Reactive adapted assistance for wheelchair navigation based on a standard skill profile

M. Fdez-Carmona, C. Urdiales and F. Sandoval

***Abstract*— Mobility assistance for wheelchair navigation is typically based on the shared control paradigm. Traditionally, control swaps from user to machine depending either on a trigger mechanism or on a explicit user request. Alternatively, in collaborative control approaches both user and robot contribute to control at the same time. However, in this case it is necessary to decide how much impact the user has in the emergent command. User weight has been estimated based on his/her command efficiency or on the environment complexity. However, the user's command efficiency may change abruptly, whereas the environment complexity depends on the user's skills. In this work we propose a collaborative control approach where this weight is determined by the user's ability to cope with the situation at hand with respect to an average person. This estimation relies on an standard navigation skill profile extracted from a large number of traces from real users. This approach has two major advantages: i) the user receives more assistance only when needed according to his/her own skills; and ii) we avoid an excess of assistance to prevent loss of residual skills. The proposed system has been tested with a group of people with disabilities. Tests prove that resulting efficiencies are similar to other collaborative control approaches although the amount of assistance is reduced.**

I. Introduction

Mobility is a key factor to cope with Activities of Daily Living (ADL). According to 2012 statistics, the highest percentage (6.9%) of the more than 36 million Americans with disabilities indicated their disability was related to ambulation [1]. People whose mobility is affected by a disability may require assistance to remain autonomous. Statistics demonstrate the growing needs for experienced personal care attendants (PCA) by persons with disabilities. However, due to the increasing unavailability and cost of experienced PCAs, the rapidly-growing needs for more personal assistance in this population are unmet [2]. When an on-site professional PCA is not available, a persistent demand exists for quality alternative assistance. In some cases, robotic power wheelchairs may help. As reported in [3], assistive technology may empower users to live independently and safely by allowing them to manipulate their natural environments either independently or through assisted-control mobility. It was estimated that in 2003 7,1 Million people depended permanently or temporarily on a wheelchair. Analyses in the USA have shown that only 50% to 60% of people in need of a power wheelchair are in fact able to use state-of-the-art equipment. An additional 20% to 25% could be accommodated if more intelligent controls and user interfaces were available[1].

In order to combine what the user and the robot propose to do, robot wheelchairs typically follow the so called Shared Control paradigm, also known as Dynamic Autonomy or Mixed-Initiative [4]. There are different approaches to shared control. In *safeguarded navigation*, the mobile is controlled by the human except when a potentially dangerous situation is detected [5] [6] [7]. Frequently, shared control approaches [8] [9] [10] rely on a basic set of primitives like $AvoidObstacle$, $FollowWall$ and $PassDoorway$ to assist the user in difficult maneuvers. These primitives can be triggered manually, by the user, or automatically, when sensors detect a specific situation. In extreme, the user just points a destination and gives all control to the robot [11]. In these cases, systems try to predict the user's intention -and minimize the cognitive load of the process-, but many authors agree that prediction of human intention often fails and users prefer to contribute more to control [4] [12]. In [13] it is proposed to introduce a third source of control -a remote PCA- in the loop to cope with more complex situations.

In all approaches above, only human or robot are in control at a given time instant. This means that users never deal with difficult situations. Lack of practice with these maneuvers may lead to loss of residual skills. Besides, control switches provoke discontinuities that may lead to anxiety and frustration. In order to avoid this problem, in collaborative control approaches [14] [15] [16] [17], user's and robot's commands are mixed in a continuous way so that people may contribute as much as possible to every decision.

Purely reactive collaborative control approaches [14] [15] [16] basically rely on weighting user's and robot's commands according to local efficiency metrics and then combining them into a single vector. The emergent command is closer to the user depending on how well he/she is coping with the situation at hand. These systems adapt to the user in the sense that they provide more help when needed. In order to gain more inertia towards sudden movements or punctual changes, other methods rely on modeling the user's intention. Parametric models specify the user's driving behavior in a fixed a priori structure to predict intention [18]. However, clear definition and adequate tuning of parameters related to human behavior is usually complex. Alternatively, implicit models rely on learning the adequate response to a given situation for each user [17]. This approach requires

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training. Proposed training methods include driving the wheelchair through a standard test course and comparing user's commands with a so-called ideal input signal. This signal basically depends on the environment and the target at the moment. Help is provided depending on the difference between the user's input and the ideal one. It takes time to train the wheelchair for each user. Besides, there is no ideal command to solve a situation: as long as the user can cope with the problem adequately, no assistance needs to be provided. In order to cope with these problems, we propose to a novel methodology to modulate assistance depending on the user's skill profile. The main advantages of the proposed method is that it requires no training and user's performance is not compared to an ideal. Instead, we use the standard user skill profile that we proposed in [19].

