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Sensorworld – A Simulator for Resource-Bounded Intelligence

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Abstract

Within this paper, Sensorworld is proposed as a platform for the evaluation and comparison of resource-bounded intelligence, and its effectiveness is proven through the implementation of a series of simulations on effectiveness, utility and energy consumption on bold, cautious and energy-aware agents.

1 Introduction

Resource-bounded networks (e.g. Wireless Sensor Networks) benefit from the application of intelligence software which is capable of making opportunistic decisions, and performing such resource-aware tasks as topology management, routing and data gathering within their environment. In a broad sense, such intelligence software could be viewed as an agent.

The degree of commitment to intentions is viewed as a high-level characteristic of rational agents [7] because it has great effect on the performance of agents within a dynamic and unpredictable environment. In the perspective of reconsideration design, such commitment policies can be categorized as bold or cautious or possibly hybrid. Generally, it represents the intelligence level of an agent. A rational agent should not remain committed to its existing intentions (as a bold agent does). Neither should it constantly reconsider its intentions (as a cautious agent does). A smart agent should be able to change its commitment when necessary. In addition, it should be able to cooperate with other agents to enhance the performance of the whole network.

The evaluation of such intelligence characteristic of resource-bounded sensor networks is the major concern of this paper. The effectiveness comparison of intelligence schemes should be based on a commonly acceptable sampling platform. Various platforms have been proposed for the evaluation of the performance of networks. However within these platforms, multiple strangling factors make it difficult to identify the real effect of intelligence schemes. Within this paper, the Sensorworld platform, which is originally revised from Tileworld [7, 10, 12, 11], is adopted to evaluate and compare the intelligence levels of divergent schemes.

2 Related work

Evaluation of an intelligence mechanism is difficult, for it involves various environmental uncertainties, which make its effectiveness hard to calculate. Such uncertainties will be even harder to analyse when combined with the various assumptions. In most existing cases, the authors evaluate their protocol with different sets of parameters and assumptions, which make comparisons even more problematic.

2.1 Existing simulators

It would be useful to have comprehensive guidelines for evaluating a specific protocol and compare it against other commonly-used evaluation platforms. For example, J-Sim [6] is a component-based, compositional Java simulation environment built upon the notion of the autonomous component programming model. Similar to COM/COM+, Java Beans, or CORBA, the basic entities in J-Sim are components. But unlike the other component-based software packages, J-Sim mimics the IC design architecture in the closest possible way. The behaviour of J-Sim components are defined in terms of contracts. The major limitation of J-Sim is that it supports only one MAC protocol - 802.11.

OMNeT++ [9] is a C++ simulation platform frequently used for WSN simulations. An OMNeT++ model consists of hierarchically nested modules. The depth of module nesting is not limited, which allows users to reflect on the logical structure of the practical system in the model. The modules are programmed in C++ using the simulation library. Modules, with their own parameters, communicate through message passing which can contain arbitrarily complex data structures. Parameters can be used either to customize module behaviour or to parameterize the topology of the network.

Various other simulators exist, with their strengths and weaknesses. For example Ns [8], as a discrete network event simulator, offers support for simulation of TCP, routing, and multicast protocols over networks. GloMoSim [5, 18] is a scalable simulation environment for wireless network systems, which uses a layered approach that is similar to the OSI seven-layer network architecture. SENSE [13] is designed to be a sensor network simulator which supports the NullMAC protocol [2].

These simulators base their simulation on distinct layers, such as the MAC layer, routing layer and so forth, all of which are related to intelligence, resulting in many interacting factors that make the evaluation complex [4]. Quantification of utility

and costs is also more difficult within existing platforms. In addition, although the above-mentioned simulators can all perform WSN-based simulation, they lack of pertinent methodologies, which we need for evaluating intelligence levels of differing schemes.

2.2 Basic requirements for the evaluation of resource-bounded intelligence

BDI agents are highly rational intelligent agents, and are also an adequate intelligence model for next generation WSN applications [14, 15]. In order for the performance evaluation and comparison of different categories of agents, a simulation platform should at least be able to provide both adequate utility quantification and effective agent performance evaluation tools within a random environment. Therefore, although the above-listed simulators provide various WSN simulation platforms, they are not directly applicable for the simulation and comparison of high-level WSN intelligence.

