ARCHITECTURE FOR HUMAN-ROBOT COLLABORATIVE NAVIGATION

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Abstract: Various situations of mobile platform navigation controls require a collaboration between a human agent and autonomous navigation modules. This work presents a new approach for collaborative control between such two agents, based upon a three-layer architecture. An arbitration scheme is proposed in the deliberative layer as well as a collaborative planning method for trajectory following based upon optimal control theory in the sequencer layer. The collaborative control signal in the execution layer is a weighted summation of each agent control signal. This collaborative architecture could be used for the shared control of vehicles such as motorized wheelchairs. Experimental results illustrate the efficiency of the proposed control architecture.

1 INTRODUCTION

The shared control of a robotic platform falls into two categories: the first one corresponds to situations where the various agents compete to find the best control action to be selected and applied (Skrzypczyk, 2005). The second category corresponds to a collaborative approach aiming at achieving a given goal (S. Katsura, 2004; Q. Zeng, 2008; C. Urdiales and Sandoval, 2007). This paper focuses on a collaborative approach to shared control between a human agent onboard a mobile platform, such as a motorized wheelchair for example, and an autonomous navigation module. The autonomous navigation module relies on its proximity sensors (sonar, infrared, laser range finder, etc.) in order to perform the navigation task; its ability to sense the surrounding environment is therefore, limited by its perception and interpretation capabilities. Based upon its own sensory system, the human agent can contribute to extend the autonomous module capabilities by providing a control signal that allows the platform to avoid non-detected dangers and improve its navigation performance. Inversely, in situations where human perception and control suffer momentarily from a lack of attention, the autonomous navigation module may be able to compensate and avoid imminent dangers. Furthermore, various types of maneuvers in constrained environments, such as doorway passing or parking, may exceed the human agent capabilities and require the help of the autonomous agent.

Previous work on collaborative navigation control focused on the decision problem (A. Huntemann and al., 2007; T. Taha and Dissanayake, 2007; Y. Qi and Huang, 2008; T. Okawa and Yamaguchi, 2007) (i.e. the determination of the navigation task), while the planning aspect, i.e. the determination of the sequence of platform actions that may be used) is left to the responsibility of the Autonomous Navigation Module (C. Urdiales and Sandoval, 2007; Q. Zeng, 2008). Usually, there are more than one sequence of platform actions that can be used to reach a given goal and the one selected by the Autonomous Navigation Module is not necessarily what the Human agent would do if he was responsible of the planning. This paper presents two contributions: the first one consists of a reactive arbitration scheme that allows two agents with different perception modalities to avoid perceived obstacles. The second contribution consists of a collaborative architecture that efficiently includes both agents control signals at decision and planning levels. In addition, we provide a formal approach to the integration of the Human Agent plan during the elaboration of the Autonomous Navigation Module plan. This method is based upon the multi-agent optimal control theory (Cruz, 1978; Simaan and Cruz, 1973; Y. C. Ho and Olsder, 1982).

The rest of the paper is organised into 4 sections. Section 2 presents the deliberative obstacle avoidance scheme. In section 3, the collaborative architecture is

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discussed. Experimentations and conclusion are presented in section 4 and section 5, respectively.

2 OBSTACLE AVOIDANCE DELIBERATIVE APPROACH

2.1 Problem Statement

The main goal of this work is to design a system that can allow a Human Agent (HA) and an Autonomous Navigation Module (ANM) to collaborate during navigation tasks of a mobile platform. Given an environment map and the current mobile platform configuration (position and orientation), the ANM agent aims at helping the HA to reach a given destination without colliding with obstacles, as perceived by the ANM. The help mentioned here is related to the fact that the ANM agent is continuously supervising the HA control signal and intervenes only to avoid collisions. Since the two agents perception systems differ, various situations may occur in which:

- a danger is perceptible by the ANM agent alone: we designate by S_{am} the set of such events; navigation control priority should be given to the ANM;
- a danger is perceptible by the Human agent alone: we designate by S_h the set of such events; navigation control priority should be left to the HA;
- a danger is perceptible by both agents: we designate by S_{ham} the set of such events; navigation control should be based upon deliberation;
- a danger is not perceptible by any of the two agents; a collision is unavoidable.

