An Environment-based Methodology to Design Reactive Multi-agent Systems for Problem Solving

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Abstract. Even if the multi-agent paradigm has been evolving for fifteen years, the development of concrete methods for problem solving remains a major challenge. This paper focuses on reactive multi-agent systems because they provide interesting properties such as adaptability and robustness. In particular, the role of the environment, which is effectively where the system computes and communicates, is studied. From this analysis a methodology to design or engineer reactive systems is introduced. Our approach is based on the representation of the problem's constraints considered as perturbations to stabilize. Agents are then defined, in the second place, as a means of regulating the perturbations. Finally, the relevancy of our proposition is justified through the development of two solving models applied to real and complex problems.

1 Introduction

Even if the multi-agent paradigm has been evolving for fifteen years, the development of concrete methods for problem solving remains a major challenge. This paper addresses this problem by proposing a methodology aimed at designing reactive multi-agent solutions. Such systems rely on reactive agents, which are simple entities that behave following their perceptions [14]. We focus on reactive systems because they present interesting features such as self-organization/emergent phenomena, robustness, adaptability, simplicity and redundancy of the agents (and consequently low cost agent design). It has been shown that this approach is efficient for tackling complex problems such as life-systems simulation/study [31] [21] [26], cooperation of situated agents/robots [38] [27] [9] [26], problem/game solving [8] [10],...
However, it is difficult to extract a generic method to build reactive-based solutions facing (distributed) problems. This difficulty is due to the complexity of such systems where agents and interactions are numerous and where global dynamics are complex to control and/or predict.

As it has been emphasized in [31] and [28], the environment plays an important role in reactive multi-agent systems (MAS). It is the main place where the system computes, builds and communicates. In the problem-solving framework, it is clear that one reactive agent can neither handle a representation of the problem nor compute its solution. The resolution is obtained from numerous agent-agent and agent-environment interactions [14] [31] [21]. Agent interactions are reactions to perceptions, they participate directly in the solving processes, but they do not provide a means to express the problem. So, the representation of the problem can only be defined through the environment model. In this paper we re-examine the role played by each element in collective systems, by focusing on the environment. This work is motivated by the necessity of clarifying the common points used in different environment-based techniques and reactive agent-based MAS. Thus we present a synthetic view on reactive systems by considering existing collective solving systems such as the pheromone-based approach and the eco-resolution model. This analysis allows us to propose a methodology aimed at building environment-based solving systems.

The proposed methodology establishes the link between the representation of the problem, expressed as environmental constraints, and agent behaviors, which are regulation items of the environmental perturbations. This method contrasts with classical approaches that involve defining agents and interactions by following the expected organization (as proposed in [27] [28]). In our case, agents are defined in the second place, and build as regulation processes depending on the problem model. The environment is clearly defined as a first-class entity of the multiagent system ([42] as shown the importance of such an approach in multiagent conception).

The paper is structured as follows. Sect.2 presents a re-examination of reactive MAS from an automatic control point of view and classical collective models are analyzed. In Sect.3 the four main points of the methodology are introduced, first with a general point of view and then in detail considering a concrete use. This section ends with a comparison to related work. Section 4 illustrates the methodology through two examples of applications: the satisfaction-altruism model for decentralized cooperation between situated agents and a Physics based model for localization and target tracking. Finally, in Sect.5, we conclude on the proposed methodology and present some future work.

2 Examination of Collective Processes

2.1 Expression of Reactive MAS within the Automatic Control Approach

As opposed to the socio or bio inspired approaches, we propose a more pragmatic engineering method for defining reactive agent-based problem solving systems. Our approach is closely tied to the standard regulation loop defined in automatic control. The goal of the problem solving is to build a solution, stable in time and space, considering the formulation of a problem that has its own topology (i.e. how the problem is structured in space) and dynamics (i.e. how the problem evolves). Thus, the MAS can be considered as a regulation (or filtering) process. As a consequence, solving a problem leads to defining the parameters of the regulation loop in order to obtain a stable output (solution level) considering the variations of the input (problem level).

