Efficiency based collaborative control modulated by biometrics for wheelchair assisted navigation

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Abstract— **This paper addresses a new collaborative control method for robotic wheelchairs. The original method was specifically designed for disabled people who are unable to drive a robotic wheelchair on their own. Its main novelty was that the wheelchair just provided the amount of help needed at each moment, to avoid loss of residual abilities. This wheelchair was tested by volunteering in-patients in Casa Agevole at Fondazione Santa Lucia (FSL) in Rome.**

However we found that in-patients with severe cognitive impairment were not able to complete complex trajectories despite wheelchair help. Thus, this works presents the improvement of these control techniques, more suitable for severe patients. We present a modified efficiency based collaborative control scheme based on modulation of assistance using biometric sensors, as well as preliminary results of this technique.

I. INTRODUCTION

People with cognitive and/or physical impairments are sometimes unable to fully control motorised wheelchairs. Thus, they might just need some additional support to navigate that can be provided by a robotic wheelchair. Residuary driving skills can be considered a part of the so-called residual abilities. Doctors try to preserve and train those residual abilities as part of rehabilitation. Hence, we intend to give the user the minimum necessary help to drive a wheelchair.

There are typically two approaches to human-robot wheelchair control: shared control and safeguarded operation. In shared control interaction, human controls robot movements depending on the situation. The degree of control is different depending on the implementation. For example, within some implementations user just provides final target and robot takes control [1] [2] [3] [4]. Another possibility is using a set of behaviours which are triggered manually or automatically during manoeuvres [5] [6] [7] [8]. In other cases, event triggers can activate several behaviours at once [9], so that the resulting action is an emergent behaviour, combination of elemental behaviours. On the other hand, safeguarded operation implementations [10] [11] [12] give full control to human operator. Besides, robot takes control in safeguarded operation only if a hazardous situation is detected.

In both approaches, there is a sharp switch between user and robot control. The other main shortage is the lack of learning: user does not acquire new driving skills while using the system.

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The authors presented a new approach to shared control in [13] [14]. In this approach, user and robot commands are weighted by an efficiency function in a reactive, emergent way as presented in Section II.

This approach was tested with volunteering in-patients in Casa Agevole, a ”concept house” designed using the Universal Design guidelines. Casa Agevole is located in Fondazione Santa Lucia, in Rome.

In order to be a general solution, the house has a symmetric distribution. Each side has an adapted bathroom and bedroom so that it can be used either by patients with right of left side paralysis. Kitchen and living room conform an unique space previous to the bedrooms. Since this space is where persons expend most of time, experiments took place within this living area.

During the aforementioned Rome tests with in-patients presenting different degrees of disability, initial results exposed some weaknesses. We found that patients with poor cognitive capabilities or just too stressed were unable to complete complex trajectories even with help. In that situations, shared control was providing too little help for these patients. Naturally, an increase of robot control with respect to human one solved the problem, as described in Section III. However, it is desirable not to adopt this solution unless necessary Hence, in this work we propose to use biometric sensors to detect people condition.

Preliminary results in our laboratory of this improvement, shown in Section V, prove the feasibility of this approach. Finally, Section VI presents conclusions and future work.

II. COLLABORATIVE NAVIGATION SYSTEM

Robotic control architectures may be either deliberative, reactive or hybrid, and even in this last case, classic 3T hybrid schemes include a reactive layer at low level. Reactive navigation schemes are particularly suitable for our purposes because they may deal with several sensors and goals in a simple way. In our case, we can accept human commands, provided via the most appropriate interface, as one goal and the desired target as another one, which should be reached by the robot by any given navigation architecture. In our case, the robot uses a DLA scheme [15] just with a Potential Field Approach (PFA) reactive layer [16]. We assume that humans will contribute with deliberative planning that tend to avoid local minima. It must be noted that human and machine goals might not coincide all the time, but this is easily handled by PFA by simply using two goals.

As in any purely reactive PFA approach, in our system every obstacle is modelled as repulsion force and the goal as an attractive one. Hence, the sum of repulsing and attracting forces determines motion velocities in each point.

