Construction of Numerical Potential Fields with Reactive Agents

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1. INTRODUCTION

In the context of unknown environments, this paper deals with autonomous robots navigation for exploration and foraging tasks. This remains a hard problem when the environment contains complex obstacles (dead ends, mazes,..).
Artificial Potential Fields (APF) is a well known approach to deal with navigation of autonomous agents. They are computed to define attractive forces towards goals and repulsives ones from obstacles. However, the APF approach has a critical drawback: the possible existence of local minima [1] (e.g. positions where the different forces equalize). The only solution to avoid this drawback is to know/perceive the whole environment [2]. As a consequence, the solution for autonomous agents equiped with limited perception consists in marking the environment in order to use it as a shared memory. This approach, inspired by pheromones mechanisms in ant colonnies, provides good solutions but requires a lot of agents and time for their emergence.
If robots have a representation of the whole environment, it is possible to use optimal planning algorithms to obtain the shortest path from a position to another. One of these algorithms [2] is reexamined in this paper for two reasons. Firstly, it quickly computes optimal paths. Secondly, its incremental principle allows to translate it in a multiagent system that does not require the assumption of the whole environment representation. The algorithm [2] is based on the precomputation of a **numerical potential field expanding from the goal** of the agent. Then, an agent can reach its goal by performing a simple gradient descent. This paper demonstrates how this precomputation can be translated into a mark based process involving reactive agents and how it can be efficiently applied to foraging tasks.

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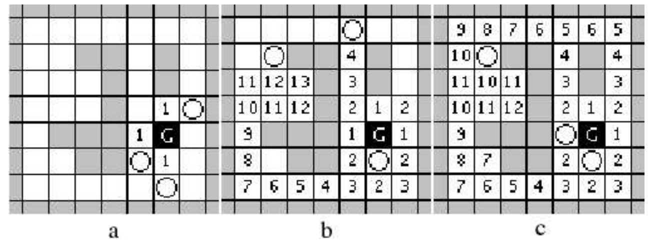

Figure 1: Collective construction of the potential field with 3 agents (steps 2, 17 and 65)

2. WAVEFRONT COMPUTATION WITH REACTIVE AGENTS

Barraquand and colleagues proposed in 1991 a robot path planning technique based on the precomputation of a numerical potential field **free of local minimum** [2]. This technique builds an APF incrementaly; the field increases from the agent's goal (lowest potential value) to all accessible positions in the environment (namely the wavefront expansion). It is an application of the classical Distributed Bellman-Ford (DBF) algorithm, which computes the lowest cost path between two vertex in a graph. The interest of computing the wavefront expansion is that an agent, placed in this potential field, has just to follow the negated gradient to reach the goal by the shortest path. The key idea of the paper is to build such potential fields thanks to the actions of reactive agents that do **not know the environment**.
For this purpose, numerical potential fields values are defined as simple marks that agents can deposit or update. The environment is assumed to be discretized in regular cells. Each agent is located in a cell. An agent can move and perceive the 4-neighbors cells. The marks defined here are simple integer values. Contrary to pheromones, this approach does not require diffusion and evaporation mechanisms. Agents can only read or write one value per cell.
These simple abilities allow the agents to explore the environment and mark it at the same time. Before launching

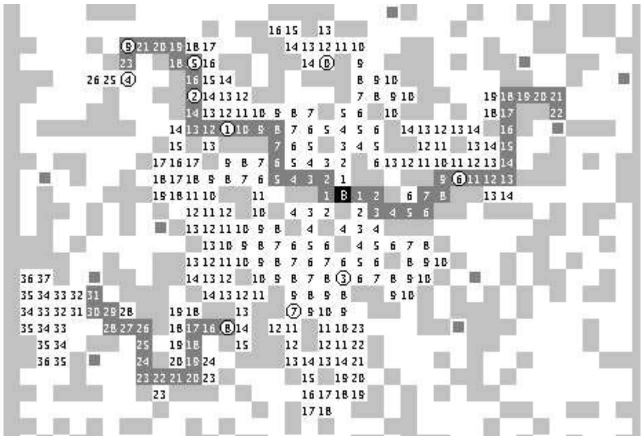

Figure 2: Resolution of a foraging problem with 10 Marker-trail-agents (step 27).