II. A STANDARD SKILL BASED NAVIGATION PROFILE

In order to decide how much assistance a person needs, it is necessary to compare his/her performance to an expectation. Typically, the expected performance is an analytical solution to the on-going navigation problem or to some ideal trajectory[2]. However, a person does not need to achieve an ideal to cope with ADL. It is enough to reach a standard efficiency, that needs to be determined. However, people tend to solve the same problem in different ways and no standard individual exists.

In [19] we proposed a method to build a standard navigation profile. In order to cope with variability, the proposed profile was skill-based and reactive. We did not work with full trajectories or complex maneuvers: we only dealt with instant solutions to local situations. Besides, we did not set any ideal or analytic solution to the problem. Instead, we clustered data from 3 years of tests with more than 80 volunteers at Fondazione Santa Lucia (FSL), a large rehabilitation hospital in Rome. Most volunteers were inpatients presenting a different degree of disability, both physical and cognitive. All volunteers were asked to drive a Meyra 2 Runner wheelchair equipped with a frontal Hokuyo laser using a joystick in different indoor environments without assistance. Data stored in our traces included laser sensor readings (millimeters), relative goal location with respect to the wheelchair (millimeters), user joystick command (radians), and wheelchair heading (normalized radians). All data was local and relative to the robot position.

All gathered data was employed to decide how efficiently an average user would cope with all the different situations that may be faced during indoor navigation. First, we determined how many different situations our volunteers had found. Any complex situation can be decomposed into a set of simpler ones, so we defined situations at local level to avoid complexity. It is stated in [20], that all maneuvering situations can be categorized into six possible configurations that: i) fully describe all possible obstacle configurations (mobile and goal locations) and; ii) are mutually exclusive. After we clustered our raw data into these situations using a binary decision tree, each bin included a large number of cases coming from very different people facing similar situations during their respective trajectories. These situations include High Safety or Low Safety Goal in Region (HSGR and LSGR), High Safety Wide or Narrow Region (HSWR and HSNR) and Low Safety Wide or Narrow Region (LSWR and LSNR).

Then, we unsupervisedly split each bin into as many subclasses as needed depending on the wheelchair heading with respect to the (local) goal. We used a k-medoid clustering algorithm based on Euclidean distance and the Davies-Bouldin index [21] to choose the appropriate number of subclasses ($k(i)$) for each bin i.

Resulting subclasses represent how many different situations an individual may face depending on his/her relative position to the goal and local environment. Solutions provided by the different individuals to each situation could be very different, depending on their driving habits and preferences and also on their (potential) disability. To obtain the prototype of each subclass, we averaged all elements in the subclass, weighting them by their respective efficiency. This process filtered out low efficient solutions and outlayers:

$$CP(i) = \sum_{j=1}^{N(i)} \frac{\eta_j c_j}{N(i)} \tag{1}$$

$N(i)$ being the number of commands in class i, c_j the vector command and η_j the efficiency of command c_j. This average tends to be close to the most efficient **and** frequent command in the subclass.

Since we are working at reactive level, η must be calculated locally, at each given location/time instant. In [22], we defined η as the average of three different factors roughly corresponding to the properties of a navigation function [23]:

$$\eta_{sm} = e^{|\alpha_{dif}|} \tag{2a}$$

$$\eta_{dir} = e^{|\alpha_{dest} - \alpha_{dif}|} \tag{2b}$$

$$\eta_{sf} = 1 - e^{|\alpha_{min}|} \tag{2c}$$

Smoothness (η_{sm}) is locally evaluated (Eq. 2a) as the angle (α_{dif}) between the robot heading and the input motion vector (Fig. 2). *Directness* (η_{dir}) is locally measured (Eq. 2b) in terms of the angle (α_{dest}) formed by the provided motion vector and the direction towards the next partial goal provided by a global planner (Fig. 2). *Safety* (η_{sf}), is evaluated (Eq. 2c) in terms of the angle to the obstacle (α_{min}) whose distance is minimum with respect to the heading direction (Fig. 2). All resulting prototypes are presented in Fig. 1.

