Performance Guided Approach for Hardware and Software Resources Management for Autonomous Mobile Robotic Mission

Lotfi Jaiem, Robin Passama, Lionel Lapierre, Karen Godary-Dejean, and Didier Crestani

Authors are members of the Laboratoire d'Informatique Robotique et Microélectronique de Montpellier (LIRMM), UMR 5506, Université de Montpellier, 161 rue Ada, 34 095 Montpellier Cedex 5, France
{jaiem,passama,lapierre,Karen.Godary,crestani}@lirmm.fr
http://www.lirmm.fr

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Abstract. Mission performance is a large concept. It is rarely addressed in the context of autonomous mobile robotics. This paper proposes a generic framework addressing the concept of performance for autonomous mobile robotic mission. Moreover it presents an approach to manage the mobile robot hardware and software resources during the mission execution according to performance objectives. Simulation results illustrate the proposed approach on a patrolling mission example.

Keywords: Performance, resources management, autonomy, robot.

1 Introduction

Achieving autonomous mobile robotic mission in real conditions is a challenging goal. The robot has to perform its mission autonomously under many constraints. Baker and Yanco defines in [1] different autonomy modes from teleoperation to full autonomous mode. The maximum autonomy is defined in [2] as the ability to conduct an operation without interaction with outside. This interaction includes any external flow of information and resources between the robot and the external system (human control, energy, shared perception, etc.). As a result, true autonomy requires, between others, for the robot, the ability to decide in which way it will perform its mission under performance constraints. In connection with autonomous behavior modeling, autonomous systems are defined in [3] as the result of *autonomic constitution action* of an identity under uncertain circumstances. As example, it consists on choosing the sensors used, the robot velocity and the control algorithms all over and during the mission. Then, the robot must be also able to react if unexpected events occurs like obstacle avoidance or resource failure [4] in order to keep guaranteeing the required performances. If the mission becomes unfeasible, the robot must be able to identify this situation and may change its objectives (going to safe or starting zone, return to its docking station, etc.).

This short analysis shows that the robot hardware and software autonomous configuration is an important part of true autonomy for autonomous missions under performance constraints and unforeseen events. However the concept of performance is not clearly defined in robotics.

Generally, the performance can be defined as the result of the robot action and the efficiency is evaluated from the user's viewpoint. Some works evaluate specifically the performance of a specific single-robot task, like human following [5] or performance assessment of a group of collaborative robots [6]. Industrial robotics defined many performance criteria like speed, acceleration, repeatability, accuracy, etc. International standards (ANSI/RIA R15.05, ISO/9283) are defined too. However, industrial and mobile robotics contexts are quite different (environment, localization, repetitiveness, energy limits, etc.), and the performance concept is not clearly defined for autonomous mobile robotic missions.

However, some papers globally consider the mobile robot context. Cabelos et al. define in [7] performance metrics for mobile robot navigation. They propose a classification according to safety (collision, obstacle clearance), trajectory (path length, smoothness) and duration to accomplish a task. Several performance metrics are identified in [8] depending on mobile robotic task: SLAM (precision, scalability and consistency), motion control (accuracy, speed, robustness of path following), obstacle avoidance (path length, time, collision, and obstacle clearance), grasping (grasp quality, stability, computation time), visual servoing (convergence/computation time, positioning error) and autonomy/cognitive task (learning time, stability, robustness). This work underlines the influence of the environment and of the robot sensing and acting capacities on the performance. The problem of robotic mission guarantee is tackled in [9] using properties (liveness, safety) formal verification but the considered mission is still simple. Moreover nothing is proposed to overcome unforeseen problems during mission execution. However, today there is still a lack of standards concerning performance evaluation metrics on mobile robotics.

This brief analysis shows that performance is a multiform concept which is strongly dependent on the considered mission, experimental context and user's objectives. Most of works focus on some aspects of performance, neglecting some others. So, there is a need for generic mission performance definition in the context of mobile robotics. Next paragraph presents the experimental context of the presented work and the terminology used.

2 Experimental Context

This part presents the experimental mission description and the principle hardware and software robot characteristics. Simulation illustrates the proposed approach and it is based on the real robot and environment characteristics.

