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Assessing Information Utility in Cooperation-based Robotic Systems

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Abstract

In this article we propose a measure of information utility that can be used to enable more effective cooperation in multi-robot systems (MRS). After giving some background in the area and making some references to the state of the art, we present an observation model for a MRS, based on which we devise a formal method to assess the information utility. The method puts on emphasis the optimization of the balance between performance gain and cost increasing due to resources usage, including communication. Then, the proposed method is used to simulate and assess information utility on a MRS performing a consume mission. We conclude with a discussion and directions for future research.

1 Introduction

Multi-robot systems (MRS) have been widely investigated for the last decade [1, 2]. These systems employ teams of cooperative robots to carry out missions that are either inherently distributed in time, space, or functionality, and cannot be achieved by a single robot, or where a multi-robot solution is more efficient, cost effective, reliable and robust than a single robot solution. Most of the work in MRS has been devoted to the definition of different architectures, mostly behavior-based, that rule the interaction between the behaviors of individual robots [3, 4].

Communication is a central issue of MRS because it determines the possible modes of interaction among robots, as well as the ability of robots to build successfully a world model, which serves as a basis to reason and coherently act towards a global system goal. Communication may appear in three different forms of interaction [1]: (1) *via environment*, using the environment itself as the communication medium (stigmergy); (2) *via sensing*, when an agent knowingly uses its sensing capabilities to observe and perceive the actions of its teammates; and (3) *via communication*, using a communication channel to explicitly exchange messages among the agents, thus compensating perception limitations.

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Arkin [5] demonstrated that sometimes cooperation between robotic agents was possible even in the absence of communication, however this is a weak form of cooperation and it may me very inefficient. Matarić [6] showed that the ability to distinguish other robots from the rest of other objects provides sufficient power to overcome interference. Balch et al. [7] made simulation studies of three typical multi-agent tasks, using the three basic communication types referred above, and found that communication improves performance significantly in tasks with little implicit communication and that more complex communication strategies (goal-oriented) offer little benefit over basic communication (state). Within CEBOT framework, Fukuda et al. [8] studied methods that seek to reduce communication requirements, by increasing the awareness level of individual cells. Parker [9] investigated the impact of awareness on a MRS and concluded that it improves performance, regardless of team size. Tambe presented STEAM [10], a general model of teamwork, which includes a heuristic that attempts to follow the most cost-effective method of attaining mutual belief in joint intentions, by managing a tradeoff between communication and team incoherence costs. Stone and Veloso [11] proposed a method for inter-agent communication, which assumes that agents alternate between periods of limited and unlimited communication. Although previous work on communication structures for MRS has led to some useful conclusions and design guidelines, there is no a principled formalism that can be systematically used to assess information utility and support the efficient use of communication in MRS. Current architectures (e.g. [3, 4]) extensively use explicit communication, not taking care, giving low emphasis, or using no principled heuristics to avoid the communication of redundant information. As communication is always limited, either in resources applied to perceive the world or in bandwidth of a communication channel, using efficiently those resources is crucial to scale up cooperative architectures for teams of many robots, without limiting them to simple reactive and loosely-cooperative systems, with very limited or no awareness. This paper starts to bridge this gap.

Section 2 presents a discrete event dynamic observation model for a MRS. Section 3 uses this model to introduce a method to assess the information utility, which is viewed as a balance between performance gain and cost increasing (resources usage), where communicated information is measured through the concept of information entropy [12]. Section 4 then presents a simulation model of a MRS performing a consume mission, in which the proposed method is used to assess information utility. Section 5 discusses the simulation results and gives some future research directions.

2 Observation model

This section presents an observation model for a multi-robot system (MRS) composed of n robots, which are controlled in order to cooperatively perform a given mission.

