# Towards a shared control navigation function: efficiency based command modulation

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**Abstract.** This paper presents a novel shared control algorithm for robotized wheelchairs. The proposed algorithm is a new method to extend autonomous navigation techniques into the shared control domain. It reactively combines user's and robot's commands into a continuous function that approximates a classic Navigation Function (NF) by weighting input commands with NF constraints. Our approach overcomes the main drawbacks of NFs -calculus complexity and limitations on environment modeling- so it can be used in dynamic unstructured environments. It also benefits from NF properties: convergence to destination, smooth paths and safe navigation. Due to the user's contribution to control, our function is not strictly a NF, so we call it a pseudo-navigation function (PNF) instead.

**Keywords:** Shared control, navigation function, Potential fields, mixed initiative control, power wheelchairs, assistive robotics

## 1 Introduction.

Europe is aging fast, nearly 20 percent of its population will be above 60 years old in 2050. [1]. The loss of functional abilities during senior age increases dependency. More specifically, loss of mobility is a functional loss with severe impact on user capabilities. Mobility plays a central role in an independent lifestyle, as enabler of many other activities. Since human and economical resources to assist persons with dependencies are not enough, enabling technologies have become very important lately.

In some cases, a robotic wheelchair is needed to increase the user's independence. Most these wheelchairs follow the shared control paradigm. Shared control addresses human-robot interaction in navigation. There are two basic criteria to model robot and user interaction in shared control: i) safeguarded operation (the user is in charge unless a potentially dangerous situation is detected [2]); and ii) shared control (the robot performs specific maneuvers on user's demand or by automatic triggering). Shared control maneuvers may range from specific tasks such as "cross door " or "follow corridor" [3, 4] to fully autonomous navigation to designed targets [5, 3].

Shared control navigation traditionally results into more or less abrupt target and trajectory changes. Users also disfavor these discontinuities. Medical doctors don't support these approaches either because robots always perform all challenging tasks alone and hence, residual user abilities decay on time [6]. Our shared control algorithm -collaborative control- addresses these discontinuity problems.

We propose a new shared control algorithm -collaborative control- based on Navigation Functions (NF). NF is a cost function for the optimization paradigm, first described in [7]. The NF's properties guarantee smooth convergence to an unique minimum in the space where they are defined. This paper describes how Collaborative Control approaches human-robot collaboration to a NF based autonomous control as much as possible. Human intervention introduces unpredictable variations, making impossible to obtain a NF from them in all situations.

The paper is structured as follows. First, we present the state of the art in shared control. Then we describe the theoretical model of collaborative control and its benefits. The next section describes mathematical model linking NF and collaborative control. An improved version of collaborative control, is depicted in Section 5. Then, we use a set of experiments to test validity of these improvements. Finally, we present the conclusions of this work.

## 2 Related work

The main task of this work is to help wheelchair users to navigate in a safe and comfortable way. Autonomous robots typically solved navigation through two different approaches: i) deliberative algorithms (a high level model uses sensory information to identify current situation and/or generate a response from a discrete set [8, 9]), ii) reactive algorithms (an equation links sensory information with motor responses, using physic models or insect-alike behaviors [10, 11]).

Optimization techniques belong to this latter approach: we minimize an scalar cost function using negative descend gradient. Generated vector field describes an optimal path to a destination. The scalar function can be obtained using optimal methods such as wavefront propagation algorithms [12] and shortest path algorithms [13] or heuristic methods like maximum clearance algorithms [14]. Potential Fields Approach (PFA) is also a family of feedback motion planning algorithms inspired in obstacle avoidance methods. PFA overlaps several artificial potential fields: an attractor potential field to target and repulsor potential fields to avoid obstacles. They are a simple version of cost functions, suitable for fast path recalculation but not very accurate or stable [15]. Local minima is another PFA mayor limitation.

We originally proposed a continuous and implicit shared control algorithm -collaborative control- based on obstacle avoidance methods [16]. Collaborative control extends autonomous navigation algorithms into the shared control domain.

Collaborative control combines user and robot commands into an emergent command in a reactive way. More specifically robot commands are generated with a modified version of PFA [17]. This technique can combine several goals and constrains in a continuous way, e. g., user intentions could be modeled as an additional target into the potential field.