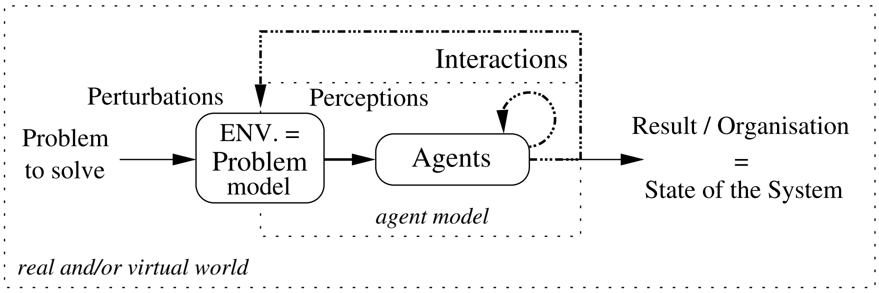

Fig. 1. Environment based solving principle

The environment is defined as the input layer of the regulation loop, see Fig.1. It translates the variations and the topology of the problem and presents them to the agents. The organization is the output layer of the system. It represents the state of the system on a spatial and temporal level. The regulation mechanism is defined by the agents' actions and their interactions. These interactions have been divided into two categories. The first characterizes the agent-agent interactions, which compose the direct branch of the regulation loop that is considered, in automatic control, as amplification. This can be compared to positive feedback defined by Muller in [28]. The second, called the negative feedback, is the regulation loop carried out by agents-environment interactions (these different kind of interactions are detailed in Sect. 3.2). The environment is modified by both the problem and regulation dynamics.

2.2 Analysis of Classical Collective Solving Models

In this section, we re-examine two widespread techniques of collective problem solving: the eco-resolution and the pheromone-based models. This re-examination considers the automatic control point of view exposed in the previous paragraph. The goal of this section is to evaluate the place of the environment and of the regulation mechanisms in these methods.

Eco-resolution The eco-resolution model [13][8] relies on the agentification of all the elements of the problem. As a consequence the environment is divided in a set of agents (for instance in the Towers of Hanoï problem, the disks and the stacks will be defined as agents). Each agent is defined by the same reactive model (the eco-agent model). An eco-agent has only 3 possible states: satisfied, dissatisfied and attacked. It has 3 possible behaviors: (i) searching a place to flee when attacked, (ii) attacking the agents that hinder its actions, (iii) running an action to be satisfied. The resolution relies on the fact that when an agent is attacked, it has to search a place to flee. If such a place does not exist it has to attack its hinderers.

In this model each agent has to be satisfied to consider the problem solved, corresponding to the achieving of a stable state (the solution representation). An agent tries to move when attacked by another agent. This attack represents a perturbation in the environment. The model then ensures that the attacked agent tries to flee in order to regulate this perturbation (local interaction). If this locate regulation cannot be performed, due to the presence of hinderers, the attacked agent propagates the perturbation by attacking new agents. This "recursive" process corresponds to the generation of a collective process, i.e. a solving process at the macro level, leading to the whole solution (details in [13]). However, this model can presents instable processes such as loops or oscillations. It is then necessary to enhance agents' perceptions and/or introduce knowledge on the system state, as presented in [10] for the N-Puzzle solving.

Pheromone-based Algorithms The well known pheromones-based algorithms are typical environment-based solving systems. Agents drop artificial pheromones in the environment in order to create shared information (these pheromones are chemical substances diffusing and evaporating). Here we illustrate the principle on the construction of an optimal path between a nest and a resource place. The problem is represented by the nest, the resource and an obstacle that define two possible paths of different length (as presented in [7]). Agents drop pheromones as they move, then the pheromone is initially distributed along the two possible paths (probabilities to choose one of them are equal). For the agents this repartition of pheromones represents an absence of information. The resulting state of the environment, and consequently of the problem, can be considered to be totally perturbed.

In order to allow the emergence of the optimal path, a reinforcement mechanism is defined by a simple agent behavior. Agents move preferentially towards directions with the maximum amount of pheromones. Consequently ants concentrate pheromones on the shortest path (details in [7]). This concentration involves a reduction of the initial perturbation of the environment state. The reinforcement mechanism leads, in time, to a stable state where only one path is built and used between the nest and the resource. This state is characterized by equilibrium between the problem dynamics, made material by the diffusion/evaporation phenomenon, and the resolution dynamics induced by the agents.

In the case of pheromone-based algorithms, the emergent organization is particular. It is not included in the agents states but directly in the environment itself (areas concentrating pheromones).

