Physarum Inspired Model for Mobile Sensor Nodes Deployment in the Presence of Obstacles

Abubakr Awad(✉), Wei Pang, and George Coghill

School of Natural and Computing Sciences,
University of Aberdeen, Aberdeen, UK
{abubakr.awad,pang.wei,g.coghill}@abdn.ac.uk

Abstract. Mobile wireless sensor networks (Mobile-WSN) are useful in harsh environments due to the presence of obstacles and/or dangerous for sensors to be deployed deterministically. In this paper, we proposed a Physarum inspired autonomous, model for dynamic deployment of sensor nodes where multiple Physarum (as representation of sensors) will compete over food resources (interest points) based on chemo-attraction, and repulsion forces exerted by competing Physarums and obstacles. Our simulation results have demonstrated the high coverage performance of the model with minimal move overhead in the presence of obstacles with the least number of sensors.

Keywords: Physarum polycephalum · Hexagonal cellular automaton
Mobile sensor network · Deployment · Coverage · Obstacles

1 Introduction

In mobile wireless sensor network (Mobile-WSN) the sensors are deployed randomly to gather the information from the environment. In different applications of Mobile WSN, it is not possible to deploy the sensors deterministically. After initial random deployment sensors are required to disperse autonomously without central control to maximize the coverage and re-establish the connectivity of the network [8]. Mobile WSNs are to collect ground data for various purposes such as such as battle field monitoring, bio-environmental surveillance, earthquake observation, and wildlife reservoir [4,7,9].

Environmental obstacles (building, lakes, mountains, ...) can form holes in the network, creating sets of isolated nodes and leaving uncovered areas. Sensor coverage and connectivity problems were investigated thoroughly, and several techniques were proposed with various capability and limitations [2,12].

Physarum may not have brain, but they are capable of solving many significant problems. Physarum senses gradients of chemo-attractants and repellents and forms a yellowish vascular network which expands up to tens of centimeters in search of nutrition. The Physarum foraging behavior consists of two

M. H. Miraz et al. (Eds.): iCETiC 2018, LNICST 200, pp. 153–160, 2018.
https://doi.org/10.1007/978-3-319-95450-9_12

simultaneous self-organized processes of expansion (exploration) and shrinkage (exploitation) [11].

Many mathematical models have been proposed to simulate Physarum foraging behavior [1,5,6,10,14]. Using these models Physarum Polycephalum is capable of solving many NP-hard problems, such as finding the shortest path in directed or undirected network [16], simulating transport network [15]. Physarum can sense its environments as in maize labyrinth model [10], the applied approach allow mobile nodes to navigate in unknown environments avoiding obstacles.

Our aim is to use unconventional computational power of Physarum polycephalum to provide an energy aware distributed self-deployment algorithm for dynamic deployment of sensor nodes after initial random deployment to avoid obstacles, enhance coverage and re-establish the connectivity of the network. In this model multiple Physarum (as representation of sensors) will be competing for target points (chemo-attractants as food), and avoiding boundaries and obstacles (repellent as light). Each Physarum will consider all chemo-attractive forces (nutrient sources) and repulsive forces due to the presence of competitors (neighbor sensor), (obstacles, and field boundary) to determine its movements. Up to our knowledge this is the first paper to simulate multiple Physarums in hexagonal CA to solve the problem of node deployment in mobile WSN.

2 The Proposed Model

WSN is an example of graphically expressed problem. Given an initial random deployment of n mobile sensor nodes over a 2-D area, we formulated a hexagonal CA reaction diffusion model for dynamic relocation of sensors using multiple Physarums as a representation of mobile sensors and food sources as interest points. We have designed energy aware algorithm where the sensor energy decrease by 1% with every movement step this will give a priority to less used sensors to compete over interest points.

