Automation Magazine 4(4):60–70
34. Khatib O (1986) Real-time obstacle avoidance for manipulators and mobile robots. International Journal of Robotics Research 5(1):90–98
35. Khoury GJ, Kondraske GV (1991) Measurement and continuous monitoring of humanworkload associatedwith manual control devices. NASA JSC, Houston, TX, Tech Rep 91-011R
36. Kilkens O, Post M, Dallmeijer A, Seelen H, van der Woude L (2003) Wheelchair skills tests: a systematic review. Clinical Rehabilitation 17(4):418–430
37. Kofman J, Wu X, Luu TJ, Verma S (2005) Teleoperation of a robot manipulator using a vision-based human-robot interface. IEEE Transactions on Industrial Electronics 52(5):1206–1219
38. Kortenkamp D, Bonasso RP, Ryan D, Schreckenghost D (1997) Traded control with autonomous robots as mixed initiative interaction. In: Proc. AAAI Spring Symposium on Mixed Initiative Interaction, Stanford, USA
39. Mahoney F, Barthel D (1965) Functional evaluation: the barthel index. Maryland State Medical Journal (14):56–61
40. Mandel C, Huebner K, Vierhuff T (2005) Towards an autonomous wheelchair: Cognitive aspects in service robotics. Proceedings of Towards Autonomous Robotic Systems (TAROS 05) pp 165–172
41. Martin C E, Barber K S, Barber K S, (1999). Agent Autonomy: Specification, Measurement, and Dynamic Adjustment. In Proceedings of the Autonomy Control Software Workshop, Agents '99 : 8–15
42. Mazo M, et al (2001) An integral system for assisted mobility. IEEE Robotics and Automation Magazine 1:46–56
43. Millán, J. del R. et al. (2004) FP7 Exploratory Workshops: Workshop 5: Augmented human capabilities for empowering users and communities.
44. Miller D (1998) Assistive robotics: an overview, Springer-Verlag, pp 126–136
45. McLachlan S, Arblaster J, Liu DK, Valls J, Chenoweth L (2005) A multi-stage shared control method for an intelligent mobility assistant. In: Proc. of the 2005 IEEE 9th International Conference on Rehabilitation Robotics, Chicago, USA, pp 426–429
46. Moravec, H. (1983). Stanford cart and the CMU rover. Proceedings of the IEEE, vol. 71(7), pp. 872–884, 1983.
47. Morris A, Donamukkala R, Kapuria A, Steinfeld A, Matthews JT, Dunbar-Jacob J, Thrun S (2003) A robotic walker that provides guidance. In: Proc. of the 2003 IEEE International Conference on Robotics and Automation, Taipei, Taiwan, pp 25–30
48. Murphy RR (2004) Human-robot interaction in rescue robotics. In: IEEE Trans. Syst., Man, Cybern. C, Appl. Rev., vol 34, pp 138–153
49. Nilsson N J, (1084) Shakey the robot. SRI International, Tech. Rep. 323.
50. Nisbet P, Craig J, Odor P, Aitken S (1995) 'smart' wheelchairs for mobility training. Technol Disability 5:49–62
51. Norman D (1983) Design rules based on analyses of human error. Communications of the ACM 26:254–258
52. Parikh S, Grassi V, Kumar V, Okamoto J (2004) Incorporating user inputs in motion planning for a smart wheelchair. In: Proc. of the 2004 IEEE International Conference on Robotics and Automation, New Orleans, USA, pp 2043–2048
53. Parikh SP, Grassi V, Kumar V, Okamoto J (2005) Usability study of a control framework for an intelligent wheelchair. In: Proc. of the 2005 IEEE International Conference on Robotics and Automation,

Barcelona, Spain, pp 4745–4750
54. Parker, M.; Baker, P. S.; Allman, R. M. (2002). A Life-Space Approach to Functional Assessment of Mobility in the Elderly. Journal of Gerontological Social Work, 35(4):35–55
55. Poncela A, Pérez EJ, Bandera A, Urdiales C, Sandoval F (2002) Efficient integration of metric and topological maps for directed exploration of unknown environments. Robotics and Autonomous Systems 41(1):21–39
56. Poncela A, Urdiales C, Fernández-Espejo B, Sandoval F (2008) Place characterization for navigation via behavior merging for an autonomous mobile robot. In: Proc. of the IEEE Mediterranean Conference 2008 (Melecon'2008), Ajaccio, France
57. Prassler E, Scholz J, Fiorini P (1999) Navigating a robotic wheelchair in a railway station during rush hour. Int Journal on Robotics Research 18(7):760–772
58. Rao RS, Conn K, Jung SH, Katupitiya J, Kientz T, Kumar V, Ostrowski J, Patel S, Taylor CJ (2002) Human robot interaction: Applications to smart wheelchairs. In: Proc. IEEE International Conference on Robotics and Automation, Washington, USA
59. Scerri P, Pynadath D, Tambe M (2001) Adjustable autonomy in real-world multi-agent environments. In: Int. Conf. AGENTS 01, pp 300–307
60. Shire B (1987) Microcomputer-based scanning interface for powered wheelchair. In: Proc. Annu. RESNA Conf., San Jose California, USA, pp 541–543
61. Simpson R, Levine S (1997) Development and evaluation of voice control for a smart wheelchair. In: Proc. Annu. RESNA Conf., Washington, USA, pp 417–419
62. Simpson R, Levine SP (1998) NavChair: An Assistive Wheelchair Navigation System with Automatic Adaptation, Springer-Verlag, pp 235–255
63. Spier, E. From Reactive Behaviour to Adaptive Behaviour - Motivational models for behaviour in animals and robots. (1997) Master Thesis
64. Urdiales C, Bandera A, Pérez EJ, Poncela A, Sandoval F (2003) Hierarchical planning in a mobile robot for map learning and navigation, Physica Verlag, pp 2165–2188
65. Urdiales C, Trazegnies C, Bandera A, Sandoval F (2003) Corner detection based on adaptively filtered curvature function. Electronics Letters 39(5):426–428
66. Volosyak I, Kouzmitcheva O, Ristic D, Gräser A (2005) Improvement of visual perceptual capabilities by feedback structures for robotic system friend. IEEE Transactions on Systems, Man and Cybernetics-Part C: Applications and Reviews 35(1):66–74
67. Webster J, Cottam G, Gouvier W, Blanton P, Beissel G, Wofford J (1988) Wheelchair obstacle course performance in right cerebral vascular accident victims. J Clin Exp Neuropsychol (11):295–310
68. Weiner E (1989) Human factors of advanced technology (glass cockpit) transport aircraft. NASA TR 117528
69. de Witte L, GJ G (eds) (2002) The Assessment of Assistive Technology Outcomes, Effects and Costs. Journal Technology and Disability, IOS Press, pp 101–105
70. Yanco HA (1998) Wheelesley: A robotic wheelchair system: indoor navigation and user interface, assistive technology and artificial intelligence. Applications in Robotics, User Interfaces and Natural Language Processing pp 256–268
71. Yanco HA, Drury JL, Scholtz J (2004) Beyond usability evaluation: Analysis of human robot interaction at a major robotics competition. Journal of Human Computer Interaction 19:117–149
72. Yesavage J, Brink T, Rose T, Lum O, Huang V, Adey M, Leirer V (1983) Development and validation of a geriatric depression screening scale: A preliminary report. Journal of Psychiatric Research 17:37–49