Notation. The finite set $\mathcal{F} = \{1, \ldots, n\} \subset \mathbb{N}$ is the fleet of n robots forming a MRS. Each robot is modeled as a discrete event system, i.e. an event-driven system [13]. The finite discrete state set $\mathcal{X}$ contains all the possible and relevant states $x \in \mathcal{X}$ for a robot $r_i \in \mathcal{F}$, when performing a given mission. State transitions are synchronized with the occurrence of events at discrete points in time. The time instant associated with the occurrence of the k-th event is $t_k,\ k \in \mathbb{N}$. The finite event set $\mathcal{E}$ contains all the events $e_k \in \mathcal{E}$ that are relevant to the mission execution. The triple $o_k = (e_k, t_k, r_k) \in \mathcal{O}$ denotes the occurrence of an event $e_k \in \mathcal{E}$ at $t = t_k$, detected by the robot $r_k \in \mathcal{F}$, where $\mathcal{O} = \mathcal{E} \times \mathbb{R} \times \mathcal{F}$ is the countable set of all possible triples. The state of robot $r_i \in \mathcal{F}$ at $t = t_k$ is denoted by $x_i(k) \in \mathcal{X}$. The MRS's state at $t = t_k$ is the n-dimensional vector $\mathbf{x}(k) = [x_1(k), \ldots, x_n(k)]^T,\ \mathbf{x}(k) \in \mathcal{X}^n$. The instant time $t = t_0$ $(k = 0)$ denotes the initial time and $\mathbf{x}(0)$ denotes the corresponding initial state. The countable sequence $\mathbf{x}^*(k) = \{\mathbf{x}(0), \ldots, \mathbf{x}(k)\},\ \mathbf{x}^*(k) \in \mathcal{X}^{n*}$, is the MRS's state trajectory up to time $t = t_k,\ k \in \mathbb{N}_0$, being $\mathcal{X}^{n*}$ the space of countable sequences of elements in $\mathcal{X}^n$. The countable sequence

$$o^*(k) = \{o(1), \ldots, o(k)\},\ o^*(k) \in \mathcal{O}^*, \qquad (1)$$

is the MRS's list of events up to time $t = t_k,\ k \in \mathbb{N}$, being $\mathcal{O}^*$ the space of countable sequences of elements in $\mathcal{O}$, obeying the condition $\forall_{o_i, o_j \in \mathcal{E}},\ r_i = r_j \Rightarrow t_i \neq t_j$, which means that a robot can detect and process no more than one event at a given instant time.

A MRS is viewed here as a event-driven dynamic system, where events are the inputs to the system and state transitions are synchronized with the occurrence of events [13]. Time is included in our model in order to be able to keep track of system's performance. Since the last event occurrence, and until the next event occurrence, i.e. for $t_{k-1} \leq t < t_k$, the MRS's state has been $\mathbf{x}(k-1) \in \mathcal{X}^n$. When an event occurs at $t = t_k$, we have a triple $o_k = (e_k, t_k, r_k) \in \mathcal{O}$ that can be used, in conjunction with the current state, to compute the new MRS's state vector, through the state transition function

$$f : \mathcal{X}^n \times \mathcal{O} \to \mathcal{X}^n. \qquad (2)$$

A mission is viewed as a set of goals, representing physical and logical restrictions that must be fulfilled. Physical resources that are used to execute a given mission – a fleet $\mathcal{F}$ of n robots and a communication channel – are important to assess cost. In order to assess performance, the resource concept must be generalized. We define *resource* as any phenomena that is physically observable. When specifying a mission, we have to define a set of such resources, in order to be able to measure performance. Some examples of these resources are: space (e.g. coverage area), energy, time, number of robots, etc. Performance metrics are generally relative metrics, such as: number of tasks per robot, number of tasks per time unit, energy per robot, etc. Let $\mathcal{R} = \{1, \ldots, m\}$ be a finite set of resources that are required to assess the MRS's performance when executing a given mission, and let m be the cardinality of the set $\mathcal{R}$. Let $\mathcal{H}$ denote a space of resources measuring functions of the form $h : \mathcal{X}^{n*} \times \mathcal{O}^* \to \mathbb{R},\ h \in \mathcal{H}$. Such functions measure resources given the MRS's past history, i.e. the state trajectory and the list of events up to current instant time. Let $h_i \in \mathcal{H}$ be the measuring function of the resource $i \in \mathcal{R}$ and $a_i(k) = h_i(\mathbf{x}^*(k), \mathbf{o}^*(k))$ be the measure of the resource i at $t = t_k$. The m-dimensional vector of resources measures (positive real numbers) at $t = t_k$ is $\mathbf{a}(k) = [a_1(k), \ldots, a_m(k)]^T \in \mathbb{R}^m$.