Specifically, our wheelchair rotational and translational velocities (v_{rS}, v_{tS}) are the composition of user and robot proposed velocities in each instant. Robot rotational (v_{rR}) and translational (v_{tR}) proposed velocities are combined with user motion velocities (v_{rH} and v_{tH}) according to these equations:

$$v_{rS} = \eta_R \cdot v_{rR} + \cdot \eta_H \cdot v_{rH} \tag{1}$$

$$v_{tS} = \eta_R \cdot v_{tR} + \cdot \eta_H \cdot v_{tH} \tag{2}$$

In order to calculate how much a human contributes to output command, we decided to check how good he/she was doing. To this purpose, the performance of human and robot motion commands are measured by their respective efficiencies (η_H, η_R). Efficiencies span from 0 to 1, where 1 means a perfect command and 0 the worst one. Hence, better efficiencies imply more control in the resulting velocities. The resulting command (v_{tS} , v_{rS}) has also an associated efficiency, called shared efficiency η_S.

We use η_H and η_R to build commands at reactive level, by adding human and robot efficiency weighted vectors into an emergent one. As we operate at at reactive navigation level, we can only measure efficiency using local factors: *smoothness* (η_{sf}), *directiveness* (η_{tl}) and *safety* (η_{sc}). Smoothness penalises sharp direction changes. Such changes are hazardous and sometimes impossible for certain models of wheelchairs. Safety rewards keeping a certain distance from obstacles during the routes. Directiveness is higher when the user drives straightly to goals, meaning that he/she has a good sense of direction. All of them range from 0 to 1, but it is important to note that efficiencies equal to 1 are not always advisable, e.g. think of an obstacle between the wheelchair and the goal. Nevertheless, they mark the most suitable choice between human and robot at each time instant.

- Smoothness (η_{sf}) depends on the angle difference between current motion vector and proposed motion vector. Changing heading may lead to slippage or oscillations, so it is better to avoid direction changes. Also most wheelchairs are non-holonomic mobiles, so they may be unable to perform some movements. Let α_{dif} be the angle difference between the current direction and the proposed command vector, C_{sf} a constant. Hence η_{sf} will be:

$$\eta_{sf} = e^{-C_{sf} \cdot |\alpha_{dif}|} \tag{3}$$

- Directiveness (η_{tl}) reflects how well aligned is the robot with the next target. Directiveness is in inverse proportion to the angle difference between heading and next partial goal. If C_{tl} is a constant and α_{dest} the aforementioned angle difference, η_{tl} will be:

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

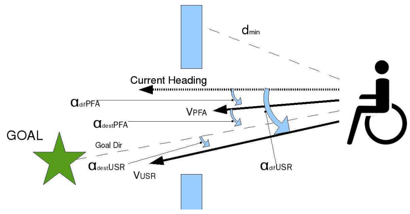


Fig. 1: Local efficiency factors

- Safety is proportional to the angle between closest obstacle and our current heading, α_{min}. Lower angles mean a more dangerous trajectory. If C_{sc} is a constant value, η_{sc} will be:

$$\eta_{sc} = 1 - e^{-C_{sc} \cdot |\alpha_{min} - \alpha_{dif}|} \tag{5}$$

Efficiency is calculated as the average of these three factors:

$$\eta = \frac{\eta_{sf} + \eta_{tl} + \eta_{sc}}{3} \tag{6}$$

Figure 1 summarises these efficiency factors.

III. COLLABORATIVE EMERGENT COMMAND MODULATION

The proposed solution worked very satisfactorily in our laboratory. Thus, we decided to move to experiments with persons with disabilities. To this purpose, we cooperated with the medical staff of Fondazione Santa Lucia (FSL) in Rome. They provided a set of volunteering in-patients with a ranked degree of disability, quantified a priory by the doctors using the Barthel index for physical disabilities and the MMSE test for cognitive ones. The MMSE or Folstein test [17] is a brief 30-point questionnaire test that provides a quantitative measure of cognitive status in adults. Even though results may change slightly depending on the number of questions applicable to the in-patient, 24 is usually the accepted threshold for dementia. The Barthel Index [18] measures a person's daily functioning, specifically the activities of daily living and mobility.

Tests were performed in Casa Agevole, as commented in the previous section. All in all, tests were satisfactory as well, as most volunteers managed to finish the proposed trajectory, which included door crossing, left and right turns, navigation through narrow spaces and direction following. However, we noticed that people presenting very low cognitive MMSE could not finish the track despite assistance. In these cases, an increase in robot control was required to complete the trajectory all way long. Tables II and I present two of these cases. Within those tables, irrelevant measures are crossed out, e.g. collaborative efficiency in autonomous trials.