## 3 Collaborative Control in Navigation Functions.

Collaborative control tries to extend NFs into the shared control domain. Thus, users benefit from a smooth navigation, headed for designated target. This algorithm combines user and robot commands into a function with the same properties as the NF gradient.

In our approach, users receive assistance on a need basis: the worse they perform, the more help they get. This improves user's acceptance and smooth control discontinuities, that affect both user and robot.

An NF $\varphi$ is a $C^2$ artificial potential function (PF) on a compact manifold $M$ such that $\varphi : M \longrightarrow [0, 1]$. Unlike other PF, it encodes a goal $\bar{q}_g$ as the unique global minimum, $\varphi(\bar{q}_g) = 0$, and achieves a maximum of 1 on the entire boundary of $M$ , i.e. $\varphi(\partial M) = 1$ without any divergence. Once constructed, one can obtain a second order autonomous controller which is guaranteed to converge to $\bar{q}_g$ for all points in $M$, by simply following the negative gradient of the NF [18].

These functions are hard to implement for dynamic environments. This is even more challenging in a real time system. Hence, they have serious limitations for unstructured environments [19].

Furthermore, NFs have severe limitations within the shared control paradigm, because commands provided by the users won't typically fit the NF properties.

In our case, any collaborative motion vector described by $\boldsymbol{V}_C$ includes a component provided by human $\boldsymbol{V}_H$ through any input device (typically a joystick) and a PFA command $\boldsymbol{V}_R$ as robotic counterpart. This approach was originally proposed in [20].

This solution, though, splits control equally between user and machine. This is not always wise: some users could perform dangerous maneuvers or generate erratic commands. Others might be completely unable to produce an adequate command to solve some specific situation. Indeed, this solution is discontinuous. Convergence issues derive from using PFA: convergence is compromised, as we have included a non analytic component ($\boldsymbol{V}_H$).

To cope with this issue we evaluated the local efficiency of commands $\boldsymbol{V}_R$ and $\boldsymbol{V}_H$. Both vectors were weighted so that control transitions are smoother. This overcomes the problem of convergence and most PFA limitations. It also improves continuity in the emergent command. Now, commands are weighted using an efficiency term ($\eta$). $\eta$ is a local, memoryless, reactive metric without any temporal information like curvature or trajectory length. PFA commands only depend on current state $\bar{q}_i$, i.e. they are purely reactive. Consequently, $\eta$ must also be obtained at reactive level, and based uniquely on local performance.

$$\boldsymbol{V}_C = \ \eta(\bar{q}_i, \boldsymbol{V}_R) \ \boldsymbol{V}_R + \ \eta(\bar{q}_i, \boldsymbol{V}_H) \ \boldsymbol{V}_H \tag{1}$$

In our approach $\eta$ weights motion commands according to their likeness to a NF. $\eta$ has one component per prerequisite of a NF. Rimon and Koditschek defined in [7] the properties of a NF. It must be:

1. smooth (at least in $\mathbb{C}^2$)
2. have a single local minimum at $\bar{q}_g$
3. maximal along the boundaries of $Q$
4. a Morse function (its critical points are non-degenerate)

The fourth prerequisite is ensured in our work by the decomposition of the space into simpler convex subspaces, as proposed in [21], so it has no impact on $\eta$. Consecuently, we define $\eta$ as the average of only three factors, one per each NF property.

$$\eta(\bar{q}_i, \boldsymbol{V}) = \frac{\eta_{sm}(\bar{q}_i, \boldsymbol{V}) + \eta_{dir}(\bar{q}_i, \boldsymbol{V}) + \eta_{sf}(\bar{q}_i, \boldsymbol{V})}{3} \tag{2}$$

By including $\eta$, into (1), we reinforce the NF conditions, as will be shown in the following subsections.

### 3.1 Smoothness

Smoothness $\eta_{sm}$ penalizes sharp direction changes in input $\boldsymbol{V}$. This corresponds to the first NF requisite: smoothness at least in $\mathbb{C}^2$. Any value implying a discontinuity in motion due to a sharp direction change will be penalized by this factor, described in (3) and defined by the angle between the vehicle heading in position $\bar{q}_i$ and proposed command $\boldsymbol{V}$ ($\alpha_{sm}$). We use a positive constant $C_{sm}$ to adjust smoothness influence on $\eta$ (see Fig. 1). Comentar un poco

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

### 3.2 Directness

Directness $\eta_{dir}$ is related to the orientation with respect to the target. A NF must be *polar*, i.e. it should have an unique minimum, located at $\boldsymbol{q}_G$. The gradient descent of such a function will always approach that minimum. Once again, it is impossible to guarantee that any command will follow this rule, but it is possible to reward such a behavior.