The MRS's performance can be evaluated through a function $p : \mathbb{R}^m \to \mathbb{R}^+$. It is assumed that $p(\mathbf{a}(k))$ is a (linear or non-linear) combination of the resources measures $\mathbf{a}(k)$ and that it always computes to positive real numbers. The function is also assumed to be monotonous increasing with performance, i.e. higher values mean better performance. Hereafter, $p(\mathbf{a}(k))$ will be abbreviated as p_k. Given the MRS's current state $\mathbf{x}(k)$ and the current vector of resources measures $\mathbf{a}(k)$, the accomplishment of the mission is evaluated through a function

$$g : \mathcal{X}^n \times \mathbb{R}^m \to \{success, fail, ongoing\}, \qquad (3)$$

where *success* means mission accomplished, *fail* means mission failed and *ongoing* means that mission still can be accomplished at a future instant time $t_j > t_k$. The mission is successful iff

$$\exists_{j \in \mathbb{N}} :\ g(\mathbf{x}(j), \mathbf{a}(j)) = success. \qquad (4)$$

If it exists such an index j, the mission execution time is $t_{mission} = t_j$.

3 Information utility

When an event $e_k \in \mathcal{E}$ occurs, we may say that it is associated with some kind of information. In a MRS, events may be classified along three classes, depending of type of conveyed information: (1) *internal events*, concerning the robot's own activities and information gathered internally by the robot (e.g. end of an internal processing task, reaching some position, etc.); (2) *external events*, concerning changes on the mission execution environment and information obtained through the robot's sensors (e.g. detection of an obstacle, finding an object relevant to the mission execution, observing the movements of another robot in the team, etc.); and (3) *received messages*, concerning information provided by other team members (e.g. detection of an environmental condition, individual state information, a negotiation bid, synchronization-related information, etc.). The first two classes of events convey information about the environment (sensing, perception) and through the environment (implicit communication and stigmergy) and are not controllable. The latter class of events is concerned with information conveyed through explicit communication and are controllable. The occurrence of an event may always be seen as some gain of information and is this information that enables the MRS to evolve in time through its state space $\mathcal{X}$, using the function (2). The event set $\mathcal{E}$ is thus partitioned into two disjoint subsets: the subset $\mathcal{E}_{nc}$ of *non-controllable events* and the subset $\mathcal{E}_c$ of *controllable events*. Thus, $\mathcal{E} = \mathcal{E}_{nc} \cup \mathcal{E}_c$ and $\mathcal{E}_{nc} \cap \mathcal{E}_c = \{\emptyset\}$. When it occurs a non-controllable event $o_k = (e_k, t_k, r_k),\ e_k \in \mathcal{E}_{nc}$, the robot $r_k \in \mathcal{F}$ gets some information. Then, it may decide to communicate to other robots the information it has just acquired, by sending them a message. When a robot decides to send a message to another robot, the former robot generates on the latter robot a controllable event $e_l \in \mathcal{E}_c,\ l > k$. The communication cost associated with controllable events is modeled through a function $en : \mathcal{E}_c \to \mathbb{R}^+$, and a communication cost per information unit $ccom$. The function en computes the entropy associated with a controllable event, i.e. the amount of information units (e.g. bits) that must be communicated [12]. Given an event $e \in \mathcal{E}_c$, the associated communication cost is $en(e) \cdot ccom$. Each state $x \in \mathcal{X}$ is assumed to have an associated constant cost per time unit, which is always positive and is given by a function $cstate : \mathcal{X} \to \mathbb{R}^+$. The mission execution cost during the time interval $t_{k-1} \le t < t_k,\ k > 0$ is given by