Due to the nature of sensor networks or other resource-bounded networks, the platform should evaluate the goodness of the network as a whole and provide metrics to measure the effects of the design on the operation of the network (by evaluating, for example, energy efficiency, communication performance).

2.3 Tileworld simulation platform

Tileworld agent evaluation platform, on the other hand, inherits the agent comparison methodology and proffers a simplified quantification for utilities and costs. Within such an environment objects are generated randomly at random positions with random lifetime, while the communication characteristics of mesh networks can be simulated through the step-by-step movement of mobile agents on Tileworld. In fact, such a platform has been proven to be effective in evaluating divergent intelligence mechanisms, such as bold reasoning policy and cautious reasoning.

Tileworld was originally proposed by Pollack and Ringuette [10, 11] and later adopted by Kinny and Georgeff [7] and Schut, Wooldridge and Parsons [12] in effectiveness evaluation of agents. Through a series of experiments, Kinny and Georgeff [7] investigated the relative performance of intention reconsideration strategies for BDI agents in different environmental dynamics, while in [12] Schut, Wooldridge and Parsons further extended the work to accessibility and determinism. The Tileworld is sufficiently powerful to evaluate intelligence performance and to demonstrate the benefits of energy-aware agents by enabling comparison with other reasoning policies.

Tileworld comprises of a grid environment on which there exist agents, tiles, obstacles and holes. An agent moves up, down, left or right once in each time step to score (utility) by filling holes with tiles. The following description is a typical description of the Tileworld scenario [10, 7]: *“The Tileworld consists of an abstract, dynamic, simulated environment with*

an embedded agent. It is built around the idea of an agent carrying “tiles” around a two-dimensional grid, delivering them to “holes”, and avoiding obstacles. During the course of a TILEWORLD run, objects appear and disappear at rate specified by the researcher. The objects include tiles, holes, obstacles, tile stores and a gas station. The “lifetime” of any given object is determined by user-specified appearance and disappearance rates for that type of object. The researcher can also specify other properties of the objects, such as their size and score. The agent’s primary task is to fill holes with tiles. To do this, it must pick up tiles, either from a tile store or from wherever it has previously dropped them, carry the tiles to a hole, and deposit a tile in each cell of the hole. If the agent successfully fills all the cells in the hole with tiles that match the hole’s shape, it is awarded with the full amount of the hole’s score. A lesser score is received for filling the holes with non-matching tiles. The agent is responsible to maintain its fuel level. It consumes fuel as it moves around the world; the more tiles it is carrying, the more quickly it burns fuel. To obtain more fuel, it must travel to the gas station and fill its tank. If the agent runs out of fuel, it cannot move for the duration of the run.”

3 Sensorworld

However, Tileworld is not yet a ready simulation platform, needing a fusion of the following characteristics:

- a) Sensor nodes have an additional sleep option;
- b) Energy consumption needs to be considered in meta-level reasoning.

In order to include these characteristics and to facilitate the comparison of performance of differing agents, revised Tileworld was introduced briefly within [14, 15] as a simulation platform for WSN intelligence.

Within this platform the environment is improved by omitting the tiles, holes and obstacles. However (data) samples are added, as shown in Figure 1. Thus an agent, which is assumed to have perfect knowledge of the environment, generates plans for visiting sample cells and scores points by moving onto the cell where the samples generated at random time and random position. Within the following simulations, the same planning scheme is adopted for different genres of agents so that the effect of planning is eliminated from the simulation results. Therefore, the corresponding comparison of effectiveness, utility and energy consumption is the real indication of the difference of the corresponding reasoning schemes. The Sensorworld environment can be considered as a typical scenario of mobile-agent-based selective data collection.

Within this paper, such a platform will be further revised into a formal tool for the evaluation of performance of resource-bounded agents. It will be re-named as Sensorworld to mark its difference to a general Tileworld environment. The rectangular grid is viewed as a regular topology for mesh

sensor networks by the state-of-art research [3, 7]. Within Sensorworld the step-by-step movement of agents is extremely similar to the migration of mobile-agents within a physical environment for collecting samples. In addition, energy and time costs can easily be quantified on Sensorworld.