The angle formed by the proposed motion command and the target direction is an obvious local indicator. This angle ($\alpha_{dir}$) should be low in a polar function: hence Eq. 4 will be maximum for angle 0°. Positive constant $C_{dir}$ fixes the impact of $\eta_{dir}$ on $\eta$.

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

### 3.3 Safety

Safety $\eta_{sf}$ penalizes commands pointing towards obstacles, and, in general, commands bringing the mobile closer to obstacles. A NF must be maximum and uniform in the boundaries of space $Q$, conformed by the environment obstacles. We should have maximum potential on those boundaries, and its gradient should be normal to it. The gradient of the repulsory field defined by a PFA generates a vector field pointing opposite to nearest obstacle. The angle between the opposite to this vector field and the proposed command ($\alpha_{sf}$) measures our deviation from a NF. The lower $\alpha_{sf}$ is, the safer and the more similar to a NF the command is. The absolute distance to nearest obstacle $d_{obst}$ is also taken into account, divided by the maximum measurable distance $d_{max}$. This correction was introduced to reduce the influence of this factor with the distance. We also use a positive constant $C_{sf}$ to avoid dominance of $\eta_{sf}$ over other factors.

$$\eta_{sf} = 1 - e^{-C_{sf} \cdot |\alpha_{sf} + \frac{d_{obst}}{d_{max}}|} \tag{5}$$

All necessary elements for $\eta$ calculation are summarized in Fig. 1.

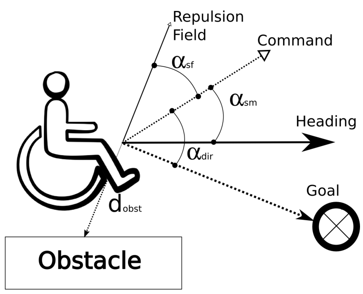


**Fig. 1.** $\eta$ calculation parameters

$C_i$ constants are used to take into account very specific tests environments or wheelchair structures, though in general they can be set to 1. For example, a wheelchair with a high center of mass should have a high $C_{sm}$ to prevent instability. A crowded environment requires high $C_{sf}$ but lower $d_{dmax}$ to properly shape $\eta_{sf}$. Their initial values must change to fit the scenario. However, these constants can be easily chosen for a standard power wheelchair operating in indoor environments.

## 4 Collaborative Control as a Navigation Function.

In this section we will analyze the link between our collaborative control and the properties of a generic navigation function $f(\bar{x})$ as defined in [7]. Our collaborative command will be compared with the divergence of a navigation function, i.e. $\boldsymbol{V}_C = \boldsymbol{\nabla} f(\bar{x})$. Divergence operator is a linear and differential operator. We will use the cartesian two dimensional divergence operator: $\boldsymbol{\nabla} = (\frac{\partial}{\partial x}, \frac{\partial}{\partial y})$.

Commands, $\boldsymbol{V}(\bar{x}, M)$, depend on the current mobile position $\bar{x}$ and surrounding map $M$. A command efficiency, $\eta(\boldsymbol{V}(\bar{x}, M), \bar{x}, M)$, also depends on the current position and map, but we will denote it just as $\eta(\boldsymbol{V}(\bar{x}))$. Efficiency is a monotonic function at any given point $\bar{x}$, with image [0,1).

### 4.1 Smoothness

We will apply divergence operator to the smoothness definition:

$$\lim_{\bar{x} \to \bar{C}^+} f(\bar{x}) = \lim_{\bar{x} \to \bar{C}^-} f(\bar{x}) \tag{6}$$

$$\begin{aligned}\nabla \lim_{\bar{x} \to C^+} f(\bar{x}) &= \lim_{\bar{x} \to \bar{C}^+} \nabla f(\bar{x}) = \\ &= \lim_{\bar{x} \to \bar{C}^+} \eta(\boldsymbol{V}_H(\bar{x})) \lim_{\bar{x} \to \bar{C}^+} \boldsymbol{V}_H(\bar{x}) + \\ &+ \lim_{\bar{x} \to \bar{C}^+} \eta(\boldsymbol{V}_R(\bar{x})) \lim_{\bar{x} \to \bar{C}^+} \boldsymbol{V}_R(\bar{x})\end{aligned}$$

Efficiency and robot commands are *continuous.* Thus, smoothness depends on the product of human commands and its efficiency. We cannot guarantee continuity in human commands. However, our efficiency function compensates this, decreasing their impact on the equation when discontinuities appear so that smoothness is mostly granted by the robot commands.