2.1 Mobile Robot

A Pioneer 3DX© ($V_{Rmax} = 0.75\ m/s$) integrating 16 sonars and 10 bumpers is used. 2 URG-04 LX Hokuyo lasers allow horizontal scanning of the environment. Lasers are used for obstacle avoidance, centering motion and robot localization. Localization is also performed using a Kinect© camera and geo-referenced QR-codes. The Kinect is also used for image capture. The robot embeds a lead/acid battery generating up to 259 Wh of energy. It communicates with an embedded laptop supporting a real time control architecture implementing the different algorithms. The laptop has its own battery, which is also monitored. Depending on algorithms and sensors used, 7 moving control laws, 3 localization methods and one image analysis control schemes (CS) are available. These CS have been evaluated with regard to the different addressed performance viewpoints.

2.2 Mission Description and Objectives

The considered mission of 187 meters long is an autonomous patrolling in the laboratory to inspect the state (open/close) of two valves (V1-V2) (Fig. 1). Table 1 presents the mission decomposed into a sequence of ($n_{obj} = 9$) **objectives O**: Go from docking station DS to the valve V1 (**traveling**), the robot rotates in the direction of V1 (**turn toward**), inspects it (**image processing**), and turns again. Then the robot travels from V1 to V2, rotates and inspects the second valve. At the end, the robot goes back to DS. These objectives are performed using n_{task} (≥ 1) concurrent **task**(s) T: Traveling objective needs both forward motion (FM) and location (L) tasks. One task (on place rotating R) is needed for turning toward a valve. Image processing is done with only valve detection (VD) task. Tasks are performed usually with n_{opt} (≥ 1) **options (OT)**. 7 OT are implemented on the robot architecture involving different hardware and/or software resources to perform FM task. These are path following algorithms SMZ with different sensors ($SMZ-US$, $SMZ-LAS$, etc.) [10]. Location task L can be performed with 3 OT (GOL is a Grid Oriented Localization technique based on laser data, KIN is the QR code localization method or ODOmeter). At the end, VD task is realized with a unique OT.

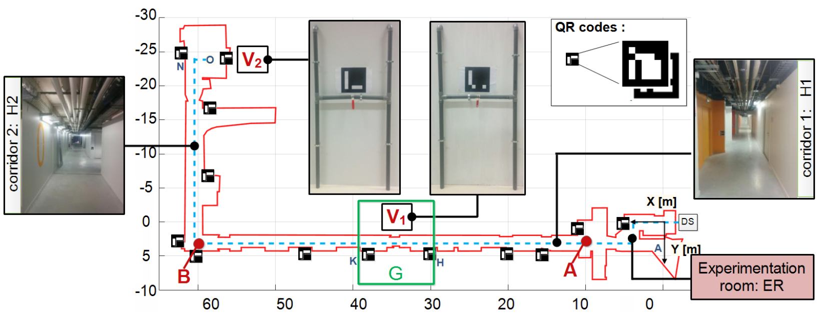

Fig. 1. Mission description.

An **Alternative Implementation** AI corresponds to the selection, for an objective, a unique OT by task T. The number of alternatives n_{alt} is the product of its corresponding n_{opt}.

For example, the first mission objective in Table 1, going from DS to V1 (T_1: FM with 7 OT and T_2: L with 3 OT) corresponds to 7×3 n_{alt} AI ($AI_0 : \{SMZ - US/GOL\}$, $AI_1 : \{SMZ - LAS/KIN\}$, etc).

Different areas can be identified in Fig. 1. In H1, human can be encountered, but not in H2. A glazed area G is also present.

The following performances constraints are defined:

- Duration axis: max $D_{perf} = 390\ s$
- Energy axis: Two indicators
  - max *robot energy*: $E_{perf_R} = 1.9\ Wh$
  - max *laptop energy*: max $E_{perf_L} = 2\ Wh$
- Safety axis: Two indicators
  - Obstacle avoidance: $S_{perf_{OA}} = True$
  - Harmlessness: max energy $S_{perf_H} = 4J$

3 Proposed Approach for Performance Management

3.1 Performance Concept

Performance concept is not defined precisely in the literature. However, several characteristics are identified: (i) The performance is linked to an objective. (ii) It has several dimensions if several performance objectives are considered. (iii) It is the result of an action. (iv) It depends on the allocated resources.