This profile in Fig. 1 covers how a "standard" user would cope with all possible situations faced in an indoor environment, so we can compare the performance of any given person to the average profile in each of them. In order to do so, we simply compare the user and the standard prototype efficiency (η_u and η_{SP}) at the current situation.

[2]Some authors simply compare the user's performance to a healthy person's in the same situation. This approach has been reported as not representative

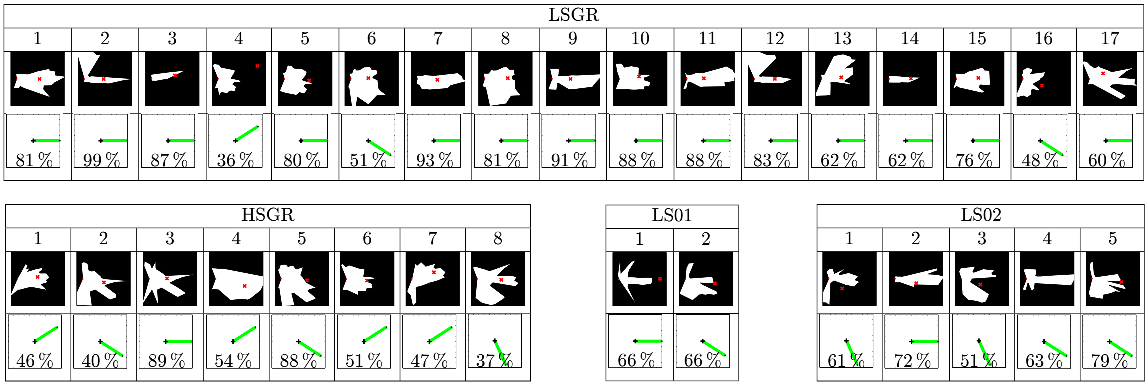


Fig. 1. Classes resulting for each of the 4 non-empty bins and their prototype efficiency

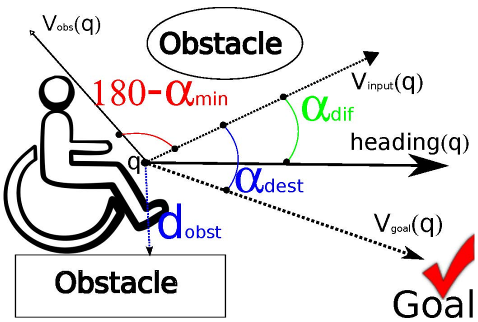


Fig. 2. Local factors (α_{min}, α_{dif} and α_{dest}) used to calculate local efficiency (η) depending on the robot heading, provided command $\vec{v}_{input}$ and obstacle repulsion force $\vec{v}_{obs}$.

This provides an estimation on how much help the input user needs to reach the standard and, hence, modulate assistance in collaborative control approaches. Next section presents the proposed algorithm to adapt assistance to each user on the fly.

III. Adaptive collaborative assistance based on a standard skill profile

Our new system is based on the collaborative control scheme proposed by the authors in [22]. In our previous system, user's and robot's commands ($\vec{v}_u$ and $\vec{v}_r$) were combined into an emergent command $\vec{v}_e$ at reactive level, weighted by their respective efficiency (η_u and η_r) as defined in Eq. 2. The robot command were obtained via a Potential Field Approach (PFA). The main advantage of this system is that users receive more or less control depending on how efficiently they are controlling the wheelchair. Its main drawback is its purely reactive nature, that leads to control discontinuities. However, the most important issue is that control is not adapted to the user's nature, but rather to his/her punctual commands. Help modulation is well accepted by users and actually it improves user performance [24]. In order to improve adaptation, we can use the skill profile described in previous section to modulate our control function ($\vec{v}_e$) originally described at [22]. At location i, it would be:

TABLE I
Volunteers

Patients	CIRS	MMSE	GDS	Barthel	IADL	Diagnosis
806	2	21.9	2	41	2	Left hemiplegia (Ictus)
808	2	22.7	12	68	2	Ictus (Left hemisphere)
907	1.9	28	9	58	3	Left hemiplegia (Ischemic ictus)
814	1.38	23	NA	28	1	Ictus
904	1.5	28	NA	92	7	Hyposthenia
905	1.38	30	NA	28	7	Tetraplegia (Guillain-Barré syndrome)
813	1.9	23	NA	28	1	Right hemiplegia (Epilepsy)
815	1.8	20	NA	96	8	Right hemiplegia (Mixed aphasia)
816	NA	23.2	12	62	2	Right hemiplegia (Mixed aphasia)

$$\vec{v}_e(i) = K(i)\eta_u(i)\vec{v}_u(i) + (1 - K(i))\eta_r(i)\vec{v}_r(i) \quad (3)$$

where k is modeled after Fig. 3 depending on how far the user performance is from the standard. It can be noted that the envelope is equal to 0.5 if η_u and η_{SP} are the same.