Specifically, in-patient number 17, who was a eighty two year-old woman with severe cognitive impairment, but mild physical impairment is a clear example. She had a 3,1 in the mini-mental state examination (MMSE) scale. However, this patient has a 47% in the Barthel Index. Thus she had no severe physical impairment.

Control type		Autonomous	PFA	PFA
k_H (%)		99	50	25
η (%)	Robot	–	N.A.	67.51
	Human	34.56	N.A.	37.92
	Collaborative	–	N.A.	**65.62**
η_{sf} (%)	Robot	–	N.A.	59.14
	Human	16.14	N.A.	30.01
	Collaborative	–	N.A.	**60.04**
η_{tl} (%)	Robot	–	N.A.	51.81
	Human	6.72	N.A.	8.08
	Collaborative	–	N.A.	**42.21**
η_{sc} (%)	Robot	–	N.A.	91.59
	Human	80.67	N.A.	75.58
	Collaborative	–	N.A.	**94.59**
Total Length	m	0.51	N.A.	5.91
Total Curvature	degrees	267.4	N.A.	142.77
Curvature	mean	-0.99	N.A.	-0.35
	dev	31.02	N.A.	10.27
Completion time	sec	33.22	N.A.	34.67

TABLE I: In-patient 17 Probes Data

Control type		Autonomous	PFA	PFA
k_H (%)		99	50	25
η (%)	Robot	–	N.A.	60.65
	Human	48.02	N.A.	74.44
	Collaborative	–	N.A.	**68.57**
η_{sf} (%)	Robot	–	N.A.	51.64
	Human	52.36	N.A.	81.59
	Collaborative	–	N.A.	**65.9**
η_{tl} (%)	Robot	–	N.A.	40.6
	Human	17.14	N.A.	51.03
	Collaborative	–	N.A.	**47.29**
η_{sc} (%)	Robot	–	N.A.	89.59
	Human	74.46	N.A.	90.9
	Collaborative	–	N.A.	**92.58**
Total Length	m	0.85	N.A.	6.06
Total Curvature	degrees	206.57	N.A.	147.22
Curvature	mean	-1.52	N.A.	0.22
	dev	16.28	N.A.	0.38
Completion time	sec	64.29	N.A.	39.57

TABLE II: Inpatient 10 Probes Data

In autonomous mode, she was given full control and she was unable to even cross the main door, which was the very beginning of the trajectory. Instead, she turned to the door frame and insisted on moving ahead. This behaviour made the wheelchair enter safeguarded mode. In this mode, the wheelchair did not perform any dangerous command.

Collaborative control was insufficient for this patient. Her commands had low efficiency but her contribution was enough to drive the wheelchair against the door frame again. The trajectory length was too short to record meaningful data.

Then doctors asked for an additional increment in robot control for a new try, so that the user had a little more *help* and hence a lower probability to get trapped.

To do so we decided to modulate collaborative control as a wave envelope. This is fairly straight in our case by simply modifying Eq. 1 and 2 as follows:

$$k_H = 1 - k_R \tag{7}$$

These factors modulate the shared movement commands. As a result, equations 1 and 2 are rewritten as:

$$v_{rS} = k_R \cdot \eta_R \cdot v_{rR} + k_H \cdot \eta_H \cdot v_{rH} \tag{8}$$

$$v_{tS} = k_R \cdot \eta_R \cdot v_{tR} + k_H \cdot \eta_H \cdot v_{tH} \tag{9}$$

Therefore, we can easily change the amount of robot control lowering k_H factors between 1 and 0. The k_H factor makes possible to include user state within shared control. In these experiments k_H was set by medical advice to 25 % for inpatient 17.

Another interesting case was in-patient 10, an 84 year-old man with similar physical conditions: a 44% in the Barthel index. However, he had significantly better MMSE (19.4) which means better cognitive skills. Theoretically, he should had been able to drive using shared control. However he was unable to cross the main door during the autonomous test. It seemed that lack of familiarity with the wheelchair, plus his physical trouble to drive it made him stressed and, at this point he was unable to drive in difficult areas. As a result, shared control was insufficient for him as well and he could not cross the main door even with help. Thus, k_H was lowered to 25% in this case and in-patient was finally able to reach the goal.