agents, the 0 value is written on the goal/home cell and all the agents are placed on or close to it.
The wavefront potential is collectively and incrementaly built around the initial value by the actions of all agents. Each agent repeatedly performs the behavior presented in Algorithm 1. For any displacement an agent computes the UPDATE-VALUE operation (Algorithm 2). This operation corresponds to a local expansion from an existing wavefront to a not yet visited cell: the shortest path from this new cell equals *1 (one move) + the shortest neighbor path to the goal*.

Algorithm 1 Exploration & Potential construction

IF there exists neighbor cells ***without a value*** THEN move randomly towards one of them and UPDATE-VALUE
ELSE move ***randomly*** towards one of the cells which are not an obstacle and UPDATE-VALUE

Algorithm 2 UPDATE-VALUE Operation

Computes $val = 1 + min(\textit{4-neighbor values})$
IF no value in the current cell *or* $val < val_{current}$
THEN (update) write val

One advantage of using marks is to improve a simple exploration which is based on random motions. Indeed agents move by favoring the not yet marked cells (first line algorithm 1). As a consequence their exploration progresses as a (partial) circular front around the starting cell. Figure 1.a shows such a progression with 3 agents.
It is important to notice that cells may need to be explored several times before building the optimal potential field. Indeed, the number of agents will not be generally sufficient to hold an entire circular front progresion. So, one exploration step (each agent moves) is not equivalent to a loop of the DBF algorithm. Figure 1.b shows such a situation (cell with value 13). However, if the environment is bounded the time necessary to obtain the complete optimal potential field is also bounded, i.e. the construction converges (fig. 1.c). The proof relies upon the hypothesis that each cell may be visited infinitely often. Then the update operation can propagate the best paths to all the cells. The random exploration of agents (algorithm 1) ensures this assumption.

3. APPLICATION TO FORAGING

In the foraging task, known as the explorer robots problem, a set of simple mobile robots have to collect rock samples in an unknown environment [3]. So the potential field construction presented above is well adapted to treat such a problem. The potential field is built during the exploration of the environment and provides very efficient paths to reenter the base. In particular these paths avoid any obstacle shapes (see fig. 2, obstacles are in grey color). If the explored area is limited these paths tend to be optimal (see previous section).
In order to allow agents to find again a discovered source, and to communicate such an information to others, the model is extended. These abilities are easily obtained by adding a simple environment-based behavior. When following the negated gradient from a source to the base the agent leaves a trail, by coloring the visited cells, in order to mark this particular path. Thus, any agent can detect such trails and follow them by a climbing behavior (trails are in dark grey color in fig. 2). As the sources can be worked out, it is necessary to add a behavior to remove the useless trails. It is done by a simple trail descent where the agent changes the cells color into the default one.
This model, namely Marker-trail-agents, is very efficent to treat discovered sources and allows a strong cooperation between agents. Numerous simulations have been fulfilled and show that the time for a complete foraging decreases dramatically while the number of agents increases. Figure 2 shows a snapshot of one of these simulations. The potential field is partially built and two trails connect sources to the base. Several agents, represented by circles, simultaneously move along these paths (note that agents can climb a trail while it is not yet connected to the base). Trails are used as a mean of communication. Indeed any agent in exploration which meets such a trail goes directly to a source.
Contrary to pheromone based techniques, the proposed approach does not require time for the emergence of routes from discovered sources to home and for removing them. Moreover, it requires the construction of only one gradient. As a consequence, the number of agents needed for the foraging task is less important than with a swarm approach.

This multiagent model is now being applied to the construction of other artificial potential fields. Moreover, new extensions are analysed through variants of the foraging problem.

4. REFERENCES

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