A performance *indicator* is a quantity that measures the effectiveness of all or part of a system (ex. robot system have two energy indicators: energy consumption on laptop and robot platform). A performance *inductor* is a lever on which acting induces influencing/configuring the system performance(s) indicator(s) (ex: to control the robot energy consumption, sensors used and robot velocity are the main inductors).

Some performance characteristics being defined, mission performance viewpoints is now addressed.

3.2 Mission Performance: Which Relevant Viewpoints?

The previous analysis demonstrates that, in mobile robotics, existing works on performance mainly concern a unique performance viewpoint and are often linked with a specific task depending on the user's interest. Moreover these works mix performance and performance indicators, performance estimation and performance evaluation.

Let's distinguish *instantaneous performance* as the performance that must be always verified along a mission from *end mission performance* that evolves during the mission but must be only respected at the end. Obviously, autonomous mobile robot mission performance cannot be mono-dimensional. So, main frame and user's oriented performance viewpoints are distinguished.

Let's consider x_r the linear robot coordinate representing its location along the mission and X_m the linear coordinate of the mission endpoint.

- **Safety (S_{perf})**: *instantaneous performance*. The robot must travel in a safe way for itself and its environment. It should be able to *avoid static obstacles* and being *harmlessness* in case of impact with dynamic obstacles. $S_{perf}(\forall x_r) = True$.
- **Energy (E_{max})**: *end mission performance*. The robot must have enough energy to execute its mission from its beginning to its end. Mission energy $E_M(X_m) \leq E_{max}$.
- **Localization** (L_{perf}): *instantaneous performance*. A mobile robot must be able to locate itself during the mission with a minimum of L_{perf} accuracy. $\forall\ x_r\ L_M(x_r) \leq L_{perf}$.
- **STability** (ST_{perf}): *instantaneous performance*. The mobile robot control must be able to ensure the control loop stability whatever the mission context and task. Practically, that implies to merge hardware, software and architectural constraints. $\forall\ x_r\ ST_{perf}(x_r) = True$.

User's performance concerns specific performance that must be respected during the mission depending on user's objectives, like:

- **Duration (D_{max})**: *end mission performance*. The mission duration is an important parameter for autonomous robot missions. $D_M(X_m) \leq D_{max}$.
- Performance associated to specific tasks: exploration (efficiency), grasping (precision), visual servoing, etc.

Now, the concept of ***Performance Margin*** is proposed. Two classes can be defined. *Boolean margin* characterizes a performance (instantaneous performances: safety, stability and localization) that can only be $True$ or $False$. *Continuous margin* (end mission performances: duration and energy) defines the gap between performance estimation and objectives. Hence, the goal is to optimize continuous performance margins with regards to the performance constraints, and to satisfy Boolean margins.

This decomposition classifies more clearly the different robotic performances studied within mobile robot research and allows addressing the problem of resources management toward performance guarantee. In the sequel, we will define the previous item as *performance axis*.

3.3 Performance Management: The Proposed Approach

The proposed approach of resources management is threefold. A preliminary phase identifies firstly the performance control inductors and configures initial conditions of the mission. Secondly, an offline performances estimation phase predicts performances behavior for the nominal mission scenario. After all, an online performance evaluation phase compares real performance behavior to the expected one and if needed adapts the robot configuration to meet performance constraints.

Preliminary Phase: The first step is to identify the performance control inductors and to build performance estimation models. Models allow predicting the future robot performances (energy and duration) or to identify whether the robot can guarantee instantaneous performances or not (safety, stability and localization). To estimate the mission performance, a detailed representation of the Nominal Mission Plan (NMP) is needed.