In both cases, efficiency is constrained by safeguarded mode so the wheelchair may not allow a user to come to harm and safety efficiency has few variations. On the contrary, global efficiency is significantly improved when these users have lesser control. User efficiency increased when she/he has less control. This happens after a few seconds of navigation. Inpatients realise that the wheelchair only moves when they move the joystick. Then, they acknowledge that the motion direction is correct and consequently they agree with the wheelchair.

k_H has proved to be a suitable method to modulate user's intervention level and improve system performance. However, this static factor does not take into account the user state during the course. Anxiety turned out to be a relevant factor in our users performance. In Section V we present a new technique to somehow include it in our collaborative control system. This will provide a a dynamic wave envelope of user intervention level.

IV. BIOMETRIC BASED k_H ESTIMATION

We want to determine the user's anxiety level in order to know how much control should be given to her/him. We will employ user physiological responses measured during navigation as indicator. Thus, the selected sensor, or sensors, needs to be wearable and, most likely, wireless. Also, data transmission should be as transparent as possible from the specific sensor. This independence will allow us to change the sensor without affecting the rest of the system, if necessary. Therefore it must use an open protocol rather than an owner one.

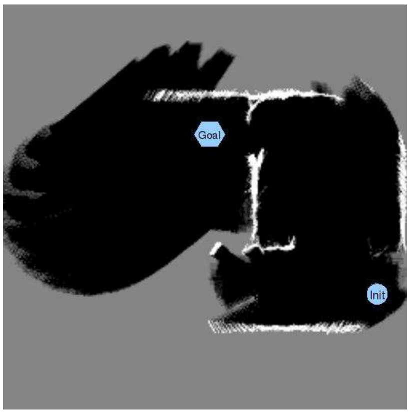


Fig. 2: Dynamic k_H experiment set up

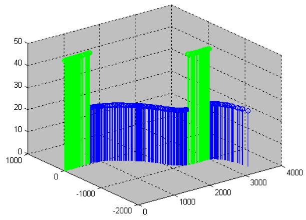
Anxiety measurement is commonly based on a set of biometric parameters: blood pressure, pulse, respiration breathing rhythms, body temperature and skin conductivity. However, we could not find commercially available light, wearable open devices at the time of the tests for all parametered to be measured, so we settled for a pulsioximeter. Doctors also pointed out that it is not possible to precisely measure anxiety and recommended a reduced set of states as with MMSE & Barthel.

Values of k_H and k_R will be set in real time as function of the readings of pulsioximeter sensor. More precisely, in our test we defined two states, each one with an associated k_H. We defined two heart rate intervals from very high (*tachycardia*) to normal values [19] taking into account user age, gender and health status. Initially user data can be compared with reference values in order to establish his/her current state. However, the data acquisition system compiles an historic of heart rate values, with the aim of improving the state determination.

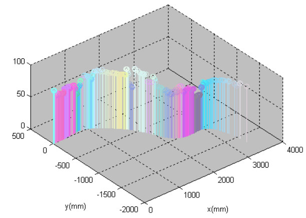
V. EXPERIMENTS AND RESULTS

In this Section we will demonstrate the extensibility of the improvement described in Section III into a dynamic system. Hence, the user will have at every moment and point of the trajectory an amount of control derived from his/her current condition and from driving efficiency.

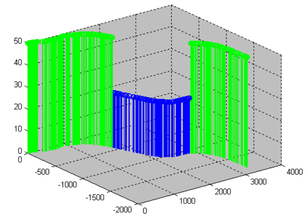
A Pioneer 2-AT was used as robotic platform for the experiments in our laboratories. The Pioneer has a range laser sensor - an Hokuyo URG - installed over it. In this platform, shared control programs communicate each other using the DLA - Distributed Layered Architecture- [15]. DLA supports intuitive expansion of agents capacities via addition of new modules. Also, DLA can combine the responses of deliberative and reactive modules through the interaction of freely distributed processes in an asynchronous way. Using the DLA architecture, user commands are sent from an auxiliary PC to the Pioneer. As long as CARMEN uses the same architecture and sensors, tests should be equally valid for it, as proven in other works by the authors [13] [14].



