

A Study of Grouping Effect On Mobile Actuator Sensor Networks for Distributed Feedback Control of Diffusion Process Using Central Voronoi Tessellations

Haiyang CHAO, Yangquan CHEN, and Wei REN

Abstract—When a team of networked mobile actuators (sprayers) are used to control the diffusion process in a region of interest with the help of the static mesh sensor networks, the question on how to group the mobile actuators into smaller subgroups is investigated in this paper to check the performance change under various grouping strategies. Our actuator path planning is based on the so-called Central Voronoi Tessellations (CVT) technique. Via extensive simulation studies, we found that, under the same total actuation resources, it is *not* definite to tell if the larger number of subgroups corresponds to a better performance.

Index Terms—Robot grouping, mobile actuator networks, coordinated control, diffusion process, pollution neutralization, Centroidal Voronoi Tessellation.

I. INTRODUCTION

THE deployment of large numbers of unmanned vehicles is rapidly becoming possible because of the advances in wireless networking and in miniaturization of electro-mechatronic systems. In the future, groups of robots will coordinate and perform challenging tasks including operation in dangerous environments, human health monitoring, and habitat monitoring for pollution detection. These applications motivate "Mobile Actuator and Sensor Network (MAS-net) project" in CSOIS, Utah State University[2]. This project combines mobility with the wireless sensor networks for monitoring and controlling the spatial diffusion process [4]. Each robot has limited sensing, computation and communication ability. But they can coordinate with each other to finish tasks like closed-loop control of a diffusing process, which is both temporal and spatial. The application of this project can be in situations like chemical, biological, radiological or nuclear (CBRN) leaking that will cause great damages. More detailed research challenges are presented in [6].

In this paper, we consider the distributed control of a dynamical pollution diffusion process using groups of mobile

actuators with an emphasis on how different grouping methods can affect the control performance. The scenario can be described as: a toxic diffusion source is releasing toxic gas/fog in a 2D domain; the diffusion process is modeled by a partial differential equation (PDE); we assume static mesh sensor networks are deployed in the polluted area to measure the density of the pollutant. Then, groups of mobile actuators are sent out to counteract or control the pollution by properly releasing the neutralizing chemicals.

The technical approach proposed in this paper is related to a number of technological areas including coverage control [3], robot motion planning control [9] and the dynamic diffusion process control [8]. In [7], a gradient based algorithm is developed for chemical tracing with swarms of mobile robots and the diffusion process is assumed to be focused and smoke-like with wind blowing. A mobile robot equipped with sensing devices is used to estimate the parameters of gas releasing process in[8]. The techniques mentioned above could give us some ideas on how to model a diffusion process and find the source of pollution. However, the diffusion processes are not fully time-varying and no further solutions on how to counteract the pollution were investigated before. The motion planning of groups of actuators in a time-varying PDE system for feedback control still largely remains an open research question.

Motivated by the application of Centroidal Voronoi Tessellation (CVT) in coverage control of mobile sensing networks [3], we use a CVT-based algorithm to solve this problem. An application of CVT in feedback control system can be found in[14]. In [14], the sensor location problem in feedback control of partial differential equation system is solved by CVT. The functional gains are served as the density functions in CVT. We also need to point out that the CVT-based robot motion control is a distributed and scalable control algorithm. In our experiment, the pollution concentration is given by the sensors that cover the area and form a mesh. A simulation platform called *Diff-MAS2D* [18] has been developed for measurement scheduling and controls in distributed parameter systems with moving sensors and actuators. Simulation result shows the effectiveness of our algorithm for different group sizes.

The remaining part of this paper is organized as follows. In Sec. II, the problem formulation is presented. In Sec. III, we give a brief introduction to Voronoi diagram and Centroidal

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Voronoi Tessellation. Section IV is devoted to introducing CVT-based optimal actuator location and path planning algorithms. In Sec. V, we analyze the tradeoff between group size and the efficiency in actuator control. The simulation results and comparisons are presented in Sec. VI. Finally, conclusions and future research directions are presented in Sec. VII.

II. PROBLEM FORMULATION

In this section, the problem on how to control a diffusion process like pollution neutralization is introduced.