### 4.2 Polar function

$$f(\bar{x}) \geq f(\bar{q}_g) \tag{7}$$

A navigation function must have one single minimum at destination $\bar{q}_g$. Necessary minimum conditions are:

- First partial derivative is equal to zero at the critical point.
- Second partial derivatives are positive.

$$\nabla f(\bar{q}_g) = \bar{0} \tag{8}$$

$$f_{xx}(\bar{q}_g) \geq 0 \tag{9}$$

$$f_{yy}(\bar{q}_g) \geq 0$$

We can expand Eq. 8 using collaborative control definition as:

$$\begin{aligned}\nabla f(\bar{q}_g) = \eta(\boldsymbol{V}_H(\bar{q}_g))\boldsymbol{V}_H(\bar{q}_g) + \\ + \eta(\boldsymbol{V}_R(\bar{q}_g))\boldsymbol{V}_R(\bar{q}_g)\end{aligned}$$

Any command at $\bar{q}_g$ pointing out of it will have a very low efficiency. The only command in this situation with high efficiency is $\bar{0}$, thus this requisite is fulfilled in any case.

We also apply collaborative control definition to Eq. 9, resulting:

$$
\begin{aligned}
f_{x_i x_j}(\bar{q}_g) &= \frac{\partial f(\bar{q}_g)}{\partial x_i x_j} = \frac{\partial \nabla_{x_j} f(\bar{q}_g)}{\partial x_i} = \\
&= [\frac{\partial}{\partial x_i}\eta(\boldsymbol{V}_H(\bar{q}_g))]V_{Hx_j}(\bar{q}_g) + \eta(\boldsymbol{V}_H(\bar{q}_g))[\frac{\partial}{\partial x_i}V_{Hx_j}(\bar{q}_g)] + \\
&[\frac{\partial}{\partial x_i}\eta(\boldsymbol{V}_R(\bar{q}_g))]V_{Rx_j}(\bar{q}_g) + \eta(\boldsymbol{V}_R(\bar{q}_g))[\frac{\partial}{\partial x_i}V_{Rx_j}(\bar{q}_g)]
\end{aligned}
$$

Efficiency has a maximum at $\bar{q}_g$, so:

$$
\begin{aligned}
&\frac{\partial}{\partial x_i}\eta(\boldsymbol{V}(\bar{q}_g)) \to 0 \\
&f_{x_i x_j}(\bar{q}_g) = \eta(\boldsymbol{V}_H(\bar{q}_g))[\frac{\partial}{\partial x_i}V_{Hx_j}(\bar{q}_g)] + \\
&+ \eta(\boldsymbol{V}_R(\bar{q}_g))[\frac{\partial}{\partial x_i}V_{Rx_j}(\bar{q}_g)]
\end{aligned} \tag{10}
$$

This factor always tend to zero. A highly variant command will have low efficiency. Highly efficient commands must have low variation and value near $\bar{0}$.

### 4.3 Maximal at frontiers

This condition is similar to previous one:

$$f(\bar{x}) \le f(\bar{q}_o) \tag{11}$$

A navigation function must be maximum at borders $\bar{q}_o$. This point must be a critical point, so necessary conditions are:

- First partial derivative is equal to zero at the critical point.
- Second partial derivatives are negative.