The emergent command gains additional inertia to work proactively. The overall effect of this new approach is that users globally receive more control in areas they can cope with, despite punctual corrections to their less efficient commands.

IV. Experiments

In order to test the proposed approach, 9 volunteering inpatients at FSL tried to complete the same path (Fig. 4) in collaborative control mode, both with and without K modulation. The volunteers' profiles are described in Table I. It can be noted that they had different conditions that did not affect equally their driving skills (e.g. left hemiplegia affects right maneuvers and viceversa). As in our previous works [14] [22], we characterized their disability profile using well known clinical scales: CIRS (Cumulative Illness Rating Scale, 0-4), MMSE (Mini-Mental State Examination (0-30)),

TABLE III
AVERAGE ESTIMATED HELP (%) ON EMULATIONS

K Mode	Diagnosis		
	Hemiplegia		Other
	Right	Left	
K fixed	70.85	63.40	66.23
K variable	58.31	52.54	53.87

TABLE IV
ANOVA TEST BETWEEN ESTIMATED HELP AND K MODE

	Df	Sum Sq	Mean Sq	F value	$Pr(>F)$
Mode	1	605.63	605.63	15.938	0.0003
Residuals	34	1291.94	38.00		

GDS (Geriatric Depression Scale (0-30)), Barthel (0-100) and IADL (Instrumental Activities of Daily Living, 0-8). It is usually necessary to use them together to describe each user. For example, volunteer 808 has a mild comorbidity, minor cognitive issues (MMSE lower than 26), signs of geriatric depression and mild physical challenges. Indeed, she needs help with her ADL. Volunteer 815 is significantly worse from a cognitive point of view, but physically much better and needs no help at all with her ADL (IADL=8).

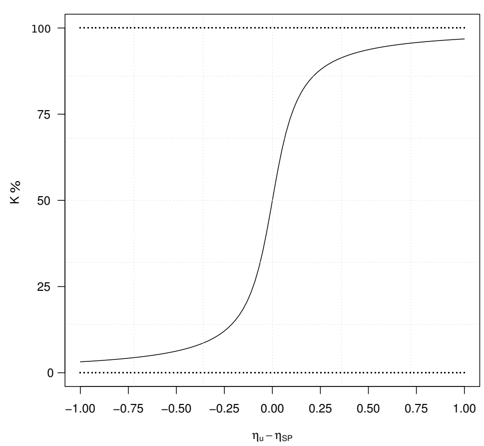


Fig. 3. Command weight $K(\Delta\eta)$ function.

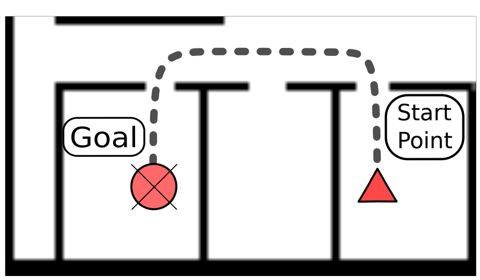


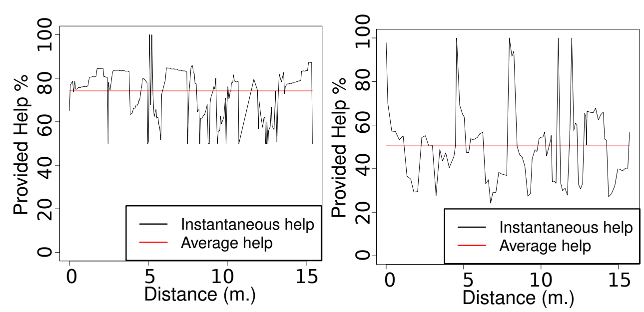
Fig. 4. Test scenario at FSL.