Figure 1 Sensorworld simulation platform

The simulation environment should contain one or more objects together with corresponding events and parameters that vary within the world and that are measurable. The environment must also contain some simple agent performance metrics that can be easily utilized to calculate an agent's ability. Clearly, the measure of intelligent behaviours of an energy-aware agent would be better measured within an agent-based sensor application environment. Within Sensorworld the communication characteristics of mesh networks are simulated through the step-by-step movement of mobile agents between sensor cells. In particular, this platform serves to compare agents of different commitment levels, namely bold, cautious and energy-aware agents. Such commitment levels are viewed as intelligence levels of the corresponding agents. This environment quantifies utilities and costs, adequately simulates communication and captures the effectiveness analysis of different genres of agents, and therefore provides an excellent platform within which to simulate energy-related and utility-based agents.

5.2 Sensorworld simulation setup

Within this section, the general parameters are discussed. Most of them are the same as those adopted within [7] so that the following simulations can inherit the platform from previous research.

In a Sensorworld environment, samples appear randomly at given positions and remain at those positions within their life expectancy, unless collected by an agent. *Sample gestation time* and *sample life expectancy* are both randomly set between upper and lower limits. The so-called *gestation time* determines the interval between the appearances of successive samples. It is denoted by '[60, 240]', which means the gestation time will be a random number between 60 and 240.

Similarly, *sample life expectancy* is set to [240, 960]. *Dynamism* γ is denoted as the ratio of the world clock rate and the agent clock rate. It represents cycles of execution undertaken by the environment within an agent cycle. The dynamism is denoted by (1, 80), as a variable within a control loop. It will be set to 1 at the beginning of the execution, and will be increased by one each time, until it reaches 80. Relative lifetime, defined as $\text{lifetime}/\gamma$, is adopted to denote the lifetime of samples within environments with dynamism γ . The higher the dynamism, the lower the relative lifetime of samples is, and therefore the lower the probabilities of collection of these samples are before they disappear and vice versa. *Unit Perception Cost* p and *Unit Reasoning Cost* r are adopted to denote the cost of perception for each step and the cost of reasoning once (including deliberation cost and planning cost). Here the cost of migration of mobile agents onto a neighbouring sensor cell is normally much greater than the costs of other perception and belief revision functions. Therefore within Sensorworld, perception costs equal approximately to the migration costs or hopping costs. In order to express their magnitudes, r and p are normalized to 0, 1, and 2 units correspondingly during the following simulations. Although such quantification provides only a relative degree of resource consumption, it satisfies the requirements for comparison of different intelligence schemes on time and energy consumptions. In a static environment where there is no mobile agent, p denotes the cost of hopping a message to the agent's neighboring sensor cell.

Traditionally the reasoning cost refers to time cost. However, a sensor node is critically energy limited and therefore, the simulation will be extended to energy cost as well. So within Sensorworld there are basically two contributory costs, namely *time cost* which is denoted with the subscript t and *energy cost* which is denoted with the subscript e . Therefore the reasoning costs on time and energy are separately denoted as r_t, r_e , while the perception costs on time and energy are separately denoted as p_t, p_e . Energy and time costs are both proportional to the number of loops executed and therefore are defined as $r_t = r_e = r$ and $p_t = p_e = p$. For example, a scheme with $r=2, p=1$ means it costs 2 units of energy and 2 units of time to reason once, and 1 unit of energy and 1 unit of time to migrate once. However for the selection of *sleeping*, there is only time cost, no energy cost.

Within this paper, energy threshold is set to 50,000 units to denote the energy boundedness of the sensor subset, while each step costs one energy unit. So with the neglecting of energy expense on reasoning, within its lifetime each agent is qualified to move 50,000 time steps.

4 Commitment policies of agents

Various agent characteristics can be evaluated and compared on Sensorworld. However for the purposes of this discussion, only single-agent-based commitment policies are evaluated and compared. Different commitment policies are applicable to resource-bounded networks. A WSN's perception, belief-

generation, deliberation, and action are controlled by the control loop of mobile agents. In order to demonstrate the function of commitment policies on agent performance, the algorithms of bold, cautious and energy-aware policies are discussed within this section.

4.1 Practical reasoning of bold and cautious agents

On an abstract level, the control loop of a BDI agent, as shown in Figure 2 [17], has a belief generation function (including perception function $See()$ and belief revision function $Brf(B, \rho)$), a reasoning function (including option generation function $Options(B, I)$, deliberation function $Filter(B, D, I)$ and planning function $Plan(B, I, Ac)$), and an execution function (including taking out head task function $Head(\pi)$, execution function $Execute(\delta)$), mediated by a lower-cost meta-level control function.