These can be expressed as:

$$\nabla f(\bar{q}_o) = \bar{0} \tag{12}$$

$$
\begin{aligned}
f_{xx}(\bar{q}_o) &\le 0 \\
f_{yy}(\bar{q}_o) &\le 0
\end{aligned} \tag{13}
$$

We can expand these equations using previous results:

$$
\begin{aligned}
\nabla f(\bar{q}_o) &= \eta(\boldsymbol{V}_H(\bar{q}_o))\boldsymbol{V}_H(\bar{q}_o) + \eta(\boldsymbol{V}_R(\bar{q}_o))\boldsymbol{V}_R(\bar{q}_o) \\
f_{x_i x_j}(\bar{q}_o) &= \eta(\boldsymbol{V}_H(\bar{q}_o))[\frac{\partial}{\partial x_i}V_{Hx_j}(\bar{q}_o)] + \\
&+ \eta(\boldsymbol{V}_R\bar{q}_o)[\frac{\partial}{\partial x_i}V_{Rx_j}(\bar{q}_o)]
\end{aligned}
$$

Efficiency properties guarantee these restrictions. Efficiency has a minimum at $\bar{q}_o$, which implies:

$$\eta(\boldsymbol{V}(\bar{q}_o)) \rightarrow 0$$
$$\frac{\partial}{\partial x_i}\eta(\boldsymbol{V}(\bar{q}_o)) \rightarrow 0$$

This is, all second derivatives are zero at $\bar{q}_o$.

### 4.4 Summary

Relationship between navigation functions and efficiency factor can be summarized with these requisites, provided by efficiency factors:

- Discontinuities are compensated by efficiency function
- Efficiency has a single minimum at $\bar{q}_o$
- Efficiency has a maximum at $\bar{q}_g$

However, this collaborative control solution still has some drawbacks: i) It is purely reactive: it won't prevent potentially dangerous situations nor recall previous hazardous situations. It just avoids them with the information at hand in a given time instant. ii) User's commands have no specific predominance over the robot's ones or viceversa: user's and robot's commands will have always a relative impact. iii) Users should override control when they are performing remarkably well, to avoid frustration and reward their effort, as commented.

It needs to be noted that human commands are typically hard to predict, specially for persons with different disabilities. Similarly, a dynamic environment is not that predictable either. However, we can predict up to some point a given user's efficiency coping with a given environment structure if we analyze how well this person has driven since the last significant change. This can be used to provide some inertia to the proposed collaborative navigation technique and, hence, overcome the commented limitations in an attempt to approximate better a NF.

## 5 Modulated Collaborative Control

The previous section concluded with the limitations on purely reactive user's and robot's command combination. Our present target is to make emergent commands fulfill NF properties. We introduce a new factor $K$ in Eq. 1 to modulate user-computer control ratio. This factor works like a *wave-envelope* to provide efficiency dependent inertia, i.e. people who consistently drive well at a given environment area receive more control despite punctual errors. A similar concept was successfully introduced in [22] to include user's biometric information into collaborative control. $K$ depends now on the average $\eta_H$ in a recent time interval. This time interval starts at the last sharp discontinuity point of $\eta_H$, to take into account that persons may drive differently at different areas of the environment depending on their specific disability. High $\bar{\eta}_H$ values will provoke high $K$ values. Emergent commands are now generated using Eq. 14.

$$\boldsymbol{V}_C = (1 - K(\bar{\eta}_H))\ \eta_R\ \boldsymbol{V}_R + K(\bar{\eta}_H)\ \eta_H\ \boldsymbol{V}_H \tag{14}$$

$K$ is a discrete step function that depends on $\bar{\eta}$.

The more user's performance decreases, the more assistance is provided. According to the PCM model [23], users accept this approach better because it prevents abrupt control changes. We give more control to the robot when the user clearly performs poorly and viceversa. User will be rewarded more control by sustained efficient driving. This inertia intends to skip punctual issues and focus on area trends. Users will also perceive consistent control increases and feel a higher degree of control.

| Navigation command | $\eta$ difference (%) | | | | Command angle average difference ($^o$) | |
|---|---|---|---|---|---|---|
| | $\eta_{sm}$ | $\eta_{dir}$ | $\eta_{sf}$ | $\eta$ | Mean | Std |
| Autonomous PFA | 4.13 | 10.51 | -3.30 | 3.78 | -0.84 | 46.33 |
| Collaborative control | 18.64 | 20.30 | 0.12 | 12.92 | -1.62 | 50.24 |
| Modulated Collaborative control | 15.49 | 18.13 | -3.53 | 9.98 | 3.74 | 46.68 |

**Table 1.** NF likehood of navigation commands

Our first proposal for $K(\bar{\eta}_H)$ function was a direct proportionality. However doctors recommended us to use a discrete set of $K$ values instead because they did not feel $\eta$ can be measured with precision. Hence we defined four cases: i) warning, ii) bad performance, iii) average driving, iv) good performance. Using data from previous collaborative control tests [24], we identified those cases as: i) unfinished tests, ii) low performance tests, iii) average tests and iv) healthy user tests. We took as $\bar{\eta}_{Hi}$ the average $\eta_H$ value of each identified case.