The main problem consists in establishing an arbitration scheme that will produce the desired decision scheme outlined above.

2.2 Preliminary Considerations

We assume that, at the beginning of the navigation task, a map of the environment and the destination configuration are available to the ANM. At each step k, each of the two agents provides a control signal based upon their current perception of the environment. From the perspective of the arbitration scheme to be designed, a control signal is considered to be safe if its application does not lead to collision for an obstacle belonging to S_{am} or S_{ham}.
We designate by $U_h(k)$ and $U_c(k)$ HA and the ANM control signals respectively. Since both agents are not competing, a reasonable choice for the collaborative control signal consists of selecting a weighted sum of both signals $U_h(k)$ and $U_c(k)$. The agent with higher priority will have the largest control signal weight. Solving the deliberation problem is equivalent to finding the weight relative to each agent. For simplicity, we designate these weights by $\alpha(k)$ and $(1-\alpha(k))$ with $\alpha(k) \in [0,1]$ where $\alpha(k)$ is the ANM control signal weight at step k. The following expression corresponds to the collaborative control signal $U(k)$:

$$U(k) = (1-\alpha(k))U_h(k) + \alpha(k)U_c(k) \tag{1}$$

Given $U_h(k)$ and $U_c(k)$, the deliberative control problem consists of determining the value of $\alpha(k)$ at each step k.

2.3 Approach for Solving the Deliberative Problem

The precedence of U_h over U_c must be taken into account when solving the above problem. Indeed, the ANM should not generate its control signal without taking into account the motion direction implied by the HA control signal. This constraint is important in order to allow the platform to follow the HA control signal whenever several ways exist to safely achieve a maneuver. For example, in front of an obstacle belonging to S_{ham}, the HA decision on how to avoid it must be complied with. Similarly, in the absence of any danger, the ANM should generate a control signal U_c close to U_h since there is no need to help the human agent in such a situation.
A criterion, called non-collision index $P(k) \in [0,1]$, must be defined in order to allow the arbitration scheme to assess the risk of a collision if one of the two control signals were to be used alone. $P(k)$ should be small if a collision is likely to happen. The following expression is a good candidate to represent the non-collision index:

$$P(k) = e^{-C\frac{1}{d^{min}(k)}} \tag{2}$$

where $d^{min}(k) > 0$ represents the minimum distance between the platform position and the nearest obstacle in the direction of motion. The value of the index decreasing rate C depends upon the navigation context. Given the expression of $P(k)$, we define the Human agent non-collision index $P_h(k)$ and the ANM non-collision index $P_c(k)$ as:

$$P_h(k) = e^{-C\frac{1}{d_h^{min}(k)}} \tag{3}$$

$$P_c(k) = e^{-C\frac{1}{d_c^{min}(k)}} \tag{4}$$

where $d_h^{min}(k) > 0$ represents the minimum distance between the platform configuration and the nearest obstacle if only $U_h(k)$ was applied and $d_c^{min}(k) > 0$ represents the corresponding distance if only $U_c(k)$ was applied. Given $P_h(k)$ and $P_c(k)$, the value of $\alpha(k)$ is derived as:

$$\alpha(k) = \frac{P_c(k)}{P_h(k) + P_c(k)} \quad (5)$$

Arbitration Scheme Description
The arbitration scheme has two phases: the supervision phase and the correction phase. Let us define P_h^0 as a minimum predefined non-collision index. The system is in the supervision phase if $P_h(k) > P_h^0$. Otherwise, the system is in the correction phase.
Supervision Phase:
During this phase and at each step, the deliberative module computes $P_h(k)$. If $U_h(k)$ leads to a safe motion, the following condition holds: $P_h(k) > P_h^0$. The ANM generates $U_c(k)$ close to $U_h(k)$ since there is no need to help the human agent. But the deliberative module will set $\alpha(k)$ to 0 so that $U(k)$ is exactly equal to $U_h(k)$ according to equation 1. Therefore, the platform is under the control of the human agent.
Correction Phase:
When $P_h(k) <= P_h^0$, a collision may happen if $U_h(k)$ is applied directly. Perceiving the obstacle, as part of S_{am} or S_{ham}, the ANM generates a control signal $U_c(k)$ in order to avoid collision. Since $U_c(k)$ is safer than $U_h(k)$, the non-collision index $P_c(k)$ will be greater than $P_h(k)$. According to equation 5, the value of $\alpha(k)$ is greater than 0.5, allowing a greater contribution of the ANM control signal into the collaborative control signal. In the extreme case when $U_h(k)$ is very unsafe, $\alpha(k)$ will be close to 1 and the collaborative control signal $U(k)$ will be close to $U_c(k)$.
On the basis of this arbitration scheme, the collaborative control system will behave as specified in Section 2.1.

2.4 Limitation of the Arbitration Scheme

The proposed arbitration handles correctly the three cases mentioned Section 2.1. However, since the list of cases was not exhaustive, the arbitration scheme may not correctly avoid all situations of collisions. For example, an obstacle belonging to S_h on the left of the platform and a second one belonging to S_{am} in front of it, while the platform is moving straightforward, may cause the ANM to generate a control signal $U_c(k)$ that will induce a motion on the left, thus leading to a collision.
The next section presents a complete collaborative architecture designed to test the proposed arbitration scheme.

3 COLLABORATIVE NAVIGATION ARCHITECTURE

The subsumption (Brooks, 1986) and the three-layer architectures (E. Gat and Murphy, 1998) are among well-known robotic architectures used for platform navigation applications. The subsumption architecture is associated with reactive behaviour-based robots. Since upper layers interfere with lower layers, they cannot be designed independently. The three-layer architecture consists of a Deliberative Layer for navigation task selection, a Sequencer Layer for reactive planning and an Execution Layer for low level effector control. Due to its modular concept, we select the three layer architecture as the basis of the collaborative control architecture presented here. This collaborative architecture has the advantage of providing a high level of decoupling between layers, each layer (deliberative, sequencer or execution layer) can be designed without attention to the roles of the other layers of the architecture.

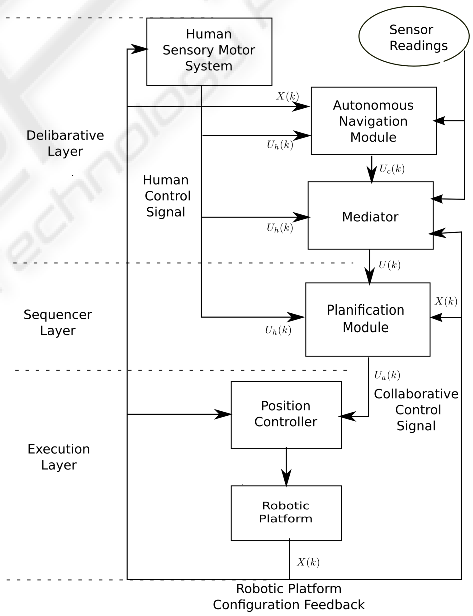

Figure 1: Collaborative Architecture for Navigation.

3.1 Deliberative Layer

The Deliberative Layer is the top layer of the proposed architecture. It has the core of the ANM and the Mediation module.

3.1.1 Autonomous Navigation Module

The role of this module is to provide at each step k a control signal $U_c(k)$ that leads to safe motion. When an obstacle is perceived, it uses a collision avoidance algorithm based upon the Virtual Field Histogram approach (VFH) (Borenstein and Koren, 1991). Figure 2 illustrates how the ANM control signal can be generated using a VFH based obstacle avoidance approach.