$$\Delta c_k = \Delta cc_k + (t_k - t_{k-1}) \sum_{i=1}^{n} cstate(x_i(k-1)), \quad (5)$$

where

$$\Delta cc_k = \begin{cases} en(e_k) \cdot ccom & , e_k \in \mathcal{E}_c, \\ 0 & , e_k \in \mathcal{E}_{nc}. \end{cases} \quad (6)$$

The cumulative mission cost up to time $t = t_k$ is given by the recursive function

$$c_k = \begin{cases} 0 & , k = 0 \\ c_{k-1} + \Delta c_k & , k > 0 \end{cases} . \quad (7)$$

Suppose that it occurs an event $o_k = (e_k, t_k, r_k),\ o_k \in \mathcal{O}$. Let $v : \mathcal{O}^* \to \mathbb{N}_0$ be a function that computes the time index of the very last event occurrence detected by the robot $r_k \in \mathcal{F}$, given the list of events (1) up to time $t = t_k$. If the proposition

$$\exists_{o_w=(e_w,t_w,r_w)\in\mathcal{O}^*} :\ r_w = r_k,\ t_w < t_k,$$
$$\forall_{o_m=(e_m,t_m,r_m)\in\mathcal{O}^*}, r_m = r_w, t_m > t_w \Rightarrow t_m = t_k.$$

is true, the function v returns the index $w,\ w \in \mathbb{N}_0$ that satisfies the proposition, otherwise it returns 0, i.e. o_k is the first event occurrence detected by robot r_k. The event occurrence o_k is viewed as an information gain, but it has also an associated cost, given by the function

$$\Delta ic : \mathcal{X}^{n*} \times \mathcal{O}^* \to \mathbb{R}^+,\ \Delta ic \in \mathcal{H}. \quad (8)$$

Note that this function belongs to the space $\mathcal{H}$ of resources measuring functions. The computation of $\Delta ic(\mathbf{x}(k), \mathbf{o}^*(k)) = \Delta ic_k$ depends on whether the event is non-controllable or controllable. Let $w = v(\mathbf{o}^*(k))$. If $e_k \in \mathcal{E}_{nc}$,

$$\Delta ic_k = (t_k - t_w) \cdot cstate(x_{r_k}(w)). \quad (9)$$

If $e_k \in \mathcal{E}_c$,

$$\Delta ic_k = (t_k - t_w) \cdot cstate(x_{r_k}(w)) + en(e_k) \cdot ccom. \quad (10)$$

The relative performance variation due to the event occurrence o_k is given by

$$\frac{\Delta p_k}{p_k} = \frac{p_k - p_{k-1}}{p_k},\ k > 0. \quad (11)$$

The relative mission cost variation due to the event occurrence o_k is given by $\Delta ic_k / c_k,\ k > 0$. The *information utility* associated with the event occurrence o_k is measured by the dimensionless ratio

$$u_k = \frac{\frac{\Delta p_k}{p_k}}{\frac{\Delta ic_k}{c_k}}. \quad (12)$$

The average *information utility* during the mission execution is

$$\overline{u}_k = \frac{1}{k} \cdot \sum_{i=1}^{k} u_i,\ k > 0. \quad (13)$$

Let $l(k)$ be the number of controllable events up to time $t = t_k$. The influence of explicitly communicated information on the average information utility can be assessed by the quantity

$$\overline{uc}_k = \begin{cases} 0,\ l(k) = 0 \ \vee \ \overline{u}_k = 0, \\ \dfrac{\sum_{i=1}^{k} \left\{ \begin{array}{l} u_k,\ e_k \in \mathcal{E}_c \\ 0,\ e_k \in \mathcal{E}_{nc} \end{array} \right\}}{l(k) \cdot \overline{u}_k},\ otherwise. \end{cases} \quad (14)$$