Our standard skill profile models all indoors local navigation situations. It links a local situation with a navigation command and efficiency, so it can be used

TABLE V
ANOVA TEST BETWEEN ESTIMATED HELP VARIANCE AND K MODE

	Df	Sum Sq	Mean Sq	F value	$Pr(>F)$
Mode	1	0.0035	0.00359	52.907	2.016e-08
Residuals	34	0.0023	0.00006		

in any indoors experiment set-up. We can compare user and standard profile solutions at the same situations, and study user performance. Table II briefs the results of the proposed tests. It includes average emergent efficiency $\bar{\eta}_e$ and completion time $\bar{t}$. We have also estimated the average amount of help provided in terms of the contribution of the robot to the resulting command at each point. We also provide Disagreement, the angular difference between v_e and v_u, that provides an estimation about how comfortable users are with assistance [14]. As a whole, it was expected that volunteers with poorer scales performed worse. Since the proposed path involved mostly left maneuvers, it was also expected that people with right hemiplegia performed worse in general. We can observe that this is mostly true: $\bar{\eta}_e$ for volunteers 813, 815 and 816 is under 30% in non-modulated mode and it takes them more than 150s to finish the proposed path, that other volunteers completed in approximately one minute. Volunteer 814 has similar difficulties because his physical skills are severely affected (Barthel=28, IADL=1). Volunteer 904 also yields a poor performance but, in his case, it obeys to a large disagreement: he is fighting assistance more than a 20% of the time. This effect was reported in [14] for people with excellent cognitive skills that rejected assistance when they noticed their trajectories were corrected. It can be immediately noticed that modulation clearly improves results, but not equally: people with worse performance clearly benefit more from adaptation. Efficiency for volunteers with right hemiplegia, for example, grows over a 60%. People who were already above a 60% improve just a 4-5% instead. This reflects how adaptation helps to equalize performance and move towards a (non-perfect) standard. Our goal, however, was not just to boost performance, but to help as less as possible and only when necessary to avoid frustration and loss of residual skills.



(a) Non-modulated K mode (b) modulated K mode

Fig. 5. Assistance provided to volunteer 904.

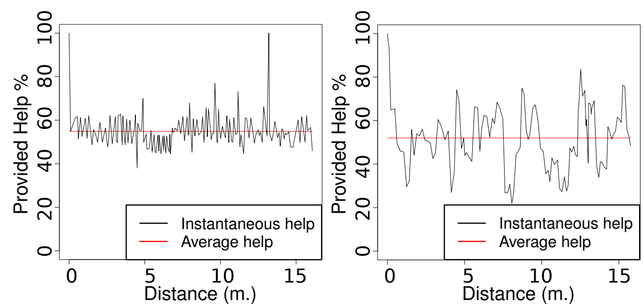
It can also be observed in Table II that $\bar{H}elp$ is lower in adaptive mode in all cases. Table III shows how assistance

TABLE II
EXPERIMENT RESULTS

User	K Mode	$\bar{\eta_e}$ %	$\sigma(\eta)$	$\bar{t}$ (secs)	$\overline{Help}\%$	$\sigma(Help)$	$\overline{Disagreement}$ (%)	$\sigma(Disagreement)$	$\bar{K}$	$\sigma(K)$
806	Fixed (50)	28.274	0.008	65.521	67.155	0.013	19.715	0.02	50	0
	Variable	67.687	0.035	49.601	52.962	0.037	1.507	0.001	50.427	0.028
808	Fixed (50)	30.043	0.014	65.924	68.173	0.014	19.048	0.023	50	0
	Variable	62.706	0.041	65.239	52.65	0.039	2.724	0.001	51.743	0.028
813	Fixed (50)	27.912	0.011	158.683	71.687	0.013	19.195	0.011	50	0
	Variable	61.156	0.03	58.807	52.811	0.025	2.666	0.002	50.699	0.018
814	Fixed (50)	29.168	0.011	179.181	69.064	0.019	18.395	0.014	50	0
	Variable	61.108	0.043	51.441	59.5	0.041	0.836	0.001	45.381	0.032
815	Fixed (50)	28.622	0.015	167.218	69.727	0.018	17.255	0.016	50	0
	Variable	60.908	0.044	63.007	59.438	0.036	0.369	0.002	43.339	0.032
816	Fixed (50)	27.846	0.01	154.686	71.146	0.017	19.626	0.012	50	0
	Variable	69.721	0.041	47.506	62.683	0.013	0.863	0.001	40.353	0.009
904	Fixed (50)	25.226	0.007	189.855	74.206	0.011	21.524	0.009	50	0
	Variable	67.171	0.042	44.679	50.482	0.031	0.828	0.007	52.961	0.021
905	Fixed (50)	60.934	0.013	113.286	55.436	0.005	1.984	0.003	50	0
	Variable	64.645	0.037	40.319	51.645	0.025	1.292	0.003	51.99	0.018
907	Fixed (50)	60.265	0.033	98.159	54.873	0.006	1.2	0.005	50	0
	Variable	66.608	0.024	49.479	52.021	0.022	0.888	0.001	50.279	0.019