Suppose a pollution diffusing process evolves in a convex polytope in \mathcal{R}^2 denoted as Ω . The concentration function $\rho(x, y) : \Omega \rightarrow \mathcal{R}_+$ is used to represent the pollutant concentration over Ω . The whole process can be modeled with the following partial differential equation (PDE):

$$\frac{\partial \rho}{\partial t} = k \left(\frac{\partial^2 \rho}{\partial x^2} + \frac{\partial^2 \rho}{\partial y^2} \right) + f_d(x, y, t) + f_c(\tilde{\rho}, x, y, t), \quad (1)$$

where k is a positive constant representing the diffusing rate; $f_d(x, y, t)$ shows the pollution source; $\tilde{\rho}$ is the measured sensor data; $f_c(\tilde{\rho}, x, y, t)$ is the control input applied to the system which represents the effect of neutralizing chemical sent out by mobile actuators to counter-act the pollutants.

The control objectives are:

- Control the diffusion of the pollution to a limited area.
- Neutralize the pollution as quickly as possible without making the area of interest overdosed.
- Minimize the size of polluted area which is heavily affected.

To achieve the above control requirements, the following functions need to be minimized:

$$P_{total}(t) = \int_{\Omega} \rho(q, t) dq \text{ for } q \in \Omega. \quad (2)$$

where P_{total} is the total pollutant left in Ω at time t .

When considering a partition of Ω , we can use the following equation to replace (2):

$$\mathcal{K}(P, \mathcal{V}) = \sum_{i=1}^n \int_{V_i} \rho(q) |q - p_i|^2 dq \text{ for } q \in \Omega, \quad (3)$$

where $P = (p_1, \dots, p_n)$ represent the locations of n actuators, $|\cdot|$ is the Euclidean distance. n robots partition Ω into a collection of n polytopes $\mathcal{V} = \{V_1, \dots, V_n\}$, $p_i \in V_i$, $V_i \cap V_j = \emptyset$ for $i \neq j$.

To minimize \mathcal{K} , the distance $|q - p_i|$ should be small when the pollution concentration $\rho(q)$ is high. But it is not a wise strategy to drive all actuators very close to the pollution source, because the diffused pollutants far away from the source need also be neutralized quickly to minimize (3). A necessary condition to minimize \mathcal{K} for coverage control in a static gradient field is that $\{p_i, V_i\}_{i=1}^n$ is a centroidal Voronoi tessellation of Ω [3]. The CVT algorithm is further extended [1]. It is based on a discrete version of (3) and the concentration information comes from the measurements of the static, low-cost mesh sensors.

III. INTRODUCTION TO VORONOI DIAGRAM AND CENTROIDAL VORONOI TESSELLATION

Here we give a brief introduction to the Voronoi diagram and Centroidal Voronoi Tessellation [19]. The Voronoi diagram is to partition a plane with n points into convex polygons such that each polygon contains exactly one generating point and every point in a given polygon is closer to its generating point than to any other.

Given an open set $\Omega \subset \mathcal{R}^N$ and a set of points $\{z_i\}_{i=1}^k$ belonging to Ω , let $|\cdot|$ denote the Euclidean norm in \mathcal{R}^N and let

$$V_i = \{q \in \Omega \mid |q - z_i| < |q - z_j| \text{ for } j = 1, \dots, k, j \neq i\} \quad (4)$$

$$i = 1, \dots, k.$$

The set $\{V_i\}_{i=1}^k$ is referred to as a Voronoi tessellation or Voronoi diagram of Ω and each V_i is referred to as the Voronoi region or Voronoi cell. The members of the set $\{z_i\}_{i=1}^k$ are referred to as generators of each cell V_i .

A centroidal Voronoi tessellation (CVT) is a Voronoi tessellation of a given set such that the associated generating points are centroids (centers of mass with respect to a given density function) of the corresponding Voronoi regions. It is defined like this: given a density function $\rho(q) \geq 0$ defined on Ω , we define the mass centroid z_i^* of V_i for each Voronoi cell V_i by:

$$z_i^* = \frac{\int_{V_i} r \rho(q) dq}{\int_{V_i} \rho(q) dq} \text{ for } i = 1, \dots, k. \quad (5)$$

We call the tessellation defined by (4) a Centroidal Voronoi Tessellation if and only if

$$z_i = z_i^* \text{ for } i = 1, \dots, k.$$

So, the points z_i are not only the generators for the Voronoi regions V_i but also the mass centroids of those regions.