2.1 The Model State of Cellular Automaton (CA)

In order to model mobile-WSN, we considered a CA grid in the two-dimension space, which is divided into a matrix $(X \times Y)$ of identical hexagon cells, in which every cell $c_{(i,j)}$ has six neighbours. In this grid a set of m sensors $(S = s_1, s_2, \ldots, s_m)$ are competing on a set of n interest point $(IP = ip_1, ip_2, \ldots, ip_n)$. The state of a cell $c^t_{(i,j)}$ at time t located at position (i, j) is described by its type as in Eq. 1, whether it is an interest point, a sensor, an empty cell, or an obstacle cell (Ex:- physical obstacle, boundary wall).

$$CT_{(i,j)} = \{\text{“}FREE\text{”}, \text{“}OBSTACLE\text{”}, \text{“}INTEREST\_POINT\text{”}, \text{“}SENSOR\text{”}\} \tag{1}$$

An interest point is defined by its mass, and a sensor is defined by its energy, similarly to the original Physarum competition model, where chemical is defined by its mass, and Physarum is defined by its mass respectively.

2.2 Area Hexagonal Tessellation

We considered hexagonal deployments that minimize redundancy, and avoiding that more than one node senses and processes the same event [13]. The area is dynamically tessellated by regular hexagons with its side equal communication radius (Rc). The vertices and the centers of the regular hexagons will be identified as the interest points to be filled up with food source to attract Physarums. It has been proved that such node placement technique maximizes the area coverage using a minimum number of nodes [3].

2.3 Cellular Automaton (CA) Model Rules

In our model, each sensor is a self organized computational unit. Each of them aims to achieve the maximum utility based on its local environment by choosing appropriate behaviors. The CA model rules are mainly based on the diffusion equations combined with Physarum heuristics in competition settings, where multiple sensors (Physarums) will compete for these interest points (Food resources). Each sensor will execute the diffusion process (as defined in Eqs. 2, 3) to explore its neighborhood within its communication radius (R_c). Each sensor at iteration (t) uses the values of its six neighbours cell to calculate the value of the energy at the next iteration ($t + 1$).

$$SE^{t+1}_{(i,j)} = SE^{t}_{(i,j)} + \sum_{(k,l)} \begin{cases} \left(SF * SD * SE^{t}_{(k,l)}\right) - SE^{t}_{(i,j)}, & \text{if } S\_AA_{(i,j),(k,l)} = 1 \\ 0, & \text{otherwise} \end{cases}$$

$$\forall (k,l): \; i-1 \leqslant k \leqslant i+1, \; j-1 \leqslant l \leqslant j+1, \; k \neq l$$

$$SF = 1 + S\_AttForce^{t}_{(i,j),(k,l)} + S\_RepForce^{t}_{(i,j),(k,l)} \tag{2}$$

where,

$SE^{t+1}_{(i,j)}$ defines the diffusion of sensor energy for the next generation $(t + 1)$ at cell $c_{(i,j)}$.

$SE^{t}_{(i,j)}$ is the current energy of the sensor at iteration (t) for cell $c_{(i,j)}$.

SF is the forces affecting a sensor.

SD is the sensor diffusion coefficient.

$$S\_AA_{(i,j),(k,l)} = \begin{cases} 1, & \text{if } CT_{(k,l)} = \text{“}FREE\text{”}\ OR\ \text{“}INTEREST\_POINT\text{”} \\ 1, & \text{if } CT_{(k,l)} = (\text{“}SENSOR\text{”})\ AND\ (SID_{(i,j)} = SID_{(k,l)}) \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

where,

$S\_AA_{(i,j),(k,l)}$ defines whether a sensor at cell $c_{(i,j)}$ is available to diffuse towards a neighbouring cell $c_{(k,l)}$.

$SID_{(i,j)}$ is the ID of the sensor.

In our model, we have addressed a 1% decrease in sensor energy (Physarum mass) with each movement step. Simply, sensor superiority in competition is directly proportional to sensor energy, a key point for load balancing and will give a priority to less used sensors to process messages and replace failed nodes. The process of searching for interest points will be executed for several rounds until all interest points are filled or other stopping conditions are met. Sensors failed to occupy interest points will not move and stay in stand-by for fault repair. This will minimize node displacement, and help to enhance the network lifetime.