3 Methodology for Building an Environment-based Solving System

3.1 General Description of the Methodology

Existing environment-based solving techniques are generally presented by referring to a set of implicit or explicit concepts (such as biological behaviors, emergence principles, regulation loops, etc). Defining a methodology allows to clarify the implicit methods used for the construction of many environment-based systems. The two previous sections establish the role of the environment that can be considered as the place where the problem constraints are expressed and the multi-level resolution of these constraints thanks to agent behaviors. This analysis leads to define a conception methodology for environment-based solving processes, which is composed of four main steps:

1. ***Defining the problem's model, i.e. the environment***. It has to represent the problem to solve on both a topological and dynamic level (details in next section). Modeling an environment implies also for the designer to define almost an environment structure (for spatial representation, which can be discrete or continuous) and the laws that govern its dynamics (as analyzed in [42]). Note that the environment can be totally a virtual one or include elements of the real world. In this last case, the environment can be considered as an enhanced real world.

2. ***Defining agent perceptions***. Agents must be able to perceive the environmental perturbations modeling the problem. They have to detect states and dynamics that are considered as problem constraints, in order to solve them. Means of perception abilities are tackled in the next section.

3. ***Defining agents' interaction mechanisms*** in order *to reduce the perturbations*. These mechanisms are defined in 3 levels:

   (a) Provide individual and local reactions to the perceived constraints, i.e. actions from agent to the environment.

   (b) If these local actions are inefficient in some situations or can lead to conflicts, even considering their combination, provide direct interactions (agent-agent(s)) that enable cooperative processes. They have to reduce conflicts/constraints perceived by agents and to perform complex tasks (involving several agents).

   (c) Provide actions to regulate the previous processes (local and cooperative) when they present instability risks (amplifications, loops, etc..)

4. ***Measuring/Observing the result as an emergent structure***, in terms of agents (position, dynamics,...) or in terms of environment (structure, topology,...) as defined in [29]. This structure is the consequence of the two dynamics of the solving principle (i.e. the dynamics of the problem on one side and the resolution dynamics on the other). This result can only be measured and/or observed at a macroscopic level. Measuring organization in reactive MAS is a recurrent problem. The next section gives some clues in order to tackle with this issue.

A fifth optional step may be considered. It consists to iterate on the third step after the measuring/observing phase. Indeed, the designer can discover, while measuring/observing the resolution, that it neglected some constraints or that instable behaviors are not taken into account (these ones are generally difficult to forecast). Modifying agents' interaction can then improve the system efficiency (it is the parameter settings phase of the system). This phase can be a process of trail and error and/or learning/optimization process with specific algorithms such as gradient descent methods.

3.2 Detailled Points on the Methodology

The previous section describes the general meaning of the proposed methodology. The goal of the current section is to give some clues in order to cope with each point of the methodology. The key principles given are not necessarily exhaustive but they represent the main directions that a designer can follow in order to build up a reactive MAS solving process.

How to Build up a Problem's Model ? Two main characteristics have to be taken into account to build up an environment representing the problem's model: its topology and dynamics (as emphasized in [42]).
As for the *topology*, there are two main possibilities whether the problem's topology must be discretized or not. In fact, this choice depends also on what kind of approach is used to deal with the agents' decision processes and moves. Indeed, if the agents have to follow a probability law to compute their next position, the choice of a discrete representation is more relevant. For instance, if pheromones [33] or Markov models [5] are key elements for the agents' decision process, using a discrete environment is the best choice. By contrast, if the moves are computed considering Physics based force fields [17], [25], the environment has to be continuous to better fit to agents' behaviors.
Two main methods are widespread in order to deal with the *dynamics*. One is a bio-inspired method using digital pheromones [33], [34]. In this case, the dynamics of the environment is tied to the evolution of the amount of pheromone (evaporation, aggregation, diffusion,...). The second is a Physics based approach and is linked to artificial potential fields [1] or force fields (gravitational or electrostatic) such as these used in Co-Fields [25]

How to Perceive the Problem's Constraints ? The perception of the problem's constraints that take place in the environment depends strongly on their representation. Yet, we can use generic models such as the model for active perception proposed in [41]. This is composed of 3 main modules (sensing, interpreting, filtering) that can be adapted to specific application. As for the proposal of this paper, since only reactive agents are taken into account, the last two modules (interpreting and filtering) are reduced to their minimum. Hence, the key point is the definition of the constraints' sensing. This can be direct thanks to a definition of an artificial vision-like ability (or smelling-like ability if it concern pheromones) or indirect when the agents sustain the influences of fields present in the environment.

