

# Demo: The Implementation of Stigmergy in Network-assisted Multi-agent System

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## ABSTRACT

Multi-agent system (MAS) needs to mobilize multiple simple agents to complete complex tasks. However, it is difficult to coherently coordinate distributed agents by means of limited local information. In this demo, we propose a decentralized collaboration method named as "stigmergy" in network-assisted MAS, by exploiting digital pheromones (DP) as an indirect medium of communication and utilizing deep reinforcement learning (DRL) on top. Correspondingly, we implement an experimental platform, where KHEPERA IV robots form targeted specific shapes in a decentralized manner. Experimental results demonstrate the effectiveness and efficiency of the proposed method. Our platform could be conveniently extended to investigate the impact of network factors (e.g., latency, data rate, etc).

## KEYWORDS

multi-agent system, stigmergy mechanism, digital pheromones, deep reinforcement learning

## 1 INTRODUCTION

Multi-agent system (MAS) is a large-scale system which composed of numerous agents with simple intelligence connected through the network. Because of its autonomous and distributed characteristics [1], this system can exhibit intelligent behaviors to complete high-complexity tasks by each single agent. However, in a distributed MAS, it is difficult to coordinate each agent who can only observe local information, while a centralized MAS faces severe issues due to huge amount of computing and communications overhead.

Stigmergy is an indirect communication mechanism existing in social insect species, which relies on "pheromones" deposited in the environment to coordinate individual insects' activities, and exhibit strong robustness with a simple form [2]. Inspired by federal learning [3], we propose a decentralized control model based on stigmergy mechanism in network-assisted MAS. In particular, we employ digital pheromones (DP) to simulate existence of pheromone

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MobiCom '20, September 21–25, 2020, London, United Kingdom

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ACM ISBN 978-1-4503-7085-1/20/09.

<https://doi.org/10.1145/3372224.3417318>

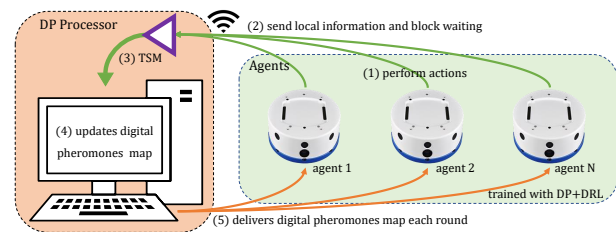


Figure 1: Decentralized control model based on stigmergy mechanism.

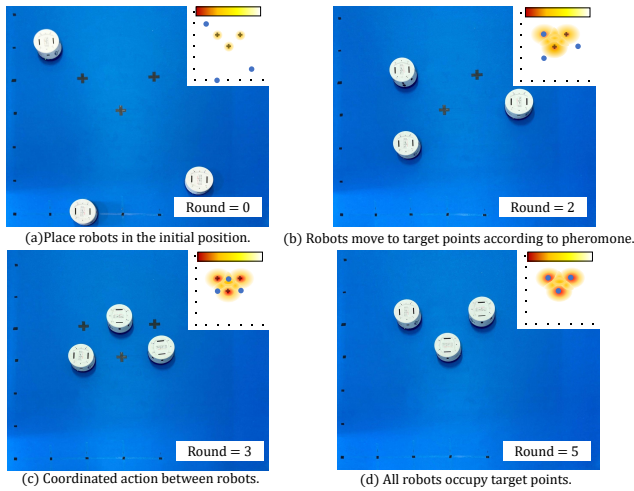
in the environment, and use them as medium in stigmergy mechanism to enable indirectly communicate between agents [4]. Besides, we design an experimental scene to mobilize several distributed agents to arrive at tracking points with as few rounds as possible, and exploit KHEPERA IV robots to implement the algorithm in practical settings.

## 2 DESIGN AND IMPLEMENTATION

Based on implicit information such as digital pheromones, agents can obtain the local environmental state within the perceivable range without direct communication. Figure 1 shows this decentralized control model based on the stigmergy mechanism. It consists of two parts, that is, DP processor and agents, which form a WLAN to connect multiple distributed agents to establish communication.

**DP processor.** DP processor collects local information with the procession of temporal synchronization mechanism (TSM), and calculates the DP of agents' location based on the distance between agents and target points. With simulating the characteristics of superposition, decay and diffusion, DP processor generates a DP map and delivers it to agents each round. To prevent information mismatch when all agents communicate with DP processor, TSM is introduced to follow strict timing requirements when interacting between agents and DP processor. Similar to a buffer, TSM sacrifices part of the agents' moving time to coordinate the behavior of distributed agents, as well as reduces the probability of collision between the agents to some extent. We will investigate the impact of asynchronous methods in the future.

**Agents.** Each agent only acquire limited DP map around itself via interaction with DP processor, which determine the location of next action without directly communicate with other agents. Each agent has a definite perception range for pheromone, and the volume of pheromones decreases with the increase of distance, which attracts agents to gather at location with high pheromones volume. However, distributed agents often cannot cooperate well to accomplish tasks efficiently. Under the guidance of pheromones,



**Figure 2: The experimental platform of 3 robots with above model. The "+" in the figure represents the target points. The upper right corner of each figure represents the DP map. The darker the color, the higher the pheromones volume.**

we use asynchronous advantage actor-critic (A3C) algorithm in deep reinforcement learning (DRL) to train the agents [5], encode local environment information of agent as *state*, and calculate the difference between distance to the target points before and after each action as *reward*. This learning method can train agents' sense of collaboration to take global optimal *action* in the current state.