2.4 Modelling Multiple Physarum and Multiple Food Resources

We created a new formula to compute two forces (attraction/repulsion) acting on Physarum: The first is chemo-attraction force to food sources (interest points), and the second is the repulsion negative forces the competing Physarums exert on each other based on its mass (sensor energy), and repulsion forces exerted by obstacles and boundary wall.

The attraction/repulsion forces as described in Eqs. 4, 5 determine the movement of Physarum towards the food and away from other competitors and obstacles.

$$S\_AttForce_{(i,j),(k,l)} = \begin{cases} \dfrac{IPM_{(k,l)}}{Total\_IPM}, & \text{if } IPM_{(k,l)} = MAX(IPM_{(i,j)}) \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

where,

$S\_AttForce_{(i,j),(k,l)}$ defines the value of attraction force of $SE_{(i,j)}$ towards its neighbouring cell $c_{(k,l)}$.

$IPM_{(i,j)}$ is the current mass of the interest point for cell $c_{(i,j)}$.

$Total\_IPM$ is the total sum of all interest points mass on the grid.

$$S\_RepForce_{(i,j),(k,l)} = \begin{cases} \dfrac{SE^t_{opp(k,l)}}{Total\_SE}, & \text{if } SID_{(i,j)} \neq SID_{opp(k,l)}, \\ & \quad SE^t_{opp(k,l)} > Rep\_Limit \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

where,

$S\_RepForce_{(i,j),(k,l)}$ defines the value of repulsion force of $SE_{(i,j)}$ towards its neighbouring cell $c_{(k,l)}$.

$SE^t_{opp(i,j)}$ is the neighbor sensor energy at the opposite direction.

Rep_Limit is a limit where sensor must reach to repel neighboring sensor.

Each Physarums will execute the algorithm, to explore its neighborhood within its Rc and will find shortest pass to nearest interest point.

Algorithm 1. Slime Mould Diffusion

Formal Name: SM_DIFF
Input : $cell^t_{(i,j)}.sm$ (A slime mould in cell(i,j) at time 't')
Ensure : $cell^t_{(i,j)}.sm.mass > \mathit{Diffusion\ Limit}$

for $dir \in HEX\_Directions$ **do**
  $SM\_Forces =$
  $1 + SM\_AttForce(cell^t_{(i,j)}.sm, dir) + SM\_RepForce(cell^t_{(i,j)}.sm, dir)$;
  $diffused\_mass = SM\_AA(cell^t_{(i,j)}.sm, dir) * SM\_Forces *$
  $cell^t_{(i,j)}.sm.diffusion\_factor * cell^t_{(i,j)}.sm.mass$;
  $cell^{t+1}_{(dir)}.sm.mass = cell^{t+1}_{(dir)}.sm.mass + diffused\_mass$;
  $cell^{t+1}_{(i,j)}.sm.mass = cell^{t+1}_{(i,j)}.sm.mass - diffused\_mass$;
end

Physarums failed to occupy interest points will not move and stay in stand-by for fault repair. This will minimize maximum node displacement, and help to enhance the network lifetime since node movement exhausts energy.

3 Experimental Results

The core model was implemented in Java with Processing package https://processing.org/ being used for graphical simulation. All the experiments were repeated for 30 times using the same parameters of diffusion equation as in [14] (Table 1).

Table 1. Parameters values for the experiments

Parameter	Value
SD	0.1
SE	3000
IPM	3000
REP_LIMIT	5

In this experiment, Physarum as a representation of sensors were placed in a 2D (50×50) hexagonal grid with obstacles for sensor communication (lake, mountains, etc. ...). In harsh environment even sensors random deployment over all the interest area may not be feasible. In this research sensors were deployed in selected areas away from obstacles (Fig. 1-a). The sensors are homogeneous, they have same sensing and communication radii, where $R_s = 2$, and $R_c = 5$. All the sensors move with the same speed and the same energy.