Which Kind of Interaction Models for Reactive Agents ? Basically, interactions in MAS can be defined considering two orthogonal axes [14]. On one side the type of the interaction (which can be direct or indirect) and on the other side its nature (cooperation or competition).
Concerning the type of the interaction, indirect ones are usual in reactive systems because, due to the limit of each entity, the environment is used as a shared memory. Agents have indirect "communication" via their changes of the environment (for instance dropping a mark [37], a pheromone [31], etc.). Such an approach is very efficient to self-organize numerous entities and enable stigmergy processes [6][26]. It is well suited to steps 3-b and 3-c of the proposed methodology.
Direct interaction, involved in particular in step 3-a of the methodology, can take three forms: (i) one agent that physically acts on the environment (that can possibly produce an environment-agent reaction), (ii) an agent-agent interaction (which can be a physical interaction or a message/signal exchange) and (iii) one agent interacting simultaneously with several others (through a signal emission, its physical presence, etc.).
The nature of the interaction can be abstracted in two categories: cooperation and competition. Generally cooperative interaction/actions are defined to solve conflicts or to perform difficult tasks that cannot be performed by only one agent. Reactive coordination can be placed in this category [14]. By contrast, competitive interaction or attacking actions can be defined as direct influences (as for instance in [8] [35]). Such interaction can express conflicts between agents and trigger some behaviors solving them such as the escape behavior in Eco-Resolution [13].

How to Measure the State of Balance of the System ? The characterization of the equilibrium of the system is a complex issue from both a theoretical and practical point of view. In the context of problem solving, two kinds of situation have to be considered depending on whether the problem is static or dynamic. The difficulty of expressing equilibrium in complex systems is similar to that encountered in biology for stable organisms. To avoid the static connotation of the term equilibrium, the notion of homeostatic process is used to qualify a stable organization/entity whatever its dynamics [6].

In the case of a static problem, where the constraints do not change in time, the equilibrium of the solving system can be characterized by a stable state in which the agents stop interacting. This is the simplest case to consider.
When the problem is dynamic, the task is much harder because the state of balance of the system depends on whether there is equilibrium between two dynamics (the problem and the solving process). Thus, state of balance cannot be considered only as a measure of the interaction activity of the agents. Consequently, a measure of the equilibrium (and by translation, a measure of the organization) has to be designed. Much of the related work deal with the issue of the measurement of the organization. In many cases, this measure is closely tied to the intrinsic nature of the problem [17]. Another solution consists of designing a measure based on the mechanisms of the system. For instance, the entropy can be one of these measures. Entropy can be considered as a global estimation of the organization of the system on a global topological level [2], as a local consideration of the dynamics of each agent [32] or both of the two methods [20]. None of the propositions in the related literature deal with the nature of the local mechanisms, however.
The issue of measuring the organization of a MAS is central when deploying a problem solving application. Indeed, it is not only required characterizing the state of balance of the system but also for evaluating its performance and, by extension, the way of improving it by using learning algorithms for instance.

3.3 Related Work

Cybernetics Work. Cybernetics was defined by Weiner ([39]) as the study of control and communication in the animal and the machine. During 1940's cybernetics introduced the feedback principle, or retroactive loop. With such a loop, a system can adapt its actions to its own outputs. This approach is well suited to stabilizing a system towards a predetermined goal. Although this approach concentrated on the development of individual entities, its influence on the swarm approach was important. Indeed, it emphasized that social insects are also machines and that regulation loops exist at the colony level. Work of the last decade has developed the study of social systems involving numerous entities (social insects, collective robots, particle systems). In particular, such work has shown the importance of the loop in linking agents to the environment ([31][28]). This main loop, allowing collective solving, is present in our representation of an environment-based solving system (Fig. 1). In a sense, this loop is similar to that defined in cybernetics for one agent. We apply a similar approach in that we consider regulation at the agent level but also at the macro/collective level.