The BDI reasoning is partitioned into two components, deliberation and planning. Triggered by desires, the agent deliberation determines an intention by reasoning within a tree-like or graph-like decision network in order to find an optimal decision. Typically, the deliberation process can be simulated by weighing a set of possible choices and selecting the optimum choice from this set. To reason requires the agent to possess not only the knowledge about the environment and the corresponding action abilities, but also some sort of performance measure, especially when it faces a huge amount of divergent goals. The deliberation result leaves how to do it for subsequent plan refinement. Current BDI models advocate this separation of concerns.

```

B, I  $\leftarrow$  B0, I0;
While .T. do
   $\rho \leftarrow See()$ ;
  B  $\leftarrow Brf(B, \rho)$ ;
  D  $\leftarrow Options(B, I)$ ;
  I  $\leftarrow Filter(B, D, I)$ ;
   $\pi \leftarrow Plan(B, I, Ac)$ ;
  While not (Succeeded(I, B) or Impossible(I, B)) do
     $\delta \leftarrow Head(\pi)$ ;
    Execute( $\delta$ );
     $\pi \leftarrow Tail(\pi)$ ;
     $\rho \leftarrow See()$ ;
    B  $\leftarrow Brf(B, \rho)$ ;
    If Reconsider(I, B) then
      D  $\leftarrow Option(B, I)$ ;
      I  $\leftarrow Filter(B, D, I)$ ;
       $\pi \leftarrow Plan(B, I, Ac)$ ;
    End if
  End while
End while

```

Figure 2 Practical reasoning of a BDI agent system

The meta-level reasoning function $Reconsider()$ serves to trigger reconsideration (red block), after executing possible actions. Two kinds of reconsideration policies, bold and

cautious policies are compared in Kinny and Georgeff's experiments [7].

4.2 Practical reasoning algorithms of a bold agent

A bold agent never stops to reconsider its intentions. This means the condition for the red block within Figure 2 is never true. So the commands in this block are never executed.

4.3 Practical reasoning algorithms of a cautious agent

A cautious agent stops at every possible chance to reconsider its intentions. This means the condition for the red block within Figure 2 is always true. So the commands in this block are executed once within each cycle.

4.4 Reasoning algorithms of an energy-aware agent

The energy-aware BDI approach was proposed in [14], as a solution to the intelligence modelling of WSN applications. Within Sensorworld the BS agent is viewed as a WSN nucleus [16], while each mobile agent is viewed as a WSN electron, which activates neural sensor cells in turn and collects data from them. The BS agent which is situated at the centre of the Sensorworld and the mobile agents affiliated constitute a WSN atom. This atom is dynamic in topology, since the mobile agent hops all the time for collecting samples. In the case of Figure 1, the WSN atom will be denoted as I^1 , according to [16]. The red dotted circulars are dynamic orbits of sensor electrons. The dispatched mobile agents must optimise their itineraries by trading-off between effectiveness and energy cost so as to meet the energy constraints and at the same time to achieve reliable performance. The effectiveness of the WSN MAS in data collection is determined by the rationality of the agents involved.

```

If U(r) > max(U(s); U(p)):   G  $\leftarrow Opt(B, I)$ ;
                               G  $\leftarrow Map(D, G)$ ;
                               I  $\leftarrow Wgh(I, G)$ ;
                                $\pi \leftarrow Plan(I, \pi)$ ;
                                $\delta \leftarrow Head(\pi)$ ;
                               Execute( $\delta$ );
                                $\pi \leftarrow Tail(\pi)$ ;
                               Exit();
else if U(p) > max(U(s); U(r)):  $\delta \leftarrow Head(\pi)$ ;
                               Execute( $\delta$ );
                                $\pi \leftarrow Tail(\pi)$ ;
                               Exit();
else:                         Sleep();
                               Exit();

```

Figure 3 Reconsideration judgments of energy-aware agents

The reconsideration of an energy-aware sensor agent is decided by a meta-level judgment function depicted in Figure 3, where $U()$ is the utility function, and s, r, p denotes option sleeping, reasoning and perception (action) separately. It decides among perception, sleeping, or deliberation based on the meta-level reasoning rules, as proposed within [14]. The

degree of commitment to intentions is viewed as a high-level characteristic of an agent, representing level of intelligence. For an energy-aware agent, the degree of commitment is decided by utility, that is, if reasoning generates the highest utility gain, then the agent will reconsider. Within this option the option generating function (function Opt) checks the available options, which are mapped onto utility and assigned with real values from experience and beliefs by a mapping function (function Map). The best goal is selected through a comprehensive weighing of all the surviving goals committed as an intention (function Wgh), which is then planned by Plan() to a set of sampling or actions and the actions will be gradually executed; while if action win, then the agent will Execute(); otherwise the agent will sleep to save energy. The agent will modify intentions and the corresponding status if it is necessary to do so. This is the most critical difference between energy-aware agents and traditional agents such as bold or cautious agents.