The area is virtually tessellated by regular hexagons with its side equal communication radius. All the vertices and the center of each hexagon (interest points = 82) will be filled with food source to attract Physarums (Fig. 1-a). We conducted three experiments scenarios; one folds (82 sensors), 1.5 folds (123 sensors) and two fold (164 sensors) the number of interest points. Physarums will execute the the proposed algorithm in Sect. 2. Physarum will sense its surrounding environment and define obstacles within its R_s, and will communicate with other Physarums in its R_c range. The algorithm will be repeated until at least 90% of interest points are filled or after 30 rounds are executed (Fig. 1-b).

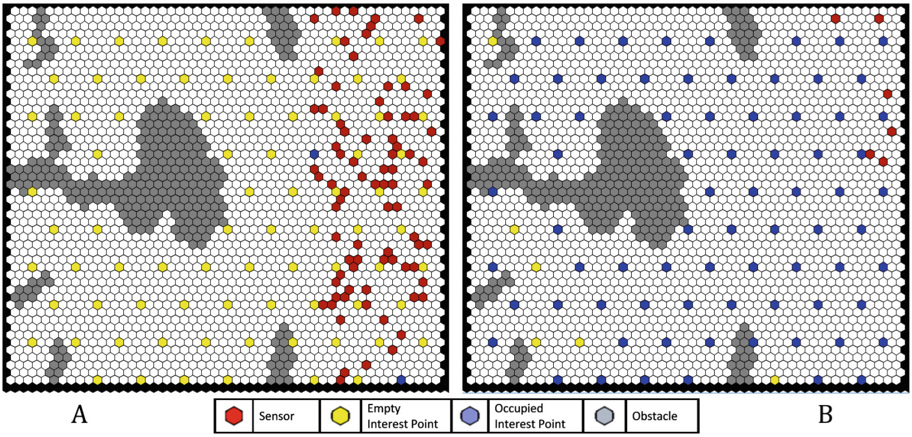

Fig. 1. (A) The initial sensor deployment and (B) the relocation of sensors after 30 round execution of the proposed model for the first scenario (82 sensors).

The outcome of the experiment showed that percentage of coverage, and the total number of moves to fill interest points were nearly similar in the three scenarios (Fig. 2). After the first round about 50% 0f coverage is achieved with an average one step/sensor. There after the sensors disseminate all over the area away from wall boundaries and obstacles with least number of sensors (one fold) and with minimal number of movement (Fig. 2).

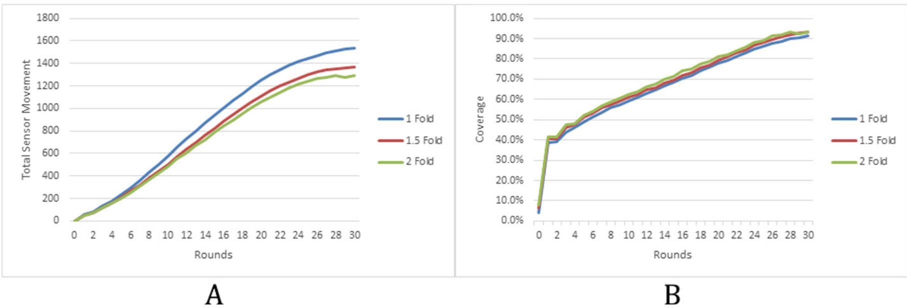

Fig. 2. (A) Movement steps and (B) Area coverage versus number of rounds for the three scenarios.

4 Conclusion

In this study, we presented a novel Physarum inspired energy aware model for dynamic deployment of mobile sensor nodes in the presence of obstacles. This model simulated Physarum complex foraging behavior based on hexagonal cellular automata and reaction diffusion system, where multiple Physarums will sense the surrounding environment, and will compete over the interest points based on chemo-attraction and repulsion forces exerted by obstacles, and competing Physarums. Simulation results have demonstrated the high coverage performance of the model with minimal move overhead even in the presence of obstacles with the least number of sensors.

Acknowledgement. Abubakr Awad research is supported by Elphinstone PhD Scholarship (University of Aberdeen). Wei Pang and George Coghill are supported by the Royal Society International Exchange program (Grant Ref IE160806).