MAS Methodologies. The multiagent community has proposed a set of methodologies for the design and the analysis of MAS, such as Gaia [43], Adelfe [3], Promotheus [30]. Most of these methodologies focus on agent definition and

their interactions, especially on deliberative agent architectures. For instance, Adelfe methodology aims at designing adaptive MAS [3] considering the AMAS agent architecture (for adaptive MAS). This one relies on agent's attitude, competences, beliefs and interactions language. Then the "cooperation failures" activity, defined as the A7-S2 step of the Adelfe methodology, is defined following social attitudes, such as incomprehension, ambiguity, uselessness, which are not suitable to our reactive-based approach.
One particularity of our methodology is to focus on the problem-solving framework considering collective systems. In existing works, methodologies are generally devoted to software engineering, using object-oriented methodologies [3] and organizational concepts such as role and group.
Nevertheless, an extended version of Gaia methodology presents interesting elements in relation to our proposition. In particular, this methodology defines the environment as a primary abstraction of MAS [44]. Authors propose to first define the environment by considering resources that can be sensed and consumed by agents. They point out the possibly constraints induced by their accessibility. In the first step of our methodology, we let the designer defining the constraints' representation, and then defining agent resources can be a way to model them. The second phase of the environmental modeling proposed in [44] concerns agents perception. As for us it is emphasized that they depend on both the environment model and the concerned application. Next phases of this methodology do not focus on reactive-based solving processes.

Concerning methodologies devoted to reactive-based systems our approach can be compared to the constructivism method, exposed in [15]. The constructivism methodology aims at designing reactive Multi-Agent Systems for the solving of spatially defined problems (such as features extraction in images, cartographic generalization and spatial multi-criteria decision processes). This technique, which is specific to spatialized problems (i.e. defined by a map or a picture), is based on the interpretation of the position and state of the agents. Consequently, it is not well adapted to dynamic problems. Nevertheless, as we have exposed in our proposition, the problem constraints are defined and represented in the environment. By contrast, authors deal with problems where the form of the solution is known in advance and then use it to define constraints on the agents' organization. However, [15] gives some interesting clues as to the definition of spatially defined problem constraints.

4 Application

This section presents two applications following the *four steps* of the proposed methodology.

4.1 The Satisfaction-altruism Model

This model aims at providing a means of cooperation and of conflict solving to reactive agents working in the same environment. As agents are simple, intentionality does not exist in their behaviors, and only intelligent collective processes can be considered at a macro level. So, in order to provide intentional interactions while keeping collective properties, the model extends such an approach. The *artificial potential fields* (APF) model is considered because of its efficiency for collective and individual tasks (such as individual and team navigation). This technique relies on the perception of attractive elements and obstacles present in the agents' close environment (details in [22] [1] [26]). The satisfaction-altruism model relies on this extension and on the definition of satisfaction states inspired by the homeostatic behavioral model of C. Hull [19].

1. In order to express agent intentions, the satisfaction-altruism model [35][36] introduces *new artificial fields* in the environment. These fields are *dynamically* and intentionally generated by agents thanks to the emission of attractive and repulsive *signals*. Agents broadcast such signals in order to influence their close neighbors. Repulsive signals express constraints/conflicts between agents (expression of a part of the whole problem) and positive signals express cooperative calling. Fig. 2 shows the application of the model to the foraging task. Over the working area a surface is drawn to represent the enhanced environment (i.e. obstacles plus signals). Cooperative signals are represented as hollows and repulsive signals as peaks (the latter ones are added to fields generated by obstacles). These artificial fields augment the information present in the environment in order to express agent goals and constraints. The next steps show that agents are designed to reduce these artificial perturbations.

2. To cooperate and to solve conflicts, agents must be able to perceive the signals and the presence of other agents. The key idea of the model is that agents evolve in the perceptual environment drawn in Fig. 2. So agent perceptions are limited to the detection of physical obstacles and to the reception of attractive and repulsive signals.

3. Interactions consist of agents carrying out cooperative reactions to signal reception. One interesting application of this model is the distributed resolution of access conflicts in constrained environments (several robots/agents trying to navigate in narrow passages, as represented in Fig. 3.a). In this problem there are two kinds of constraints: the presence of static obstacles and other agents (which are moving obstacles).

- (a) *Individual level* : the perception of local obstacles is used as stimulus to avoid them (a simple avoidance behavior is defined).
- (b) *Cooperative level* : If several agents are blocked, i.e. a deadlock due to the environment's topology (cf. Fig. 3.a), simple avoidance behavior will be inefficient. A cooperative mechanism, based on the emission of repulsive signals, is then added. Agents measure their local constraints, i.e. elements surrounding them, to broadcast a level of dissatisfaction (agents and walls do not have the same weight, see [35]). The cooperative reaction, which is called *altruism*, forces the less dissatisfied agents to move away in order to unlock the situation. Thanks to this mechanism, signals are propagated to all agents involved in the blocking. Fig. 3.a shows an example of a column of blocked agents where the less dissatisfied ones are at the top.