Centroidal Voronoi Tessellation has broad applications in many fields [5]. It is the solution to optimal placement of resources, but in general, CVT can only be approximately constructed.

IV. CVT-BASED OPTIMAL ACTUATOR MOTION PLANNING ALGORITHM

For the control problem of a diffusion process, or a pollution-sprayer problem, there are two control inputs for each sprayer: where to spray and how much to spray. We use a modified CVT algorithm for actuator motion planning and a simple PID controller for spraying control. Although the CVT is used to solve the static resource location problem, if the diffusion process evolves slower than the convergence rate of the motion planning algorithm and the control efforts, CVT is still a valid solution to our problem, as verified in our simulation results presented in Sec. VI.

We use a modified Lloyd's method for actuator motion planning to get a CVT diagram. Lloyd's method is an iterative algorithm to generate a centroidal Voronoi diagram from any set of generating points. It is described as below:

Given a region Ω , a density function $\rho(x, y)$ defined for all $x \in \Omega$, and a positive integer k

- 1) Select an initial set of k points $\{z_i\}_{i=1}^k$ (Actuator Starting Positions) as the generators;
- 2) Construct the Voronoi sets $\{V_i\}_{i=1}^k$ associated with generators $\{z_i\}_{i=1}^k$;
- 3) Determine the mass centroids of the Voronoi sets $\{V_i\}_{i=1}^k$; these centroids form the new set of points $\{z_i\}_{i=1}^k$;
- 4) Give the actuators (sprayers) command to move to the mass centroid points
- 5) If the new points meet some convergence criterion, terminate; other wise, return to step 2.

The Lloyd’s method is iterative so that the motions of the robots can be adaptive to the evolving of the diffusion process.

We use the second-order dynamical equation to model the mobile actuator robots:

$$\ddot{p}_i = u_i \tag{6}$$

with u_i a force input to control the robot motion determined by the following control law:

$$u_i = -k_p(p_i - \bar{p}_i) - k_v\dot{p}_i \tag{7}$$

where \bar{p}_i is the computed mass centroid of the current Voronoi cell.

The first term of (7) on the right hand side is the viscous friction artificially introduced [16]. k_v is the friction coefficient and \dot{p}_i denotes the velocity of the robot i . This term is used to eliminate the oscillatory behavior of robots described in [11] when the robot is close to its destination. The viscous term assures that in the absence of the external force, the robot will come to a standstill state eventually.

For the spraying control, or the neutralizing chemical releasing, we use proportional control. The amount of chemicals each robot releases is proportional to the average pollutant concentration in the Voronoi cell belonging to that robot.

$$u_{spray_i}(t) = -k_{pr} \int_{V_i} \rho(q, t) dq \tag{8}$$

Although our simulation is model-based, our control algorithms for each robot are not relying on the exact model information. They are based only on the sensor information that the robots can access.

V. GROUPING EFFECT ON DIFFUSION CONTROL PERFORMANCE

In this section, we discuss in detail if CVT-based algorithm could be used to large numbers of actuator groups and how to decide the appropriate grouping size according to the final performance requirements. In [1], we have shown that the CVT algorithm works well for 4 mobile actuators. It is obvious that we can achieve better control result for the pollution neutralization by using more mobile actuators. But a big group size also have tradeoffs like much more computation and communication requirements which will lower the efficiency and robustness of control system.

With the increasing of actuator numbers, we need to use the computational complexity theory to test if the CVT will bring big computation burden. There are many practical methods

for constructing Voronoi Diagrams including the naive method [19], the flip method and the incremental method. Specifically, we chose the Delaunay triangulation method based on Qhull. According to [13], the computational complexity is

$$f_r = O\left(\frac{r^{d/2}}{(d/2)!}\right),$$

where d is the dimension; n the number of input points, r the number of processed points, and f_r the maximum number of facets of r vertices. For our problem, $d = 2$.

$$f_r = O(r),$$

For simulation purpose, we use `delaunay()` and `voronoi()` functions in MATLAB to get the CVT diagrams. We found that there is no big burden on computation.