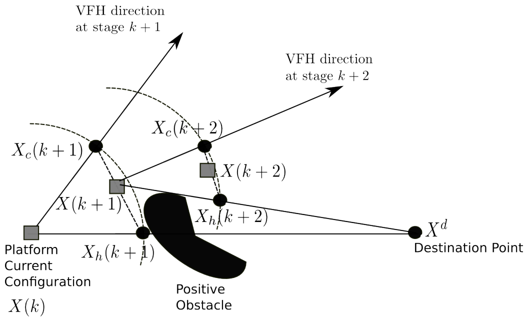

Figure 2: Trajectory Generation: At step k, the platform receives the control signal from each agent. If the Human control signal is applied alone, the platform configuration at step $k+1$ will be $X_h(k+1)$. If the Autonomous Navigation Module control signal is applied alone, the platform configuration at step $k+1$ will be $X_c(k+1)$. By applying both control signals at step k, the next platform configuration will be between $X_h(k+1)$ and $X_c(k+1)$. This configuration will be close to $X_c(k+1)$ and $X_c(k+1)$ is close to 1.

Assume that $X^d = [x^d \ y^d \ \theta^d]'$ is the platform destination configuration and $X(k) = [x(k) \ y(k) \ \theta(k)]'$ is the current platform configuration as shown in Figure 2. Based upon $X(k)$, X^d and obstacles around the platform, the Virtual Field Histogram (VFH) method is used to find the lowest obstacle density direction for platform move (Borenstein and Koren, 1991). This direction is called the VFH direction and defines the orientation $\theta_c(k+1)$. In order to find the point $(x_c(k+1), y_c(k+1))$ on that direction, we propose a method that will allow the human agent to move and stop the platform at will.
At step k, the HA provides its control signal $U_h(k)$. If $U_h(k)$ is applied without any contribution of the ANM agent control signal, the platform configuration will be $X_h(k+1) = [x_h(k+1) \ y_h(k+1) \ \theta_h(k+1)]'$. The point $(x_c(k), y_c(k))$ is selected on the VFH direction so that the Euclidian distance between $(x(k), y(k))$ and $(x_h(k+1), y_h(k+1))$ is the same as that between $(x(k), y(k))$ and $(x_c(k+1), y_c(k+1))$.

3.1.2 Mediator Module

This module uses the arbitration scheme presented in section 2.3 in order to produce the collaborative control signal $U(k)$.

3.2 Collaborative Sequencer Layer

The HA control signal can be affected by variations originating from the input modality uncertainty or hand tremors. In this section, we propose an approach that significantly reduces the impact of unwanted variations on the collaborative control. In order to present our method, let us consider the signal control diagram shown in Figure 3.

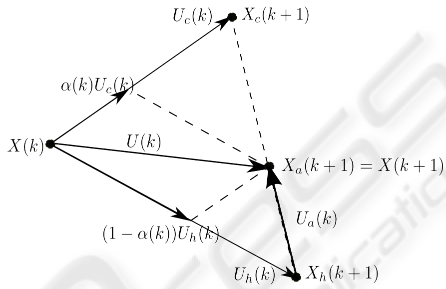

Figure 3: Control Signal Diagram. The individual application of $U_h(k)$ and $U_c(k)$ will produce the configuration $X_h(k+1)$ and $X_c(k+1)$ respectively. However, due to $\alpha(k)$, the collaborative control signal $U(k)$ will produce $X(k+1)$.

Given the value of $\alpha(k)$, there are two ways to compute the collaborative control signal $U(k)$ shown in Figure 3:

$$U(k) = \alpha(k)U_c(k) + (1-\alpha(k))U_h(k) \tag{6}$$

or

$$U(k) = U_a(k) + U_h(k) \tag{7}$$

According to equation 6 and knowing that the $U_c(k)$ is independent from $U_h(k)$, we get:

$$\frac{\partial U(k)}{\partial U_h(k)} = (1-\alpha(k))I \tag{8}$$

where I is a (3×3) identity matrix. On the other hand, according to equation 7:

$$\frac{\partial U(k)}{\partial U_h(k)} = \frac{\partial U_a(k)}{\partial U_h(k)} + I \tag{9}$$