In general, a mission (sequence of objectives) can be carried out under a set of legal, environmental, physical or functional constraints like velocity limit, sensors or algorithms efficiency areas, environment dynamism, etc. Based on these constraints and depending on the instantaneous performance requirements, the mission is decomposed into a sequence of n_{act} ($\geq n_{obj}$) **Activities** (Table 1). An activity $A_k^{c_j}$ is a part of a mission (represented with two linear coordinates x_k and x_{k-1}) where an objective can be realized under a set c_j of invariant constraints. An activity can be performed using all the possible alternative implementations AI of the objective task which corresponds to these constraints.

Table 1. Mission description/decomposition and complexity

x_{i-1} - x_i (m)	**0 - 34**			**37**	**37**	**37**	**37 - 93.5**				**93.5**	**93.5**	**93.5**	**93.5 - 187**			
Objective O_i	DS $\rightarrow$ V1			$\circlearrowleft$	$\bowtie$	$\circlearrowright$	V1 $\rightarrow$ V2				$\circlearrowleft$	$\bowtie$	$\circlearrowright$	V2 $\rightarrow$ DS			
n_{alt_i}	21			2	1	2	21				2	1	2	21			
Task T_k	FM / L			R/L	VD	R/L	FM / L				R/L	VD	R/L	FM / L			
$A_k^{c_j}$	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
n_{alt_k}	21	9	3	2	1	2	9	21	21	7	2	1	2	21	21	9	21
$V_{max}(m/s)$																	

For example, the first objective of the studied mission (Table 1) is decomposed into 3 activities: A_1) Only harmlessness safety is applied (0.56 m/s), and the 21 initial AI could be used; A_2) To ensure obstacle avoidance, velocity is reduced to 0.46 m/s since A_2 is in the glazed area G and only 9 AI involving sonars can be used; A_3) is the activity while approaching V1: only 3 AI with sonars (glazed area G) and Kinect (accurate localization) can be used. The colored boxes in Table 1 shows the maximum velocities (blue 0.46 m/s, green 0.56 m/s, orange 0.75 m/s and grey 0 m/s). These numerical limits are explained in the next section. Then, the NMP is the sequence of activities with all their possible AI depending on the initial mission and the performances constraints.

Off-line Performance Estimation: Once the NMP built, the objective is to estimate the nominal performance along the process, to determine the chosen alternative implementation AI by activity, specify the value of inductors in order to respect the performance constraints. These constraints can be respected if we are able to estimate the local performance (at activity level) of each alternative implementation AI. So, each AI must be characterized with regard to each performance axis. Hence, objectives can be reached if the duration of the activities, the energy consumption, the localization accuracy, stability and the safety, can be estimated. The second condition is the ability to estimate the global performance of the NMP mission, by composing the local performance estimation for each eligible alternative implementation.

Following the off-line estimation phase, if performance constraints can be a priori satisfied, an alternative implementation can be selected for each activity $RAS_0 = \{AI_0, ..., AI_{n_{act}}\}$. Hence, boolean margins are trues and continuous margins are positives. The second phase can now start during mission execution.

Online Performance Evaluation and Resources Management: According to the current RAS, an estimation of the performance behavior is available. Then, during the mission, real performance is evaluated and compared with the performance estimation, to decide if the mission remains feasible according to the performance constraints. For the current computed hardware and software allocation, boolean and continuous margins are periodically checked.

However, a faulty hardware component or software module can disqualify the configuration of some current or future mission activities corresponding to an alternative implementation AI using these faulty elements. Moreover, performance drift, inevitably observed, due to the dynamism of the environment generating, for example, unexpected obstacle avoidance increasing the robot trajectory and consequently time and energy. This unexpected robot behavior induces a loss of time and energy which can lead to negative performance margins. In order to consider these situations, the previous off-line performance analysis must be used on line, on the remaining part of the mission, providing in real time a new set of alternative implementations to realize the rest of activities. If a solution, selecting a new AI for each activity and satisfying the performance objectives, can be found the mission can go on. However, if the mission performance objectives cannot be satisfied, the mission aborts or changes objectives and the user is warned.

Due to a lack of place, the essential performance models are briefly presented.

4 Resources Management Implementation

Obviously, the estimation performance models depend strongly on the studied robotic system. Since the main purpose of this paper is to present the methodology, these models will be briefly explained for energy, safety and duration axes.