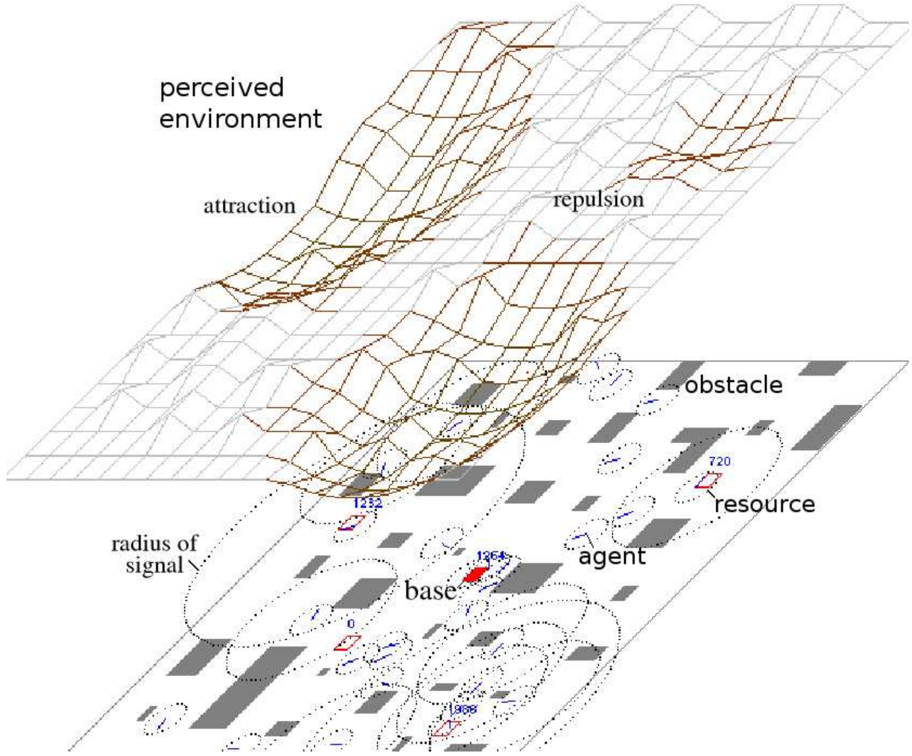

Fig. 2. Application of the satisfaction-altruism model to the foraging task (snapshot simulation step 497). On top, representation of attractive and repulsive signals as environment distortions (= the environment perceived by agents).

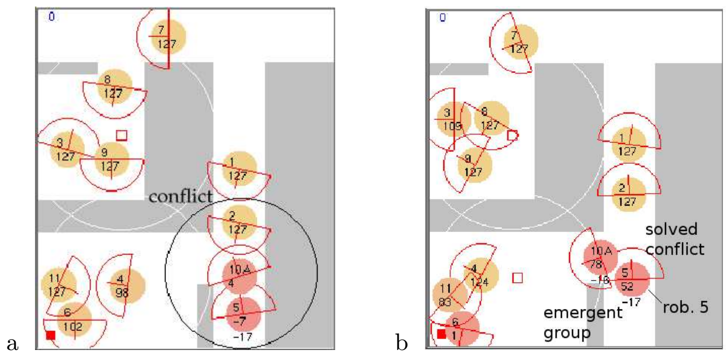

Fig. 3. Snapshots of simulated individual robots based on the satisfaction-altruism model. Example of conflict resolution. Each robot is represented by its range of perception, id number, current satisfaction and possible emitted signal value.

– (c) *Regulations* : Signal propagation can lead to oscillatory and cyclic behaviors (as in the eco-resolution model). To avoid oscillations, the notion of persistence is added to the emission of repulsive signals: a blocked agent emits its initial dissatisfaction while it is not totally free (see agent number 5 in Fig. 3.b). This behavior illustrates the necessity of regulation mechanisms in cooperative processes.

4. The observed solution is equilibrium between the problem dynamics and agent interactions. For the navigation application, the solution is characterized by coherent displacements of all the agents (note that immobilized agents express a conflicting situation). For conflicts involving several agents, repulsive signals are passed from agent to agent. As a consequence, we observe the emergence of groups of agents moving in the same direction as a coherent entity (see details in [24]). It is the case in Fig. 3.b for the two robots freeing from the conflict, noted emergent group.