If $U_a(k)$ is selected so that

$$\frac{\partial U_a(k)}{\partial U_h(k)} < -\alpha(k)I \tag{10}$$

then the second way for computing $U(k)$ is more efficient than the first method represented by equation 6. We provide a method based on the optimal control theory that allows to select $U_a(k)$.
Recall that the role of the Sequencer Layer is to provide $U_a(k)$ given $X(k)$, $X(k+1)$ and the dynamic model of the platform. If the Execution Layer has enough time to move the platform from $X(k)$ to $X(k+$

1), given the control signal $U(k)$, then its dynamic behavior can be approximated by the following linear equation:

$$X(k+1) = X(k) + U(k) \tag{11}$$

where $U(k)$ is represented by equation 7. In collaborative navigation contexts such as motorized wheelchair control, it is useful to constrain $U_a(k)$ in order to ensure smooth behavior. Large magnitudes of $U_a(k)$ should be avoided and the deviation between platform configurations $X(k)$ and the $X_a(k)$ should be minimized in order to allow the platform to follow the sequence of X_a. The following functional expression takes into account the above mentioned requirements.

$$J_a[U_a(k)] = \frac{1}{2}\sum_{k=0}^{M-1} C_a(k) + \frac{1}{2}C_a(M) \tag{12}$$

where:

$$\begin{aligned} C_a(k) = \; & [X(k) - X_a(k+1)]^T Q_a(k)[X(k) - X_a(k+1)] \\ & + U_a^T(k) R_a(k) U_a(k) \end{aligned} \tag{13}$$

$$C_a(M) = [X(M) - X_a(M+1)]^T Q_a(M)[X(M) - X_a(M+1)] \tag{14}$$

$Q_a(k)$ is a (3×3) symmetric and positive semidefinite matrix that penalizes the deviation between the platform configuration and the mediated configuration at step k;
$R_a(k)$ is a (3×3) symmetric and positive definite matrix that penalizes large sequencer control signals at step k.
The optimal sequence $\{U_a^*(k), k = 0, ..., M-1\}$ is, therefore, the sequence $\{U_a(k), k = 0, ..., M-1\}$ that minimizes the functional expression 12 under the constraint 11.

3.2.1 Solving the Planning Problem

In order to solve the optimization problem, we assume that the state vector is fully accessible to the sequencer and that the initial state vector $X(0)$ is completely known. Furthermore, we consider that $U_h(k), k = 0, ..., M-1$ is known. Using the Hamiltonian calculus (Lewis and Syrmos, 2005), we obtained:

$$U_a^*(k) = F_a(k)X(k) + F_h(k)U_h(k) + F_v(k)V(k+1) \tag{15}$$

where:

$$F_a(k) = -R_a^{-1}(k)S(k+1)F(k) \tag{16}$$

$$F(k) = [I + R_a^{-1}(k)S(k+1)] \tag{17}$$

$$F_h(k) = -R_a^{-1}(k)S(k+1)F(k) \tag{18}$$

$$F_v(k) = R_a^{-1}(k)[I - S(k+1)F(k)R_a^{-1}(k)] \tag{19}$$

$$S(k) = S(k+1)F(k) + Q_a(k) \tag{20}$$

$$\begin{aligned} V(k) \;=\; & Q_a(k)X_a(k+1) + V(k+1) \\ & + S(k+1)F(k)R_a^{-1}(k)V(k+1) \\ & - S(k+1)F(k)U_h(k) \end{aligned} \tag{21}$$