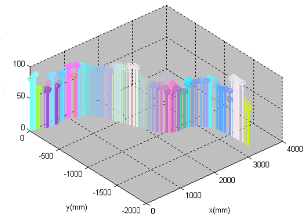
(a) k_H User 1



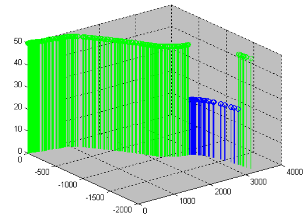
(b) η User 1



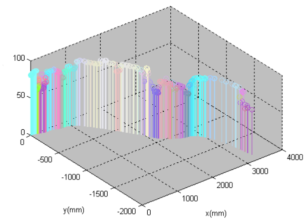
(c) k_H User 2



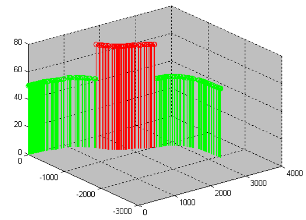
(d) η User 2



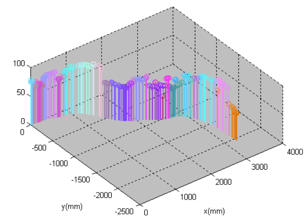
(e) k_H User 3



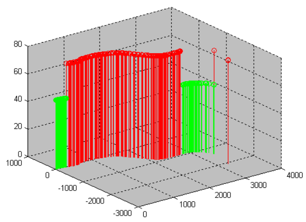
(f) η User 3



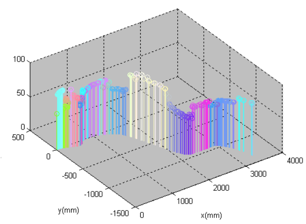
(g) k_H User 4



(h) η User 4



(i) k_H User 5



(j) η User 5

Fig. 3: Users 1 to 5 k_H and η dynamic evolution

The sensor used is a Nonin 4100 Bluetooth Oximeter[1]. This commercial device allows SpO_2 and pulse rate data acquisition in a non-invasive way, suitable for 24h monitoring. Also, its low weight and volume and Bluetooth

[1]http://www.nonin.com/products.asp?ID=29&sec=2&sub=9

radio interface makes it a good choice as wearable sensor because no proprietary protocol is necessary to access that information.

The dynamic wave envelope scheme was tested with 5 healthy subjects in our laboratory. Users had to drive the Pioneer across a predefined environment shown in Fig. 2. We observed that shared efficiency was higher when using dynamic k_H than expected with fixed values. Thus, we concluded that control modulation had a positive effect in emergent behaviour.

Users knew that the amount of control depended on their driving efficiency. This knowledge made them to pay more attention to the test and have higher efficiencies. This attention also made them to become more nervous, which perhaps is a disadvantage. The pulse rate was most of the time unchanged. Only when user approached to obstacles the pulse rate was more likely to change.

User profile information and results are summarised in table III. Also in Fig. 3 we can see the k_H and η evolution over the path in the experiments. Instantaneous values of k_H and η are plotted over its trajectory in each experiment. All the trajectories begin in the right side and end in the left side of the representation, as presented in Fig. 2. k_H values are represented using three colours: blue for 25% value, green for 50% value and red for 75% value. In the η representation, an RGB (red-green-blue) colour is assigned to every single factor taking part in global efficiency: red for smoothness (η_{sf}), green for directivity (η_{tl}) and blue for safety (η_{sc}). Every single factor contributes with its own colour and weight to the global efficiency representation. For example, a grey value of global efficiency means same amount of the three factors. If these three factors are very high, the grey η value will become white. A blue value of global efficiency implies safety predominance and same magnitude of the other two factors. An important amount of blue component is always present in η figures, because safety is guaranteed by the safeguarded mode by design.

Users with higher k_H values are more likely losing some degree of directiveness, as users know target direction but not its precise location. Another user tendency are high driving smoothness, shown as a red predominance in the η graphics. During the straight stretch users with high k_H have more balanced efficiencies, this is grey-white coloured. Predominance of blue η colour is observed near to the end of the proposed path. This is the most difficult part of the trajectory: the door crossing. In this part, efficiency is mostly due to the safety factor.

A lack of η_{sf} - and red colour - can be observed whenever the robot has predominance. This is a limitation of the PFA approach, and can be observed in the cases where k_H is low.

We concluded that there is a clear relationship between k_H and η representations. The robot drives better than humans in terms of the chosen efficiency criteria, so low k_H values usually imply higher efficiency modulus, But we will take advantage of the robot skills only if the user is unable to perform some driving manoeuvre.

The k_H may fall due to initial nervousness due to lack of experience driving robots. A similar effect happens when user has to cross the door or turn. Some users have just a higher average pulse rate than others and have lower k_H values through all the trajectory.