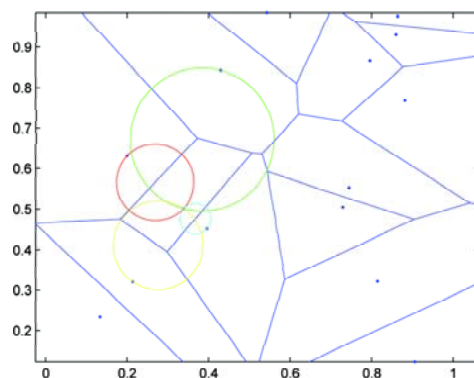


Fig. 1. Incremental Sensing to Determine the Voronoi Diagram.

Next, we will show how the CVT algorithm can be implemented in a distributed way. That is, the algorithm can be executed on a group of robots instead of a centralized one. In fact, we need only get p_i and $\bar{p}_i = C_{V_i}$ for every time step. To get a distributed implementation, each actuator needs to know the relative location of each Voronoi neighbor for computing its own Voronoi cell. If the actuator group is not so big, the simple broadcast strategy can be used so that each actuator can get information from its neighbors and compute the voronoi diagram based on that. But in the case of large numbers of actuators, the communication is limited, e.g. mesh sensor network. The actuators can follow the incremental neighbor seeking algorithm, related to [15][3]:

- 1) Initialization, set up the starting sensing range R_s , and the incremental step r_i .
- 2) Find the neighbors within R_s , update the boundary.
- 3) Increase the searching range by r_i until the boundary is closed.

Given the above discussion on computational cost and distributed way, it is feasible to consider more actuators for pollution neutralizing problem. However, we are interested in how many actuators in a subgroup or what the best grouping size is. In real circumstances, for a fair comparison, we must use the same amount of neutralizing chemicals for various numbers of groups. There should be an optimal group size given a specific performance metric.

VI. SIMULATION RESULTS

Diff-MAS2D is used as the simulation platform for our implementation. The area concerned is given by $\Omega = \{(x, y) | 0 \leq x \leq 1, 0 \leq y \leq 1\}$. The system with control input is modeled as

$$\frac{\partial \rho(x, y, t)}{\partial t} = k \left(\frac{\partial^2 \rho(x, y, t)}{\partial x^2} + \frac{\partial^2 \rho(x, y, t)}{\partial y^2} \right) + f_c(x, y, t) + f_d(x, y, t), \quad (9)$$

where $k = 0.01$ and the Neumann boundary condition is given by

$$\frac{\partial u}{\partial n} = 0.$$

where n is the outward direction normal to the boundary.

The stationary pollution source is modeled as a point disturbance f_d to the the PDE system (9) with its position at $(0.75, 0.35)$ and

$$f_d(t) = 20e^{-t}|_{(x=0.75, y=0.35)}.$$

In our simulation, we assume that once deployed, the mesh sensors remain static. There are 29×29 sensors evenly distributed in a square area $(0, 1)^2$ and they form a mesh over the area. There are 4 mobile robots that can release the neutralizing chemicals. For the robot motion control, the viscous coefficient is given by $k_p = 3$ $k_v = 1$ and the control input is given by

$$u_i = -3(p_i - \bar{p}_i) - \dot{p}_i.$$

The pollution source begins to diffuse at $t = 0$ to the area Ω and initially the mobile actuator robots are evenly distributed within the domain Ω (one by one square) at the following specific positions: $(0.5, 0.5)$ for 1×1 grouping case; for 2×2 grouping case, $(0.33, 0.33)$, $(0.33, 0.66)$, $(0.66, 0.33)$, $(0.66, 0.66)$, respectively, and so on and so forth. Figure 2 shows the initial positions of the robot groups (2×2 grouping), the positions of the sensors and the position of the pollution source as a reference. Figure 3 shows the typical trajectories of the 2×2 actuator group.