According to equation 7, the collaborative control signal is given by:

$$U(k) = U_a^*(k) + U_h(k)$$

In order to reduce variations on $U_h(k)$, the values of $R_a(k)$ and $Q_a(k)$ are selected so that the following condition holds:

$$\frac{\partial U_a^*(k)}{\partial U_h(k)} < -\alpha(k)I \tag{22}$$

3.3 Execution Layer

We assume that the robotic platform configuration $X(k)$ at step k is represented by its configuration expressed in a reference frame (working space). The Execution Layer, in the three-layer architecture, is designed to be tightly coupled with sensors and actuators. It receives a set point (or a target configuration) and, through the use of one or more control loops, tries to reach that point. However, in the proposed collaborative architecture, the Execution Layer input signal $U(k)$ is a weighted sum of two control signals. Based upon the platform dynamic equation, the current configuration and $U(k)$, the next configuration is computed and used as a set point for the Position Controller which is part of the Execution Layer. The Position Controller needs to find a control law that minimizes the deviation between the configuration obtained by applying the control law and the given configuration. Many methods exist to solve the controller problem in the case of a mobile platform (Astolfi, 1999), (Y. Kanayama and Noguchi, 1990). Recently, Belkhous (S. Belkhous and Nerguizian, 2005) proposed a new method based on Lyapunov theory. Since the Execution Layer is decoupled with the upper layers, any other platform dynamic model can be used with a minimum architecture modification.

4 EXPERIMENTS

4.1 Experimental Setup

In order to test the proposed arbitration scheme and the collaborative architecture, a first test scenario represented in Figure 4 is used on a mobile robotic platform. Starting from a rest position at $A(0,0)$, the ANM and the HA must collaborate in order to drive the platform to the destination point $E(7,0)$), by avoiding obstacles along the way. A negative obstacle is at position $B(1.5,0)$ and a positive obstacle is at $C(3.5,0)$. Furthermore, the platform must pass through a doorway at position $D(6.2,0)$ before reaching destination point E. The platform has one onboard laser range finder for obstacle detection. Due to the ranger finder position on the platform, negative obstacles cannot be detected. On the other hand, we assume that the HA is capable of perceiving negative obstacles, therefore, belonging to set S_h. For illustration purposes, we assume that the positive obstacle at position C is only perceived by the ANM through its range finder. Both agents can perceive the doorway. Hence, the positive obstacle belongs to set S_{am} and the doorframe belongs to set S_{ham}.

The second scenario intends to illustrate the collaboration when the obstacle belongs to S_{ham}. This scenario is represented in Figure 5. The mobile platform must move forward for about 1 meter, turn in order to face the doorframe and then move through the doorway. The doorway opening is $65cm$ wide, whereas the mobile platform width is $55cm$.

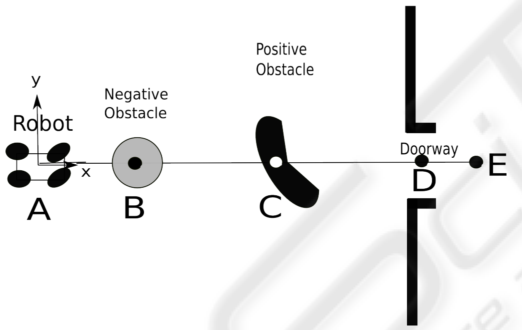

Figure 4: Navigation Scenario.

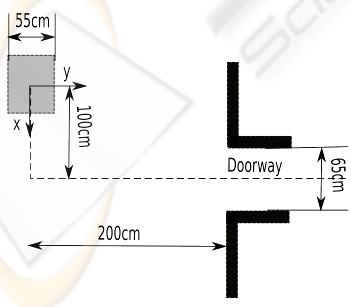

Figure 5: Doorway Passing Setup.

The mobile platform used for experiments is an ATRV-Mini manufactured by IRobot, equipped with a SICK laser rangefinder, model LMS200. Player-Stage (H. J. Toby and al., 2005) and Acropolis (Zalzal and al., 2006) softwares were used for the implementation. A standard joystick was used as the human agent input modality. The planning horizon of the sequencer layer is set to 1 and all involved matrices are set to the identity matrix I, except for $R_a(k)$ which is set to $10^{-3}I$.