6 Results of single-agent-based simulations

Within this paper, utility, effectiveness and energy cost of bold, cautious and energy-aware agents are simulated so as to present a fully comparison of performances between these differing reasoning schemes.

In detail, three genres of simulations are designed: (1) energy-threshold-based simulation, where the network will run until its energy is depleted; (2) time-threshold-based simulation, where the sensor network will run until time is depleted; (3) utility-based simulation, until the required utility is achieved.

The energy-threshold-based, time-threshold-based, and utility-based simulations are selected because they are typical scenarios of sensor network applications. Simulations are carried out on bold agents, cautious agents, and energy-aware agents each with reasoning costs r ($r = 0, 1, 2$) and perception cost p ($p = 0, 1, 2$) respectively because they are typical agent reasoning policies. Also, they represent degrees of intelligence.

6.1 Effectiveness evaluation

Some effectiveness curves of bold, cautious and energy-aware agents with $p=1$, $r=1$ and $m=0$ are displayed in Figure 4 (all blue curves). It can be seen that in a slowly dynamic environment, the performance of bold agents is better than cautious agents. But at highly dynamic environments, cautious agents outperform bold agents. These results are same to previous research [1-3].

The above results are based on the fact that the costs of meta-level reasoning are negligible. It is obvious that if the costs of meta-level reasoning are as high as the reasoning costs, then meta-level reasoning is useless from the perspective of resource conservation. In practice, the costs of meta-level reasoning have an important effect on agent effectiveness and thus should be strictly controlled so as to generate positive net utility. It can be seen from Figure 4 that compared with

energy-aware agents at $m=0$, the curve with yellow-filled mark ($m=0.1$) is slightly lower in effectiveness at high dynamism, but much lower at very low dynamism ($dynamism < 15$).

Figure 4 Effectiveness simulation at $p=1$, $r=1$ and $m=0,0.1,0.5$

6.2 Evaluation of energy consumption

This simulation scenario provides utility-threshold-based comparison on energy consumption of bold, cautious and energy-aware agents for collecting certain number of samples. The energy cost of these three genres of agents for accessing 200 samples is demonstrated in Figure 5 at the fixed costs $p=1$ and $r=1$. In general energy-aware agents, which make energy-aware reasoning, consume less energy than the other agent categories, as Figure 5 proves.

It can be seen that when $d < 10$, bold agents consume less energy than cautious and energy-aware agents. This is because when less dynamic, there are less new chances and therefore it is not worthwhile to reconsider frequently. Cautious agents spend more energy than either bold agents or energy-aware agents, because they frequently re-consider even when there is no change in the less dynamic environment. When the environmental dynamism increases to higher than 15, the energy consumptions of bold, cautious and energy-aware agents are nearly proportional to the dynamism. This is because when the samples are gestated faster with a shorter relative lifetime, it is often impossible for the agent to collect most of these samples. Therefore more energy is needed to collect the same amount of samples at high dynamisms. Under such complexity, cautious agents spend too much energy on reconsideration, while bold agents fail to change their intention when better chances appear. Both of them fail in delivering a good performance with low energy consumption. Bold agents outperform cautious agents in terms of energy consumption because the later make costly reasoning at any possible moment and consume more energy on it. An energy-aware agent, on the other hand, could take into account energy-based consideration and could 'sleep' to avoid excessive expenses of energy. Such an agent will base

its perception action on utility, and will be able to change its mind when new opportunities come up.

Figure 5 Energy cost for scoring 200 samples at $p=1$ and $r=1$

7 Conclusion

Sensorworld is proposed within this paper as an evaluation platform for the evaluation and comparison of resource-bounded intelligence.

While Sensorworld is a work in progress the efficacy of the simulation platform has already been demonstrated in effectively distinguishing the performance difference between energy-aware agents, bold agents and cautious agents.

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