which we denote as *communication utility*. This quantity measures the average communicated information utility relative to the average information utility including all event occurrences (all types of information). If the mission is successful, i.e. there is a time $t_j = t_{mission}$ that verifies condition (4), the mission's information utility index is $\overline{u}_j$, which can be used to compare two different systems performing the same mission, or to compare the performance of a given system when performing different missions. For the same mission, the communication utility is $\overline{uc}_j$.

4 Case study and results

In this section, we use the functions presented in the previous section to assess information utility during the execution of the multi-robot mission described below.

4.1 Case study description

The case study we have chosen to demonstrate the usage of the information utility measure is the *consume mission*, which is somewhat similar to the consume task described in [7]. The state space $\mathcal{X}$ for this mission contains states *Wander*, *Acquire*, *Consume*, *Move_To_Help*, *Acquire_To_Help* and *Help_Consume*. The event set $\mathcal{E}$ contains events *detect*, *attach*, *complete*, *detect_bc*, *help_rq*, *help_compl* and *timeout*. The state transition graph for a robot is depicted in Fig. 1. This graph can be used to compute the state transition function (2) for this mission. The mission of a team of n homogeneous and non-holonomic robots (differential drive robots) is to wander about a 2D environment, looking for static items of interest. Once a robot encounters one of these items (event *detect*), it acquires the item (state *Acquire*), attaches itself to the item (event *attach*) and consumes it (state *Consume*), i.e. performs some work on the item. The required time to consume the item is t_c. When a robot encounters a new item, it can request help for other robots (event *help_rq*), in order to reduce the item's consume time to t_c/n_c^2, where n_c is the number of robots consuming an item. The event *detect_bc* models the situation in which a wandering robot finds an item that is already being consumed by other teammate(s). When a robot is moving to help another robot (state $Move\_To\_Help$), if it could not reach the item within a predefined time, a *timeout* event occurs

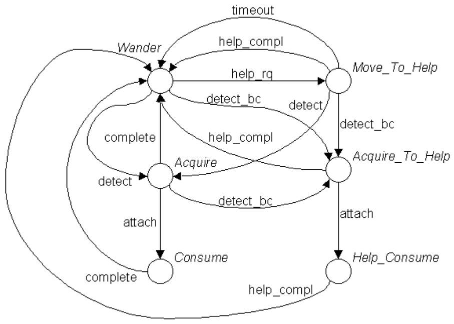

Figure 1: *State transition graph for a robot (it is common to all teammates).*

and the robot jumps to state $Wander$. The 2D environment is populated with static obstacles, which must be avoided by the robots. Robots must also avoid colliding each other. The goal of the mission is to find and to consume b items before $t = t_{max}$. The unique controllable event is *help_rq*. It is assumed that this event models the reception of a message with the 2D coordinates of a requesting help robot. Thus, its associated entropy is $en(help\_rq) = 32$ bits if we assume that each coordinate is coded through a 16 bits binary code. The number of resources for this mission is $m = 4$. Table 1 presents the meaning of the resources measuring functions we have modeled in order to assess the mission performance. The vector of resources measures at $t = t_k$ is

$$\begin{aligned} \mathbf{a}(k) &= [a_1(k),\ a_2(k),\ a_3(k),\ a_4(k)]^T \\ &= [h_{1k},\ h_{2k},\ h_{3k},\ h_{4k}]^T, \end{aligned} \quad (15)$$

where $h_{ik} = h_i(\mathbf{x}^*(k), \mathbf{o}^*(k)),\ i \in \mathcal{R}$. The mission accomplishment function $g_k = g(\mathbf{x}(k), \mathbf{a}(k))$ can be computed by

$$g_k = \begin{cases} success & ,\ a_3(k) = b \wedge a_1(k) \leq t_{max}, \\ ongoing & ,\ a_3(k) < b \wedge a_1(k) < t_{max}, \\ fail & ,\ a_3(k) < b \wedge a_1(k) \geq t_{max}. \end{cases} \quad (16)$$