Table 1 summarizes a comparison between different control modes. It covers the difference in $\eta$ between the reference NF and the different solutions presented in this section. PFA is very close to NF in terms of efficiency, and even better in terms of safety. This was expected: both are optimization algorithms and PFA has sharp discontinuities in obstacle proximity -note the lower directness.

We simulated navigation of an erratic user assisted by PFA using collaborative control. Collaborative control is closer to NF than the dangerous user alone in terms of $\eta$. Our simulated user, using collaborative control, has increased his performance from 4 % through 28%.

More important, safety is clearly improved. Finally, modulated collaborative control makes some improvement (about 3%) over these benefits. Modulated collaborative control is a more flexible algorithm than the previous one. The main target of modulated collaborative control is to meet as much as possible the properties of a NF, not to achieve the highest possible efficiency.

We also provide in Table 1 statistics of the command angle difference. PFA commands are very similar to NF ones. Collaborative control combines these two sources of information. This command preserves the resemblance with a NF (less than 2 degrees of difference and almost the same deviation) despite of the user intervention. Modulated collaborative control is less precise than collaborative control (see higher angle difference). However, modulated collaborative control provides commands more coherent with NF commands (see standard deviation decrement). Modulated collaborative control commands are a little bit biased, but more similar to the NF ones.

## 6 Experimental Results

Our modulated collaborative control system has been tested by real users in a controlled scenario in Rome, at Fondazione Santa Lucia concept House "Casa Agevole". The key idea was improving wheelchair usability within the house since we had performed there previous tests in basic collaborative mode [24].

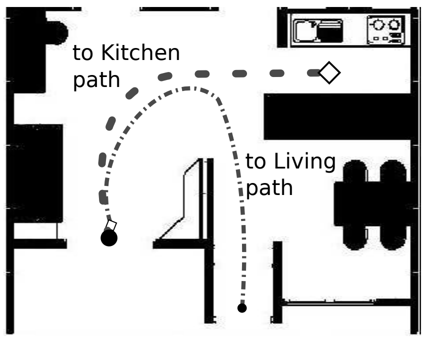


**Fig. 2.** Proposed path examples: to kitchen, and to living room

### 6.1 Experimental Set-up

Experiments consisted of accomplishing two different trajectories (Fig. 2). According to clinicians, these trajectories are frequent within the Activities of Daily Living (ADL) in a house: going from the entrance to the living room and going from the living room to the kitchen. They included narrow corridors, a great challenge both for PFA systems and novel drivers.

Experiments were performed by 10 users. Most of them had mild physical disabilities, pointed by a Barthel index over 70% and a IADL over 4 points. Cognitive scales also indicate a moderate degree of dependence.

Experiments were made using different motion planning systems in both trajectories:

– Collaborative control: This test was based on Eq. 1. It provided a reference for benchmarking as shown in Section 6.3.
– Modulated collaborative control: This experiment showed the effect of dynamically changing the amount of user control. It also showed how the variation of $K$ is perceived by user.

| Test type | | Collaborative control | | Modulated collaborative control | |
|---|---|---|---|---|---|
| Destination | | Living | Kitchen | Living | Kitchen |
| PFA efficiency (%) | $\eta_{sm}$ | 53.47 | 70.46 | 50.38 | 60.11 |
| | $\eta_{dir}$ | 67.36 | 74.49 | 65.03 | 75.36 |
| | $\eta_{sf}$ | 94.22 | 97.34 | 91.91 | 97.81 |
| | $\eta$ | 71.64 | 80.74 | 69.09 | 77.77 |
| User efficiency (%) | $\eta_{sm}$ | 73.08 | 64.97 | 65.17 | 82.83 |
| | $\eta_{dir}$ | 50.06 | 38.00 | 38.76 | 59.62 |
| | $\eta_{sf}$ | 96.30 | 97.43 | 97.52 | 97.13 |
| | $\eta$ | 73.04 | 66.78 | 67.08 | 79.73 |
| Collaborative efficiency (%) | $\eta_{sm}$ | 68.41 | 75.09 | 69.35 | 73.97 |
| | $\eta_{dir}$ | 46.26 | 54.13 | 54.33 | 54.29 |
| | $\eta_{sf}$ | 97.82 | 98.29 | 98.00 | 97.71 |
| | $\eta$ | 70.84 | 75.84 | 73.89 | 75.33 |
| Burst length (ms) | mean | 751.87 | 971.70 | 893.00 | 897.48 |
| | std | 1239.97 | 1120.42 | 1806.22 | 1751.11 |
| Distance to targets (mm) | mean | 233.69 | 269.58 | 235.43 | 260.04 |
| | std | 262.31 | 265.81 | 242.14 | 226.73 |
| Angle difference (°) | mean | -2.38 | -11.98 | 6.48 | 3.72 |