is indeed adapted to the user's condition. These results were validated using an ANOVA test, proving that provided help significantly depends on K mode (table IV). It can be observed in Table II that provided help is clearly lower in K-variable mode. The variance of assistance is also related to the k-mode (Table V). This variance grows in k-variable mode, because assistance is more adapted to the user's local needs (Table II). This fact affects Disagreement -and, hence, acceptance- very positively. In order to illustrate the importance of this effect, Fig. IV shows assistance provided through the whole path in both modulated and non-modulated mode to volunteer 904. As commented, his performance was severely affected by a high Disagreement. It can be noted in Fig. IV that the frequency of the assistance signal is clearly lower under modulation. We provide significantly less help, but also more consistently, depending on how well the user copes with the challenges in the path. His Disagrement reduces drastically from 21.5% to 0.82% and his efficiency improves to 67.1%. Besides, received help is reduced from 74.206 to 50.482%: assistance peaks are higher with respect to the plot average and also wider, but less frequent. Help is also consistently reduced in some areas that the user can negotiate on his own. The benefits of adaptation are obvious even in volunteers that did well in fixed k mode. For example, Fig. IV shows the same plots for user 907, who already had an efficiency equal to 60.2% in fixed k mode. Assistance is only reduced a 2.8% in this case, but it can be clearly appreciated that the adapted signal is much slower. This improves the resulting efficiency a 6%, and reduces Disagreement slightly, but consistently.

A final conclusion extracted from these experiments can be observed in the ANOVA test in Table IV. In previous works using collaborative control with fixed K we tried to correlate the amount of assistance provided with every clinical scale we had and only obtained a minor relationship between help and MMSE (cognitive condition). However, we could not find relationships with physical-condition/ADL related scales. In modulated collaborative control we have found a clear relationship between the modulation factor and a combination of IADL, Barthel and MMSE. This means that the envelope of the human control signal depends on his/her condition as a whole, both from the physical and cognitive point of view. In brief, we are adapting assistance to the user's condition as a whole.



(a) Non-modulated K mode (b) modulated K mode

Fig. 6. Assistance provided to volunteer 907.

TABLE VI
ANOVA TEST BETWEEN $\bar{K}$ AND DIAGNOSIS

	Df	Sum Sq	Mean Sq	F value	$Pr(>F)$
IADL:Barthel:MMSE	1	86.299	86.299	8.223	0.007
Residuals	28	293.827	10.494		

V. CONCLUSIONS

In this work we have proposed a methodology to adapt assistance to the user's needs and condition in shared control based robot wheelchairs. The proposed system is based on a standard skill profile, that we proposed in [19]. This profile shows how efficiently a standard user -modeled using real navigation tests- copes with every possible local situation in indoor environments. Our shared control algorithms combines the robot and user's response to a given situation in terms of their respective local efficiency. The main novelly of this work is that the control function is modulated by a factor that depends on the difference in efficiency between the user's response to a situation and what the standard user would do in his/her place. This process improves user's acceptance and provides better adaptation to the user's needs and condition. We have checked that the variation of the modulation factor is indeed related to the user's disability profile modeled after three different well known clinical scales combinedly: MMSE, Barthel and IADL, that take into account both cognitive and physical aspects. Tests with users presenting different disability profiles prove that modulation: i) improves average efficiency; ii) reduces the amount of help provided and its variance; and iii) improves user's acceptance (reduces Disagreement and its variation). In brief, help is provided only when needed depending on each user's skills.

Since the proposed approach is purely reactive, future work will focus on integration of this system into a hybrid architecture. The full system would allow us to work proactively and predict the best trajectories to receive the minimum amount of help in any given environment. Our goal in all cases is to empower people to achieve their ADL by providing the minimum amount of help, so loss of residual skills can be avoided.

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