Table 1: *Measured resources for assessing performance of the* consume *mission.*

$i \in \mathcal{R}$	$h \in \mathcal{H}$	**Meaning**
1	h_1	Elapsed time since the beginning of the mission.
2	h_2	Number of detected items (events *detect*, $detect_{bc}$ and $help_{rq}$) for every robots.
3	h_3	Number of consumed items (events *complete*) for every robots).
4	h_4	Average time spent in state $Consume$ for every robots.

Table 2: *Simulation parameter values for the* consume *mission.*

Parameter	Value
Workspace	
Length x Width	50 m x 50 m
Robots	
Number of robots	{1, 2, 3, 4}
Axle length	0.5 m
Velocity (maximum)	1.4 $m.s^{-1}$
Acceleration (linear)	0.9 $m.s^{-2}$
Sensor range	2 m
Communication range	{0, 20} m
Communication cost ($ccom$)	0.3125 bit^{-1}
Items	
Number of items	30
Ray	0.5 m
Consumption time (t_c)	100 s
Spacing	2 m
Minimum distance to initial pose	10 m
Obstacles	
Workspace coverage	{0, 5, 10} %
Ray	1 . . . 4 m
Spacing	3 m
$\mathbf{x} \in \mathcal{X}$	**cstate(x)**
{$Wander$, $Move\_To\_Help$}	1 s^{-1}
{$Acquire$, $Acquire\_To\_Help$}	0.8 s^{-1}
{$Consume$, $Help\_Consume$}	2 s^{-1}
Performance weights	
{α, β, γ, δ}	{10^{-10}, 0.4, 0.2, 0.4}

The performance function $p_k = p(\mathbf{a}(k))$ can be computed by

$$p_k = \begin{cases} \alpha & , \ k = 0, \\ \alpha + \beta\frac{a_2(k)}{a_1(k)} + \gamma\frac{a_3(k)}{b} + \delta\frac{t_c}{a_4(k)} & , \ k > 0, \end{cases} \tag{17}$$

where α, β, γ and δ are weights, such as $\alpha, \beta, \gamma, \delta > 0$, $\alpha \ll \beta$, $\alpha \ll \gamma$ and $\alpha \ll \delta$. The constant α guarantees that the performance function always computes to positive real numbers.

The robots' behavior along their possible states were modeled through potential field techniques and following an approach very similar to the one that is described in [7]. There were implemented five basic behaviors: *noise*, *avoid_obstacles*, *avoid_robots*, *move_to_goal* and *consume*. The robots' behavior for each state is a linear combination of those basic behaviors, with predefined weights. For example, in state *Wander*, the active basic behaviors are *noise*, *avoid_obstacles* and *avoid_robots*. The basic behavior *noise* is active for all robot's states in order to avoid local minima and maxima. Table 2 presents the mission parameters, whose values were selected empirically. The maximum mission time was $t_{max} = 11000$ s.

4.2 Results and discussion

The simulation model described above was used to gather results with different combinations of three variables: *team size*, *obstacles' coverage* and *communication range*. Fig. 2 shows the simulation results through some representative graphics. The graphs on the left show the simulation results with the robots' communication range configured to 0 m, i.e. with event *help_rq* disabled. In this situation, a robot can never reach the state $Move\_To\_Help$. Conversely, the graphs on the right show the simulation results with robots' communication range configured to 20 m, i.e. with event *help_rq* enabled. In the simulations performed to get these graphs, the multi-robot system (MRS) always accomplished the mission with success, i.e. it always consumed all the 30 items before $t_{max} = 11000$ s. Observing the graphs of t_j, we can see that the mission execution time reduction, due to team size increasing and/or due to obstacles' coverage decreasing, is more significant when we go from the single robot case to teams of two robots, than we go from two robots to three or four robots. This means that the benefit of increasing redundancy is significant for small teams and less important for more populated teams. The reduction in t_j is also more significant for teams that are allowed to use explicit communication. Obviously, obstacles' coverage influences the mission execution time, because obstacles must be avoided by the robots, thus conditioning their progression along the workspace. Observing the graphs of the ratio p_j/c_j, we can identify a local maxima in the same point (a team of 2 robots and 0% of obstacles' coverage), whether robots are allowed to communicate or not. It is also noticeable a very significant influence of explicit communication in the ratio p_j/c_j, denoting its utility for this mission. On average, communication resulted in an improvement of 35% on its value. For a team of four robots