References

1. Adamatzky, A.: From reaction-diffusion to physarum computing. Nat. Comput. **8**(3), 431–447 (2009). https://doi.org/10.1007/s11047-009-9120-5
2. Beghdad, R., Lamraoui, A.: Boundary and holes recognition in wireless sensor networks (2016). https://doi.org/10.1016/j.jides.2016.04.001. ID: 311969
3. Brass, P.: Bounds on coverage and target detection capabilities for models of networks of mobile sensors. ACM Trans. Sens. Netw. **3**(2), 9 (2007). https://doi.org/10.1145/1240226.1240229
4. Goubier, O.N.P., Huynh, H.X., Truong, T.P., Traore, M., Pottier, B., Rodin, V., Nsom, B., Esclade, L., Rakoroarijaona, R.N., Goubier, O., Stinckwich, S., Huynh, H.X., Lam, B.H., Vinh, Udrekh, Muslim, H., Surono: Wireless sensor network-based monitoring, cellular modelling and simulations for the environment. ASM Sci. J. **2017**(Special issue 1), 56–63 (2017)
5. Gunji, Y.P., Shirakawa, T., Niizato, T., Haruna, T.: Minimal model of a cell connecting amoebic motion and adaptive transport networks. J. Theor. Biol. **253**(4), 659–667 (2008). https://doi.org/10.1016/j.jtbi.2008.04.017
6. Jones, J.: Influences on the formation and evolution of physarum polycephalum inspired emergent transport networks. Nat. Comput. **10**(4), 1345–1369 (2011). https://doi.org/10.1007/s11047-010-9223-z
7. Lam, B.H., Huynh, H.X., Pottier, B.: Synchronous networks for bio-environmental surveillance based on cellular automata. EAI Endorsed Trans. Context-Aware Syst. Appl. **16**(8) (2016). https://doi.org/10.4108/eai.9-3-2016.151117
8. Li, X.: Improving area coverage by mobile sensor networks. Ph.D. thesis (2009). AAINR47481
9. Malaver, A., Motta, N., Corke, P., Gonzalez, F.: Development and integration of a solar powered unmanned aerial vehicle and a wireless sensor network to monitor greenhouse gases. Sensors (Switzerland) **15**(2), 4072–4096 (2015). https://doi.org/10.3390/s150204072
10. Nakagaki, T., Yamada, H., Tóth, Á.: Maze-solving by an amoeboid organism. Nature **407**(6803), 470 (2000). https://doi.org/10.1038/35035159
11. Reid, C.R., Latty, T.: Collective behaviour and swarm intelligence in slime moulds. FEMS Microbiol. Rev. **40**(6), 798–806 (2016). https://doi.org/10.1093/femsre/fuw033
12. Rout, M., Roy, R.: Dynamic deployment of randomly deployed mobile sensor nodes in the presence of obstacles. Ad Hoc Netw. **46**, 12–22 (2016). https://doi.org/10.1016/j.adhoc.2016.03.004. ID: 272922

13. Saha, D., Das, N.: Self-organized area coverage in wireless sensor networks by limited node mobility. Innov. Syst. Softw. Eng. **12**(3), 227–238 (2016). https://doi.org/10.1007/s11334-016-0277-7
14. Tsompanas, M.-A.I., Sirakoulis, G.C., Adamatzky, A.: Cellular automata models simulating slime mould computing. In: Adamatzky, A. (ed.) Advances in Physarum Machines. ECC, vol. 21, pp. 563–594. Springer, Cham (2016). https://doi.org/10.1007/978-3-319-26662-6_27
15. Tsompanas, M.A.I., Sirakoulis, G.C., Adamatzky, A.I.: Evolving transport networks with cellular automata models inspired by slime mould. IEEE Trans. Cybern. **45**(9), 1887–1899 (2015). https://doi.org/10.1109/TCYB.2014.2361731
16. Zhang, X., Gao, C., Deng, Y., Zhang, Z.: Slime mould inspired applications on graph-optimization problems. In: Adamatzky, A. (ed.) Advances in Physarum Machines. ECC, vol. 21, pp. 519–562. Springer, Cham (2016). https://doi.org/10.1007/978-3-319-26662-6_26