4.1 Performance Estimation Models

Since the mission plan is created, the mission duration M_D is estimated by adding the n_{act} duration of all A_k activities (1). Activities could have predefined constant duration d_k (static activities where $x_k = x_{k-1}$) or it can depend on its length ($x_k - x_{k-1}$) and velocity V_k (d_k is considered as null if it is not predefined).

$$M_D(V_k) = \sum_{k=1}^{n_{act}} \left[\frac{x_k - x_{k-1}}{V_k} + d_k \right] . \quad (1)$$

The mission safety viewpoint introduces several constraints to implement the two main safety indicators: *obstacle avoidance ability* using a Safe Maneuvering Zone (SMZ) method [10] and safe traveling (*harmlessness* of the robot movement). Obstacle avoidance needs the ability to detect obstacles and react to avoid them. The Safety Radius (SR) can be defined as the distance from which an obstacle must be avoided. The distance of reaction DoR defined in (2) must be less than SR to avoid a static obstacle (safety indicator 1).

$$DoR = \sqrt{2\left(\frac{SR}{\frac{V_\theta}{V_k}}\right) + SR^2} + \frac{V_k}{F_{CA}} + \frac{V_k}{F_R} \ . \tag{2}$$

The robot linear and angular velocities are V_k and V_θ. F_{CA} is the control loop (architecture) frequency, F_R is the refreshing frequency of the sensor data, SR is the safe zone radius.

The Pioneer size imposes that $SR \geq 0.6\ m$. So, considering the practical value of the different parameters of (2) and the different sensors frequencies, $V_{max} = 0.46\ m/s$ when sonars are efficient sensors used and $V_{max} = 1.24$ m/s when lasers can be used.

Harmlessness satisfaction (safety indicator 2) imposes that, in case of impact, an unforeseen obstacle (moving human) cannot be hurt dangerously. ISO-10218 imposes a velocity limit of 0.25 m/s. French law imposes that the impact energy must be less than $4J$. In this case, V_{max} must not exceed 0.56 m/s knowing that the robot weight is 24.5 Kg. This constraint limit is imposed in areas where human may be present. So, for the considered example, to satisfy obstacle avoidance and harmlessness constraints, the following limitations must be respected:

- Sonars are the only efficient sensors in the glazed area (G) (other sensors can be used also for obstacle avoidance). In this area $V_{max} = 0.46\ m/s$.
- Obstacle avoidance is required in the presence of human (H1 area). If lasers are used $V_{max} = 0.56\ m/s$.
- Area with no human presence (H2 area) $V_{max} = V_{Rmax} = 0.75\ m/s$.

Energy estimation models for both robot and laptop batteries are experimentally identified and expressed in [11]. They compute an energy motion estimation needed to travel over a distance $d = x_k - x_{k-1}$ at velocity V_k. For global robot consumption, instantaneous power of all sensors needs to be added. By the other hand, an experimental identification of the different AI consumption on the laptop battery has been also realized.

4.2 Resources Management

Resources management consists on determination for each activity, the alternative implementation AI (algorithms and sensors) and its parameter(s) (robot velocity) that must be locally chosen for each activity to globally satisfy duration, safety and energy performance objectives.

For the mission, the Number of Global Alternatives (NGA) is equal to the product of each number alternatives implementations (n_{alt_k}) by the n_{act} activities. It becomes quickly huge ($NGA > 10^{13}$ for Table 1). It is a classical NP-hard Knapsack problem. To solve this problem in a real time context, the algorithm proposed in [12] has been adapted to this robotic context. It allows a fast determination of sorted problem solutions. This method is based on two main hypotheses: Firstly, for each considered viewpoints (duration, laptop and robot energies) it is possible to sort locally, for each activity, the corresponding performance of all AI. Secondly, the global composition laws of the considered viewpoints must preserve globally the local sort relation. This is verified for duration and energy where adding laws can be used.