This model has been applied to different simulated problems such as collaborative foraging [36], navigation in constrained environments, box-pushing [12] and validated with real robots in conflict problem solving [24].

4.2 A Physics-based Reactive Model

Localization, with mobile or fixed sensors, is a very difficult but required task to control mobile robots in an indoor dynamic and uncertain environment. This task can be defined as finding the position of an object, mobile or not, in a well known referential. The localization is composed of two methods: localization with on board sensors (also called self localization) and localization with external sensors. The algorithms used generally stem from signal or image processing, or from the stochastic methods based on Markov Decision Processes (MDP) [16]. So, the standard localization algorithms are extremely dependent on the nature of the used sensors and deal only with one single target. There are no multi-agent based localization and tracking devices except with specialized cognitive agents [11]. Some related work, such as environment mapping and data fusion deals also with cognitive agent-based methods. In this way, tracking is considered to be a collection of temporally and spatially coherent localizations. As a means of localization, the tracking algorithms stem from the signal processing. Among the most spread out we can point out the Kalman filter, the optical flow algorithms and the particle filtering [23]. The main difficulty in designing such systems for localization and tracking is to take into account the characteristics of the used sensors while obtaining properties such as robustness and adaptation to the variation in the targets' kinetics. Considering these required properties, using a reactive multi-agent system to solve this problem seems to be adapted.

Before detailing the physics based model following the methodology exposed in Sect.3, a description of the problem is required. For this, both the topological and the dynamic point of view have to be considered.

Localization and tracking are based on the use of sensors that are spread out in the environment. The topology of the problem is tied to the gathering range of the sensors. This can be considered as an area, observable by the sensors, where the targets are expected to move. The dynamics of the problem depend on the dynamics of the targets.
These can (i) *appear*, i.e. they arrive in the observation field of the sensors, (ii) *move*, i.e. they go from one observable point of the real world to another observable point, (iii) *disappear*, i.e. they go out of the observation field.
With this description in mind, the constraints of the problem can be formalized. The topology has to take into account the range of each sensor and the topology (obstacles, walls, doors, ...) of the observed area. The dynamics of the problem have to take into account those of the targets. The structure of the model is shown in Fig. 4. From here, the proposed methodology can be applied.

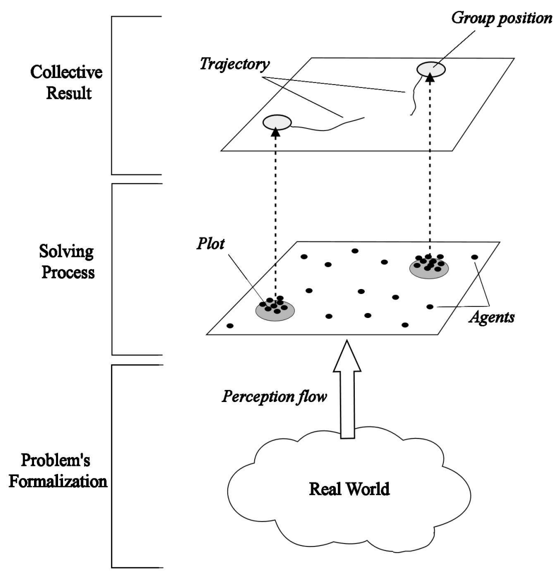

Fig. 4. Architecture of the Physics based reactive model for the localization and the tracking.

1. To start with, an *environment model* has to be defined in order to represent the problem and its constraints. For the localization and the tracking, the chosen representation is an *occupancy grid* that represents the areas of the real world observable according to the range of the sensors. The obstacles are labeled as unreachable areas of the grid. As for the dynamics, these have been translated into two main trends. First, *accumulation* of the sensing information deals

with the appearance of the targets. This accumulation leads to the construction of a plot that represents a possible position for a target. This construction can be considered as a deformation of the environment that has to be perceived by the agents. Second, *evaporation* of the plot has been designed. This deals with the disappearance of the targets. It also prevents the persistence of bad information in the environment. This evaporation tends to reduce the deformation involved in the accumulation. These two trends take into account the targets' movements. The movement of a target to a place near its last position can be considered as the appearance of this target in a place near from its last position. Since the evaporation tends to reduce the out-dated plots, this last position will disappear.
2. Then, the *perceptions of the agents* have to be defined. Without any information the agents' environment is flat. The deformation of the environment, induced by the accumulation, can be considered as a perturbation. This Physics based model has been designed for the perception of this kind of perturbation. The agents perceive the plots through the environment by means of an *attraction* force. This force is induced by the appearance of a plot and depends on its size. Thus, the agents are mass particles in a force field.
3. As for the *interaction mechanisms*, they have to be defined considering individual and collective levels and the required regulation.