Figure 1 illustrates the whole execution procedure of the system, which repeats recursively until all agents reach the target points.

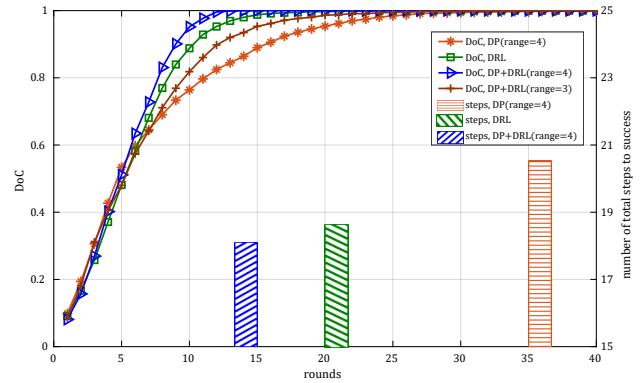
### 3 EXPERIMENTAL PLATFORM AND RESULTS

We establish an experimental platform based on a DP processor and 3 KHEPERA IV robots, and evaluate performance in terms of degree of completion (DoC) and number of total steps.

- Use a PC with a WiFi module as the DP processor, whose CPU processor is Intel(R) Core (TM) i5-3230 CPU @ 2.60GHz.
- Use 3 KHEPERA IV robots as moving agents. Since the robots are not equipped with positioning modules, we employ odometry and leverage dead reckoning method to estimate the position based on given initial position and orientation of the robots. The CPU processor of robots are Texas Instruments DaVinci DM3730 @ 800MHz.

Figure 2 gives the experimental results of 3 randomly placed robots, which shows robots reach the target points (marked by "+") from its initial position within a certain number of rounds. Similar to the real environment, we assume that a small number of pheromones exist at the target points, as shown in (a) of the figure. The amount of DP sensed by agents increases, thus motivating the agents to approach the target points in a stronger manner, which can attract more agents to approach the target points, as shown in (b), (c) and (d) of the figure.

Furthermore, Figure 3 presents the numerical results in detail. When DoC arrives at 1, it means that all robots have reached the target points, and the histogram shows the number of rounds and



**Figure 3: The performance of DP and DRL combined compared with the cases of adopting DP or DRL only.**

total steps that the robots take to complete the goal. It can be observed that compared to the cases of adopting DP or DRL only, the proposed combination of DP and DRL yields superior performance. It also can be seen that the performance is greatly reduced when the range of agents' perceptual pheromone becomes smaller (from 4 to 3). In particular, DP can attract agents to places with high pheromones volume at the beginning, and DRL can coordinate the behavior of agents when agents move around the target points.

### 4 CONCLUSION AND FUTURE WORKS

In this demo, we have demonstrated the implementation means for achieving stigmergy in network-assisted MAS. Furthermore, we have verified the effectiveness and efficiency of exploiting combined DP and DRL in a practical MAS with KHEPERA IV robots. We believe that this demo could act as a starting point, which will encourage further efforts for exploring the relationship of combining communication and stigmergic collective intelligence.

### ACKNOWLEDGMENTS

This work was supported in part by National Key R&D Program of China (No. 2019YFB1802900), National Natural Science Foundation of China (No. 61701439, 61731002), Zhejiang Key Research and Development Plan (No. 2019C01002, 2019C03131), the Project sponsored by Zhejiang Lab (2019LC0AB01), Zhejiang Provincial Natural Science Foundation of China (No. LY20F010016).

### REFERENCES

- [1] Rongpeng Li, Zhifeng Zhao, Xing Xu, Fei Ni, and Honggang Zhang. 2020. The Collective Advantage for Advancing Communications and Intelligence. *IEEE Wireless Communications* (2020), 1–7.
- [2] H Van Dyke Parunak, Sven A Brueckner, and John Sauter. 2004. Digital pheromones for coordination of unmanned vehicles. In *International Workshop on Environments for Multi-Agent Systems*. Springer, 246–263.
- [3] Brendan McMahan, Eider Moore, Daniel Ramage, Seth Hampson, and Blaise Aguera y Arcas. 2017. Communication-efficient learning of deep networks from decentralized data. In *Artificial Intelligence and Statistics*. 1273–1282.
- [4] Xing Xu, Zhifeng Zhao, Rongpeng Li, and Honggang Zhang. 2019. Brain-inspired stigmergy learning. *IEEE Access* 7 (2019), 54410–54424.
- [5] Volodymyr Mnih, Adrià Puigdomènech Badia, Mehdi Mirza, Alex Graves, Tim Harley, Timothy P. Lillicrap, David Silver, and Koray Kavukcuoglu. 2016. Asynchronous Methods for Deep Reinforcement Learning. In *Proceedings of the 33rd International Conference on International Conference on Machine Learning - Volume 48*. JMLR.org, 1928–1937.