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# Idleness Estimation for Distributed Multiagent Patrolling

## Extended Abstract

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### ABSTRACT

Distributed multiagent patrolling strategies that learn idleness estimators are improved by using the estimator output in a random decision-making process and activating interaction.

### KEYWORDS

Autonomous agents; Cognitive robotics; Distributed AI; Machine learning; Multiagent systems; Artificial Neural Networks; Robotics

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## 1 INTRODUCTION

Dismissing centralisation and complexity to acquire flexibility and robustness, for the problem of patrolling with several vehicles, can be achieved by learning decentralised strategies from centralised strategies. The work presented here contributes to Idleness Estimator (IE) strategies [8] by a non deterministic use of idleness estimates and a communication scheme for exchange of information between agents. Section 2 describes MultiAgent Patrolling (MAP). In Section 3, a method for processing idleness estimates and an interaction scheme are presented. Section 4 is devoted to the assessment and Section 5 concludes and outlines perspectives.

## 2 BACKGROUND AND RELATED WORKS

MAP aims, for a set of agents  $A$ , at checking places as often as possible and is based on a graph  $G = (V, E)$ , where  $V = \{1, \dots, N\}$  is the set of nodes and  $E$  the set of edges with travel times [3–7, 13, 15]. For a node  $v$  at time  $t$  there is a difference between  $i_v^a(t)$ , the *individual idleness* for the agent  $a$ , i.e. the time elapsed since its latest visit, and  $i_v(t)$ , the *true idleness*, i.e. the time elapsed since the last visit of any agent. Strategies may be assessed using normalized Idleness average (Iav) and Worst Idleness (WI) [6].

Conscientious Reactive (CR) agents choose the next node in their neighbourhood selecting that with the largest individual idleness [6]. The Heuristic Pathfinder Cognitive Coordinated (HPCC) strategy centralises the individual idleness of all agents and computes the true idleness. Agents weight idleness and travel time by respectively by  $r \in [0, 1]$  and  $1 - r$ , select a target node using

the Heuristic method and compute a path to this node using the Pathfinder method [1, 2, 12].

Using HPCC sequences of individual and true idleness and minimising the Mean Square Error (MSE) with respect to parameters  $\Theta$ , IE learns offline models  $m(\cdot, \cdot)$ : the mean,  $m_e$ , a linear model,  $l_e$ , and an MLP with one ReLU layer,  $r_e$ . Online, at time  $t$ , the agent  $a$  provides its vector of individual idleness  $i^a(t) = (i_1^a(t), \dots, i_N^a(t))$  to the estimator, which, after applying  $\hat{i}_v^a(t) = \min(\max(m(i^a(t), \Theta), 0), i_v^a(t))$  returns an estimated vector of true idleness  $\hat{i}^a(t) = (\hat{i}_1^a(t), \dots, \hat{i}_N^a(t))$  that is used by the Heuristic and Pathfinder methods [8].

Another strategy selects the next node by random drawing in a probability distribution over the nodes generated by a neural network trained from node sequences of HPCC [9–11]. Networks, noted  $L$ - $H$ , have an input of size  $N$  coding the current node, a width  $H$ ,  $L$  LSTM layers, and an  $N$ -dimensional softmax layer. For the RAMPAGER strategy the pretraining stage, performed by learning the edges in  $E$ , is substituted by an analytical initialisation procedure with respect to  $G$  [10].

## 3 IMPROVED IDLENESS ESTIMATORS

IE strategies are deterministic while node predictors are not. Because agents applying a deterministic individual strategy with no preassigned role would make the same decision while taking different decisions is more efficient, the decision process proposed here is random. This approach is at the opposite of the search of a convergence to a consensus [14]. The entropy of idleness used by agents to make decision is increased by adding a step to their decision process: for each node  $v \in V$  at time  $t$ , any Random Idleness Estimator (RIE) agent  $a \in A$ , after making an estimate of the global idleness  $\hat{i}_v^a(t)$ , considers this estimate as a mean  $m$  of a r.v.  $I$  supported in  $\mathcal{I} = \{0, 1, \dots, i_v^a(t) = i\}$ . The input for the Heuristic and Pathfinder methods is sampled in the distribution  $(p_0, \dots, p_i)$  with  $\forall k \in \mathcal{I}$ ,  $p_k = P(I = k)$ . Aiming at finding the less specific distribution with the specified mean, the entropy optimisation problem to solve is:

$$\begin{aligned} & \max_{\{p_0, p_1, \dots, p_i\}} \left( - \sum_{k=0}^i p_k \log(p_k) \right) \\ & \text{s.t. } \sum_{k=0}^i p_k = 1 \quad \sum_{k=0}^i k p_k = m \quad \forall k \in [0, i], p_k \geq 0 \end{aligned} \quad (1)$$

Generally it leads to solve high degree polynomials and solution is approximated by:

- $p_k = \frac{1}{i+1}$ , if  $m = \frac{i}{2}$ ,
- $p_k = a b^k$ , where  $b = \frac{m}{1+m}$  and  $a = \frac{1-b}{1-b^{i+1}}$ , if  $m < \frac{i}{2}$ ,

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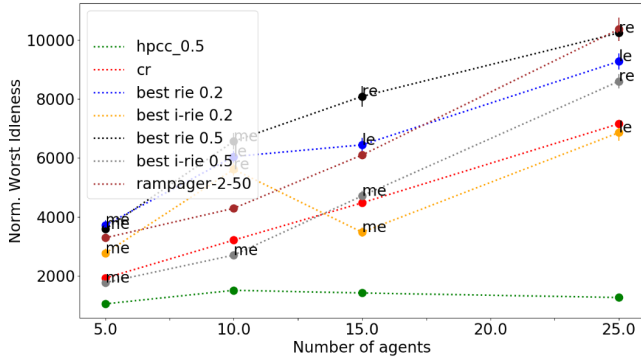


Figure 1: Normalised WI, averaged over 100 runs, on Islands.

- $p_k = a b^{i-k}$ , where  $b' = \frac{i-m}{1+i-m}$  and  $a = \frac{1-b'}{1-b'^{i+1}}$ , if  $m > \frac{i}{2}$ .

Interaction is introduced in RIE, leading to Interacting Random Idleness Estimator (IRIE). The *shared idleness* of the node  $v$  for the agent  $a$  corresponds to the minimum individual idleness of  $v$  among its own and those the agent has received from other agents. Let,  $i^{+a}(t) = (i_1^{+a}(t), \dots, i_N^{+a}(t))$  be its shared idleness. At the beginning of the run  $i^{+a}(0) = i^a(0)$ . At each time step it is incremented or reset in the same way than individual idleness. When, at time  $t$ ,  $a$  and  $a'$  are in range they are able to communicate and subject to a relation  $R_t$ , i.e.  $aR_t a'$ . Pairs of agents which are not directly in range can communicate via intermediate agents. This corresponds to  $T_t$  the transitive closure of  $R_t$ . At  $t$ , for agents  $a, b \in A : a T_t b$ ,  $a$  and  $b$  will be able to interact. Each agent  $a \in A$  apply the following rule to update its vector of shared idleness  $i^{+a}(t)$ :

$$\text{if } \exists n \in [1, |A| - 1] : a T_t a_1, \dots, a T_t a_n, \text{ then} \quad (2)$$

$$i_v^{+a}(t) \leftarrow \min(i_v^{+a}(t), i_v^{+a_1}(t), i_v^{+a_2}(t), \dots, i_v^{+a_n}(t))$$

$i^a(t)$  is used to estimate  $\hat{i}^a(t)$  but, with respect to the stochastic approach,  $i = i_v^{+a}(t)$ .