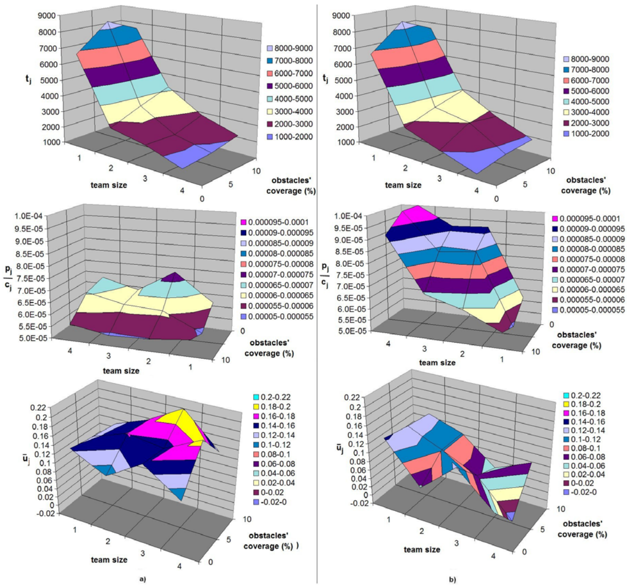

Figure 2: *Simulation results: a) on the left, without explicit communication; b) on the right, with communication range configured to 20 m.*

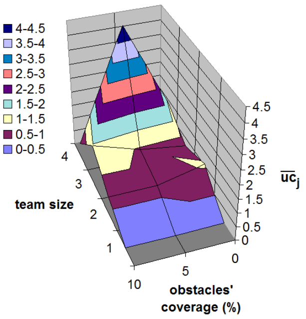

Figure 3: *Graph of communication utility.*

working in an environment with 10% of obstacles' coverage, that increase was much higher (about 94%). This increase was generally higher for combinations of teams with more robots and lower obstacles' coverage values. Now comparing the graphs of p_j/c_j ratio with the corresponding graphs of information utility $\overline{u}_j$, we can observe some correlation between the two measures, which means that optimizing the balance between performance and cost seems to be equivalent to optimize the information utility. That correlation is particularly noticeable in the absence of communication. Notice, for example, in the graph of $\overline{u}_j$ without communication a local maxima in the same point where the ratio p_j/c_j has also a maxima. Observing now the graph of communication utility (Fig. 3), we can observe that this measure has also a strong correlation with the ratio p_j/c_j, though that correlation is not so evident for the information utility measure.

5 Summary and conclusions

Although communication plays a crucial role in MRS and some authors have already concentrated on this issue, there is no a principled formalism that can be systematically used to assess information utility and support efficient communication. This paper started to bridge this gap by presenting a discrete event observation model and devising a formal method to assess the utility of information and communication for a MRS. The proposed measures of utility were used to perform a simulation study on a consume mission, whose main conclusions were: the benefit of increasing redundancy is more significant for small teams; explicit communication allows to get higher values for the ratio between performance and cost, specially in more populated teams working in environments with lower obstacles' coverage values; in the case of non-communicating teams, there is an evident correlation between the performance versus cost ratio and the information utility measure; in the case of communicating teams, communication utility is correlated with the performance versus cost ratio.

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