**Table 2.** Test average results

### 6.2 First experiment: collaborative control navigation

Results for all experiments are summarized in Table 2. There is one column for each proposed trajectory and control approach, showing the average results. $\eta$ should be a measure of how similar the navigation command is to one generated by NF. We have included another navigation performance parameter: distance to target. Real systems define not a point, but a region surrounding a target. The lower this distance is, the better the generated trajectories will be.

Emergent control commands mimic user's commands when they are efficient. Users believe they are in control most of the time. Control switches are also intuitive for users, who recover control shortly after alignement. All users achieved their final target with relative easiness.

In order to prove that the proposed profile is representative, we will compare these results with collaborative control tests. Since collaborative control is expected to adapt to each person i.e. to improve residual skills and fill in for lacking ones, resulting profiles should be closer to the benchmark profile in collaborative mode, despite the user's condition.

### 6.3 Second experiment: modulated collaborative control navigation

We used the same trajectories in the previous experiments to test the new approach in Section 5 . User commands will be combined again with a robotic control algorithm. Relative impact of each command is not fixed, now it is given by parameter $K$.

Modullated collaborative control matches average $\eta$ values with $K$ values. Thus, a user with a sustained efficiency above 50 % will have a higher amount of control, a 70 % using collaborative control.

On the other hand, users driving with low efficiency, e.g. crossing a narrow door, will have less control than in the previous experiment. Average $K$ percentage value of these tests was slightly higher than fixed $K$: 58.87 % in kitchen tests and 56.53 in living room tests.

In general, modulated control is similar to collaborative control as proposed in 6.2. Indeed, there is no major efficiency variation in average $\eta$. Collaborative control efficiency is mostly defined by user's navigation skills. Modulated collaborative control keeps the main role of the user.

However, there are very significant efficiency increases at specific locations, specifically at areas where user or robot perform particularly poorly.

The main advantage of modulated collaborative control is, consequently, a better adaptation to the user, providing information about a reliable control proportion. Time elapsed between a maximum and next minimum is about 100 ms shorter according to Table 2. Hence, adaptation is faster than in Section 6.2.

With this approach, we obtain longer tracking periods, perceived by user as a better control. Users reported to feel a better system control with this system approach.

## 7 Conclusions and Future Work

In this paper, we have presented a method to extend navigation functions into human-computer shared navigation. Navigation functions offer optimal and unique solution to the autonomous navigation problem. Our shared control algorithm, collaborative control, has been defined in terms of navigation function properties. User commands are rated in collaborative control using $\eta$ function.

This work has also presented an improved collaborative control algorithm. It has several benefits from its original version. First of all, it is self configurable. Now it is not necessary to fine tune the amount of user control, stated as $K$ constant. Modulated collaborative control system changes autonomously the instant $K$ value, according to user performance.

Finally we have presented a comparison test between original and modulated collaborative control. Modulated collaborative control preserves user predominance in navigation, adapting control in critical situations. This adaptation is not perceived by users as negative. They have, on average, the same performance.

From the user's point of view, navigation is smoother than previous version. The amount of control finally given to users reflex can be also a useful information about their state. One of the main objectives of this navigation scheme is to make user effort at her/his best, while being intuitive. The users perceived the control adaptation, and reported to ease navigation.

Further work will be made on improving these two factors: usability and adaptability. User interfaces able to provide extra information, such as force feedback joysticks will included to reinforce feedback. Adaptability can be explored using new ways of changing $K$ in terms of $\eta$.

We have seen how $\eta$ improves the convergence and stability of the resulting motion command. This allows to include different approaches within the system further than PFA.

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