4.2 Experience 1: Navigation with Obstacle Avoidance

Figure 6 shows three examples of trajectories. The first trajectory (grey curve) represents the Human agent trajectory, if he was alone to drive the platform. The second trajectory (dashed curve) represents the ANM trajectory when the signal of the HA is not taken into account. The third trajectory (continuous black curve) is the collaborative trajectory when both agents are participating. In this case, the collaborative trajectory shows that the platform was able to reach the destination while avoiding the positive and negative obstacles.

Figure 7 shows that during the negative obstacle avoidance, the ANM contribution was small, and the HA was able to avoid it without ANM control signal interference. α becomes close to 1 during the positive obstacle avoidance phase, the platform being able to avoid it despite the presence of the Human agent control signal.

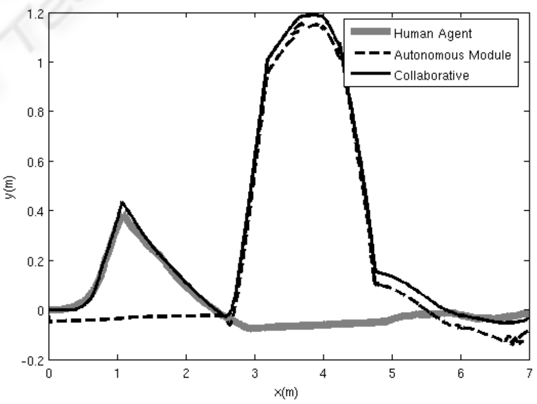

Figure 6: Example of Navigation Trajectories.

4.3 Experience 2: Doorway Passing

Figure 8 represents the evolution of α during the doorway traversing experiment. As one can notice, the contribution of the ANM changes in order to compensate for non safe HA control signals. Ten trials were performed and the platform was able to pass through the doorway.

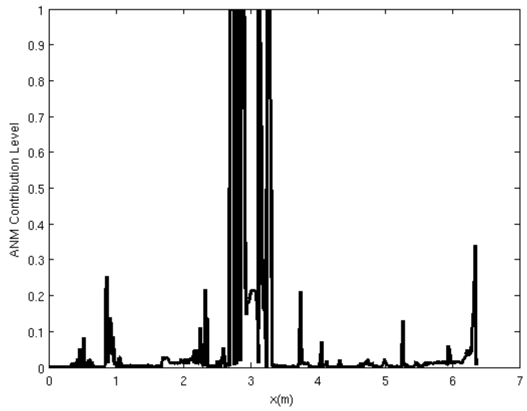

Figure 7: Collaborative Control: ANM Contribution Level α while the platform is moving on the $x-axis$.

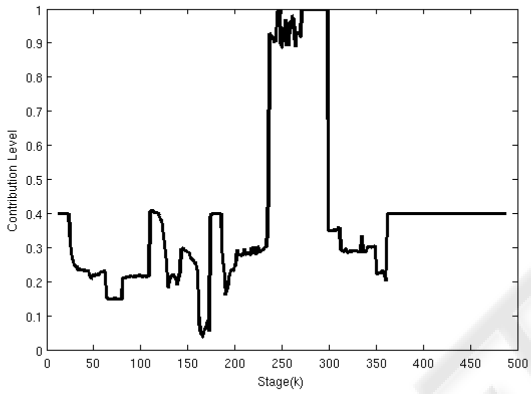

Figure 8: Dynamic Evolution of $alpha$ during doorway traversing experiment.

5 CONCLUSIONS

A robotic architecture that allows a human agent and an autonomous navigation module agent to collaborate during navigation tasks was proposed. This architecture has three layers, namely deliberative, sequencing and execution layers. In order to build the deliberative layer, an arbritage scheme based upon the value of a non-collision index is used. In the sequencer layer, both agents control signals are taken into account. Experiments performed with a mobile platform show that this architecture and its arbitration scheme can be used in robotic application in order to enhance a human agent obstacle avoidance capability. Applications such as powered wheelchair driving could use the proposed architecture.

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