Once these hypotheses verified, the proposed method uses iteratively from an initial selection and for each activity, a simple binary search algorithm (O(ln(n)) complexity). For energy sort, the velocity value is fixed while maximizing duration margin. So, the maximum (allowed) velocity is imposed for a AI to determine its duration and energy consumption. This algorithm determines a local solution AI and velocity by activity, permitting to converge globally to a solution satisfying the mission performance objectives. To maximize duration margin, the maximum respecting instantaneous performance constraints velocity is selected. During the mission, when faulty resource (hardware or software) is detected or when a performance margin becomes negative (or false for boolean margins), this method is used again from the current robot state and performances (laptop, robot energy levels, and elapsed time), to find a new RAS_i (if it exist) for the remaining mission activities.

The objective is to find the solution that consumes as energy as possible while satisfying the energy constraints and minimizes the energy margin since the most energetic AI implement more efficiently the mission tasks.

5 Simulation Results

5.1 The Simulator

The methodology of resources management is illustrated on the proposed mission context. The mission tasks and robot components characteristics are defined. The simulator generates a detailed mission description (activities, $\{AI\}$ and maximum velocity) related to the considered mission performance axis (Duration D, Safety S and Energy E). Preliminary works on the human presence probabilities and sensor failures were integrated in order to generate randomly obstacle avoidance (OA) and sensors failure (SF). Firstly, the mission feasibility is tested and resources allocation RAS_0 is given. Then, the robot progresses from activity to another with possible events (SF and OA). Mission feasibility is continuously tested and if it is no longer possible a new resources allocation RAS_i is searched.

5.2 Example

The studied mission and robot system (cf. section 3) with D, S and E axes is now considered. Table 1 summarizes the mission description (Objectives O_i) and then mission decomposition (Activities A_k). Grey color expresses constant duration objectives. Projecting the 10 m length glazed area (G) on the two ways mission is [31, 41 m] and [146, 156 m]. Zone without human presence ($H2$) linear projection coordinates are [63.5, 123.5 m]. As explained in section 4.2, these areas impact the constraints (maximum velocity and eligible $\{AI\}$) from safety viewpoint. So the decomposition in activities becomes crucial. Row n_{alt_i} in Table 1 shows the number of alternative implementations by objective. If different constraints cover the same objective, this objective will be decomposed in different activities. $A_k^{c_j}$ row shows to the number of activities by objective. Then, n_{alt_k} shows the number of AI for the corresponding activities. It is reduced if some AI cannot be used respecting safety constraints. For example, the first objective is performed with two activities. For the first one, the same set of AI is kept ($n_{alt_i} = n_{alt_k} = 21$). Moreover, n_{alt_k} is reduced to 7 for the second activity with lower velocity (sonars should be used in G area). The mission initially composed by 11 objectives is then composed by 17 activities with different constraints. Colored boxes in the last row expresses maximum linear velocity V_{max} depending on activities. In blue maximum velocity is 0.46 m/s, green 0.56 m/s, orange 0.75 m/s and white 0 m/s (on place rotation).

Once the decomposition is done, mission feasibility is tested considering the performance axis and a first resource allocation RAS_0 is calculated (Table 2). Stability, localization and safety performance are verified (= True) since velocity limits are respected by area and crucial sensors are available in the set of $\{AI\}$ by activity. Continuous margins are initially positives for duration and both laptop and robot energies (Fig. 3). These margins are computed based on the nominal execution of the mission with RAS_0.

Table 2. Generated resources allocation solutions

A_k	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	$NGA \geq$	IT
RAS_0	1	1	1	2	3	2	1	1	1	1	2	3	2	1	1	1	4	$2 \cdot 10^{13}$	724
RAS_1		1	1	2	3	2	1	1	1	1	2	3	2	1	1	1	**5**	$1 \cdot 10^{12}$	651
RAS_2								1	1	1	2	3	2	1	1	1	**6**	$1 \cdot 10^{9}$	499
RAS_3														**7**	**7**	**7**	**7**	$1 \cdot 10^{4}$	187

(1): SMZ-2LAS-US/KIN, (2): OPR/KIN, (3): VALVE ANALYSIS, (4): SMZ-2LAS/KIN, (5): SMZ-US/KIN, (6): SMZ-US/NONE, (7): CENTERING-2LAS-US/GOL

During the mission (Fig. 2), 8 obstacle avoidance (OA) occur and energy (Laptop and robot) and duration margins decrease (Fig.3). Robot energy margin becomes negative two times (33 m and 62 m linear coordinates) and respectively two switches RAS_1 and RAS_2 were done to overcome these perturbations and mission is still feasible. Table 2 shows the details of the generated solutions (AI

by activity), the number of global possible alternatives implementations NGA and the number of binary search iterations IT needed to find a new solution.