For example, user 1 in Fig. 3a. She has a high pulse at the start and, as a result, a k_H of 25%. Only when she is not turning her pulse rate decreases and, hence, she gains a k_H of 50%. Consequently, in fig. 3b we observe red predominance in straight intervals, which means high values of η_{sf} and better driving smoothness.

User 2 gets a bit stressed after the initial steps, as shown in Fig. 3d. She has a good beginning: smoothness and directivity even higher than the safety factor, shown with yellow colour. Her commands lose efficiency after turning, and the only remaining component is safety. Then, she drives specially well in straight line, marked as white points in η graphic. This has impact on her pulse rate and finally she recovers her initial amount of control, as seen in Fig. 3c.

User 3 shows a similar tendency: his pulse rate decreases during the test. He gets stressed at the beginning of the test, but he calms down as he drives. In figure 3e we can see the improvement in terms of k_H: a low value during the first meters and an increase afterwards. As a result, η has bigger module in the last metres, as in Fig. 3f.

User 4 has different k_H states than previous ones, with values of 75% and 50 %. These new values have a negative impact on the average performance: the robot drives better, but here it has lesser control. The robot has predominance at the beginning and at the end of the test, see Fig. 3g. These corners also have higher efficiency modulus than in the middle of Fig. 3h. User tends to lose directivity, but he keeps a rather safe and smooth driving in the straight stretch, represented by purple colour in Fig 3h.

User 5 has the same k_H states, as seen in Fig. 3i. He is calmed most of the time, so he has a k_H of 75%. Here we can observe how low pulse rates are related to smoother trajectories. He has only two low peaks: at the beginning and when he has to cross the door next to the course end, probably corresponding to initial nervousness and to facing complex situations. During these low k_H peaks, we can see blue predominance in its corresponding η representation, Fig. 3j. This means safety predominance, which is imposed by the safeguarded mode.

VI. Conclusions and future work

This paper has presented a biometric based method to modulate shared control for collaborative wheelchair navigation. Originally, control was shared simply in terms of efficiencies, but some users with disabilities found it hard to complete complex trajectories, either due to low MMSE or, in some cases, to stress. We propose a modulation to add these factors, static and dynamic user conditions, to the shared control equation for a better outcome. MMSE is provided by the doctors and stated a priory. The dynamic condition of the user, though, is calculated on line. In both cases, they are incorporated to the equation in a rough way, as doctors reported that fine-tuning is not feasible when

User		1	2	3	4	5
k_H intervals		0.5 / 0.25	0.5 / 0.25	0.5 / 0.25	0.5 / 0.75	0.5 / 0.75
η (%)	Robot	78.13	77.07	77.33	69.84	72.65
	Human	58.81	62.44	68.81	61.38	67.36
	Collaborative	75.86	72.60	75.71	67.30	70.00
η_{sf} (%)	Robot	59.81	61.63	63.93	42.91	48.96
	Human	51.22	54.57	66.48	58.43	78.43
	Collaborative	72.61	61.76	67.44	63.81	59.22
η_{tl} (%)	Robot	91.89	89.89	90.23	94.52	92.34
	Human	37.90	47.22	56.43	39.08	42.31
	Collaborative	68.35	73.76	76.55	55.33	68.17
η_{sc} (%)	Robot	82.36	79.36	77.56	71.83	76.42
	Human	86.98	85.50	83.41	86.92	81.00
	Collaborative	86.70	82.37	83.30	82.91	82.74

TABLE III: Users 1 to 5 probes data

working with persons. In brief, a new weighting factor k_H has been introduced as wave envelope and it is related to MMSE and heart rate bins. In the second case, bins are related to the person's average heart rate, as it is different for each user. The first approach has already been tested with persons with disabilities, whereas the second one has been tested with healthy persons in a laboratory until medical protocols are cleared. In the first case, inpatients with severe disabilities have been able to use a robotised wheelchair under circumstances where they could not do it before. In must be noted that control is still roughly retained by these in-patients, as this will have a positive effect in their residual abilities. Dynamic variation of k_H in our facilities has also returned satisfactory results with a heart rate sensor, but it is not enough to decide if a patient is stressed or not and new tests are being carried out with a wireless GSR sensor (skin conductivity) as well.

Future work will focus on testing the dynamic weighting technique to in-patients in real environments. In these cases, development of higher level layers will most likely be necessary (i.e. for better biometric signal processing or dynamic adaptation to person's diagnosis). Doctors are also interested in correlating present results with the functional disability (fd) degree of each in-patient.

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