- (a) *Individual level*: The agents are expected to compensate the perturbations in the environment. Since they are already attracted by the plots, a behavior has to be designed to reduce the plot when the agents are on it. So, a *consumption* behavior has been introduced.
- (b) *Cooperative level*: Two situations have to be considered. The first characterizes the system in its stable initial state (i.e. when there is no information given by the sensors). In this case, the agents have to be as far as possible from each other in order to better prevent the arrival of information. So, a *repulsion* behavior has been defined. This behavior is based on a Model inspired by Physics as the attraction is. In the second case, the agents have to deal with the information that deforms their environment. If the agents are expected to cooperate in the consumption of the information, they must be allowed to be near each other. So the repulsion mechanism is inhibited when the agents are consuming considering their respective potential energy. This value is computed considering the level of the plot where the agent is.
- (c) *Collective and local regulation*: As it has been defined, the environment is physically coherent (i.e. all the behaviors have been defined following mathematical formulations based on Newtonian Physics). Nevertheless, it is still conservative since the speed of an object moving in the environment, without any interaction, remains constant. Consequently, a *fluid friction force* has been introduced in order to regulate the movements of the agents.

4. Then, the *emerging collective organization* has to be observed. This is both a gathering of the agents on the percepts, which leads to a *group construction*, and a homogenous repartition of them in the information less areas. Each group can thus be considered as a localized target. The output of the system is stable when equilibrium is established between the refreshing and the resolution dynamics. Fig.5 shows of the localization and tracking solving process using the automatic control point of view applied in the proposed methodology.

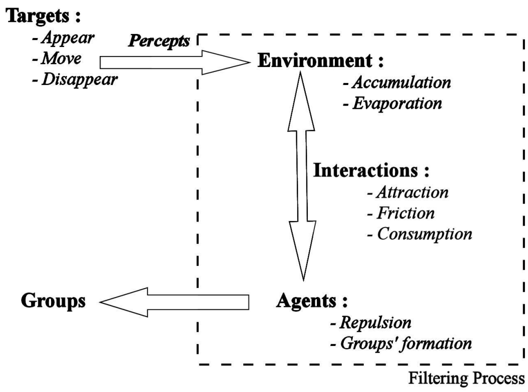

Fig. 5. Representation of the solving process as a filter.

From an application point of view, this device has been successfully applied in simulation and with real targets. It shows relevant properties compared to classical localization and tracking algorithms such as anticipation of the targets' moves, independence from the number of information sources (information sources can be added and/or remove in run time), independence from the number of targets,... (see [18] or [17] for detailed results).

5 Conclusion

This paper presents an environment-based methodology for building reactive multi-agent systems aimed at dealing with the problem solving issue. Considering the limitation of simple entities, the environment appeared to be the main element involved in a reactive-based solving problem system. First, it models the problem to solve and its constraints. Second it establishes the link between the problem on one side and the reactive solving process on the other. Finally, in some cases, it can also characterize the emergent organization.
Our approach contrasts with classical emergentist or artificial life works that define agents and interactions by following the expected emergent organization. Our proposition can be seen as a bottom-up methodology based on the representation of the problem, where constraints are translated into perturbations in the environment. These have to be regulated through agent behaviors. The

originality of our methodology is the fact of starting the building of the solving system by focusing on the environment instead of focusing on the agents, their knowledge and their behaviors as it is done in the classical approach.
The fourth step of the methodology claims that the global solution emerges from the solving process and can be characterized when the system reaches a stable state. Such a state must be measured or observed by an external agent. It is a complex task that remains an open problem. However, we propose in Sect.3.2 some clues about the characterization of this stable state.
Two detailed examples illustrate the application of the methodology: (i) a generic kernel for cooperation and conflict solving between situated agents, which is based on an extension of the APF approach (ii) a model for localization and target tracking using a Physics based approach. It appears to us that describing these models following the construction steps is a good way for their presentation/understanding.

The proposed methodology is currently applied to features extraction in image processing by using agent based active shapes that respect the B-Spline formalism. The methodology is also applied to the facilities location issue. On the theoretical level, we plan to develop some keys for the definition of the environment model as expressed in the first point of the methodology.

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