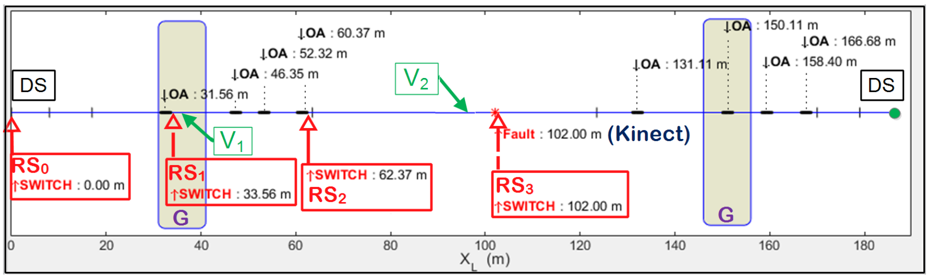

Fig. 2. Mission progress and events.

To overcome the energy lost during obstacle avoidance maneuver, the algorithm switch the selected AI (initially SMZ path following algorithm with two lasers and Kinect for KIN localization) for the activity 17 to a less consuming OT with only sonars for RAS_1 and deactivating the Kinect for RAS_2 (default odometer for localization).

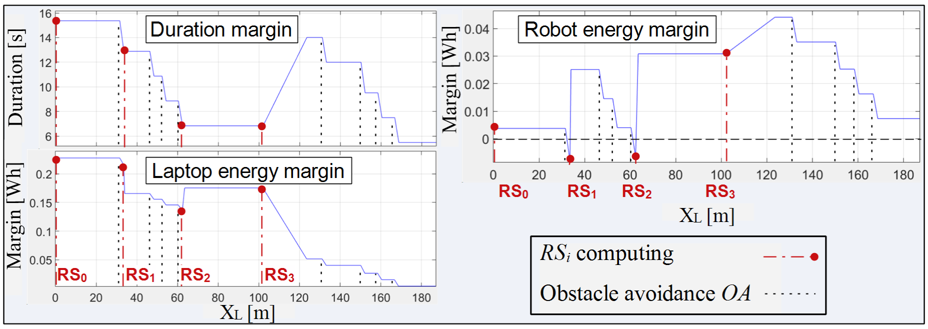

Fig. 3. Duration, Laptop and robot energy margins.

At 102 m, the kinect fails. Since it is planned to be used in a future activities in RAS_2 for activities 14, 15 and 16, a new RAS_3 is found after eliminating/filtering the sets of AI for the rest of activities. We note that robot energy margin increases because the new RAS is less consuming than the previous one. Duration margin increases too. This is due to the localization method GOL based on data lasers that allows the robot to run faster ($V_k = V_{Rmax} = 0.75\ m/s$) than with kinect $RAS_{0,1,2}$ (blurred image beyond $V_k = 0.6\ m/s$). Obviously the non-use of the kinect brings robot energy and duration gain but lower localization accuracy. Margins increase and tolerate the rest of the occurred obstacles avoidance. At the end, green boxes in Table 2 show the executed AI along the mission.

6 Conclusion

This paper proposes a methodology for autonomous resources management and a conceptualization of performance on mobile robotics. Based on mission description and regarding to performance constraints, this methodology determines which hardware and software must be used for each mission activity. From different performance axis viewpoints, the proposed simulation demonstrates the complexity of the problem and the usability of the management methodology. The robot adapts dynamically its actual and/or planned resources allocation in order to satisfy all performance constraints and under different types of internal (SF) and external (OA) disturbing events. Future works will focus on experimental implementation and illustration of the proposed methodology.

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