#### 4 NUMERICAL EXPERIMENTS

Strategies are assessed using a MAP software<sup>1</sup>: Pytrol, a simulator, MAPTrainer, to train models and, MAPTor, an annex tool. Experiments are performed with benchmark graphs, Island, A and Grid [2, 3, 5, 6, 8–12, 16], traveled by 5, 10, 15 and 25 agents applying HPCC with  $r = 0.5$ , CR, RAMPAGER, RIE and IRIE with  $r$  set to 0.2 and 0.5 for both. Each simulation is executed for 3000 steps and the WI and Iav are computed. For RAMPAGER, models already trained on a database [10] are used. For RIE and IRIE models are trained on the same database on  $i^a(t)$  and true idleness fields. In terms of validation MSE, re and le are the best models with 7120 against 7901 for me and high values confirm what has been reported: the data does not represent a function [8].

On Islands, Figure 1 shows that on the WI IRIE outperforms CR. For the Iav, machine learning strategies are better than CR and IRIE is better than RAMPAGER which outperforms RIE. On A IRIE is better than CR and RAMPAGER and IRIE are outperformed by RIE on the Iav, as well as on the WI for RAMPAGER, see Figure

<sup>1</sup><https://github.com/mothguib/>

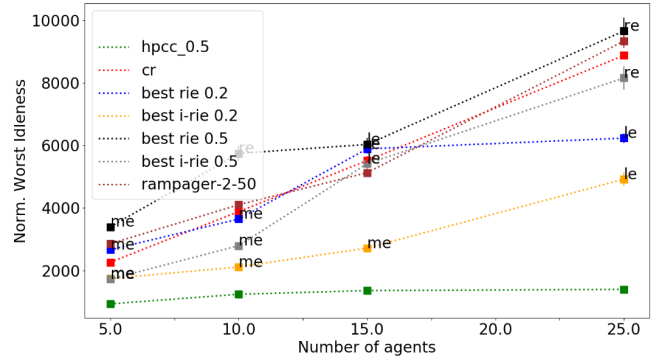


Figure 2: Normalised WI, averaged over 100 runs, on A.

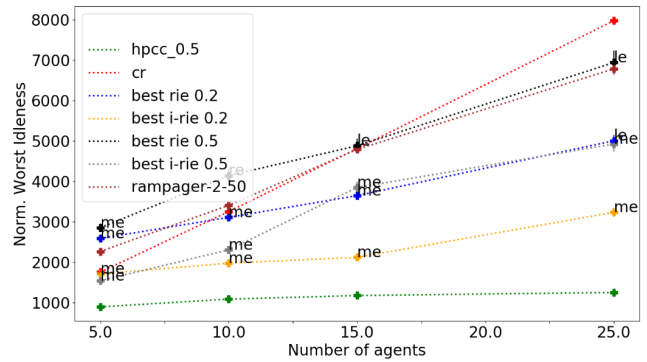


Figure 3: Normalised WI, averaged over 100 runs, on Grid.

2. On Grid, results, shown in Figure 3 for WI, indicate that IRIE is better than RIE which is better than RAMPAGER. Whatever the graph strategies showing the best performance are HPCC and IRIE 0.2 and strategies showing the worst performance are RIE 0.5 and CR. HPCC is the best strategy because it is not distributed and results highlight importance of communication: IRIE 0.2 is the best distributed strategy and IRIE is better than CR. Distributed strategies present better performance with  $r = 0.2$  than with 0.5: a lower weight for an unreliable idleness brings benefits. The best model for idleness estimation is me in 52 cases, le in 30 cases cases, and re in 14 cases. RIE has better performance than RAMPAGER and CR for respectively 62% and 67% of scenarios. There is no relation between training and simulation performances.

#### 5 CONCLUSION

RIE outperforms RAMPAGER and IRIE hinge upon opportunistic communication and interaction between agents and outperforms RIE. The mean, as idleness estimator, is the best statistical model, highlighting that the contribution of neural networks for idleness estimator is small. Directions for future work are optimization of the evaluation criterion, exchange of intent, explicit estimation of an order on nodes or a parameter of a distribution, assessment of an estimator built for a given number of agents in a situation where this number is different, and training of an estimator for a range of number of agents.

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