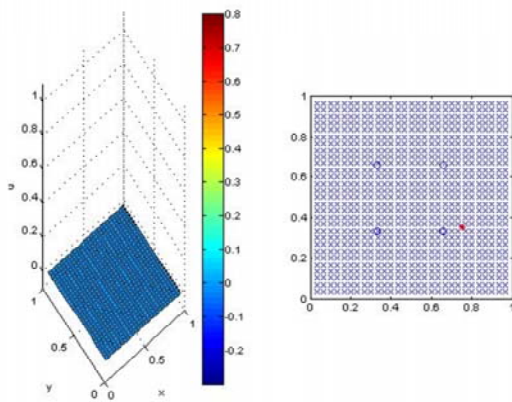


Fig. 2. Initial layout of actuators and sensors (2×2 grouping).

We choose the simulation time to $t = 5$ sec. and the time

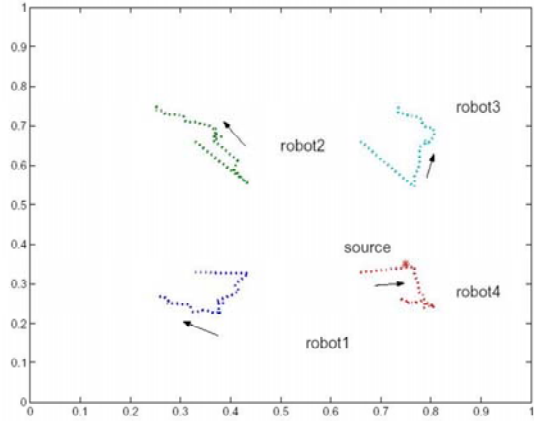


Fig. 3. 2×2 robot group trajectories for controlling the diffusion process.

step as $\Delta t = 0.002$ sec. The robot recomputes its desired position every 0.2s. To show how the robots can control the diffusion of the pollutants, the robots begin to react at $t = 0.4$ s. The system evolves under the effects of diffusion of pollutants and diffusion of neutralizing chemicals released by robots. To show the scalability of the CVT algorithm for bigger groups, the control results are shown by using 5×5 and 9×9 mobile actuators respectively. Table I shows the time to do simulations on the PC (P4-2.6G, 256M RAM) and the remaining pollutants at the end of the simulation. It can be seen that the computational load does not increase much with the increase of the number of actuator groups. In Fig. 4, the y axis is the sum of the mesh sensor measurements.

TABLE I
COMPUTATIONAL TIME FOR SIMULATION AND CONTROL RESULTS

Grouping	Time for simulation	Remaining pollutants
2×2	510 s	3.3994
3×3	582 s	0.7046
4×4	615 s	0.3372

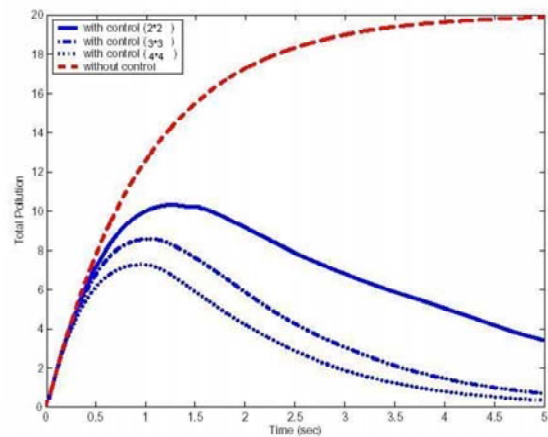


Fig. 4. Evolution of the amount of pollutants (2×2 , 3×3 and 4×4 robots).

To compare the performance of different groupings of actuators, we compare our CVT-based algorithm with the uniformly distributed case. The control laws for chemical releasing are the same. But Table II shows the different output parameter for neutralizing chemical releasing so that each actuator group has the similar total control input. In Fig. 5, the y axis represents the total pollution all the mesh sensors could detect. Detailed results including $Pollution_{max} \cdot T_{max}$ (when the pollution has a peak), and $Pollution_{final}$ are shown in Table III. The case with exactly one static actuator and one pollution source is provided as a baseline for comparison.

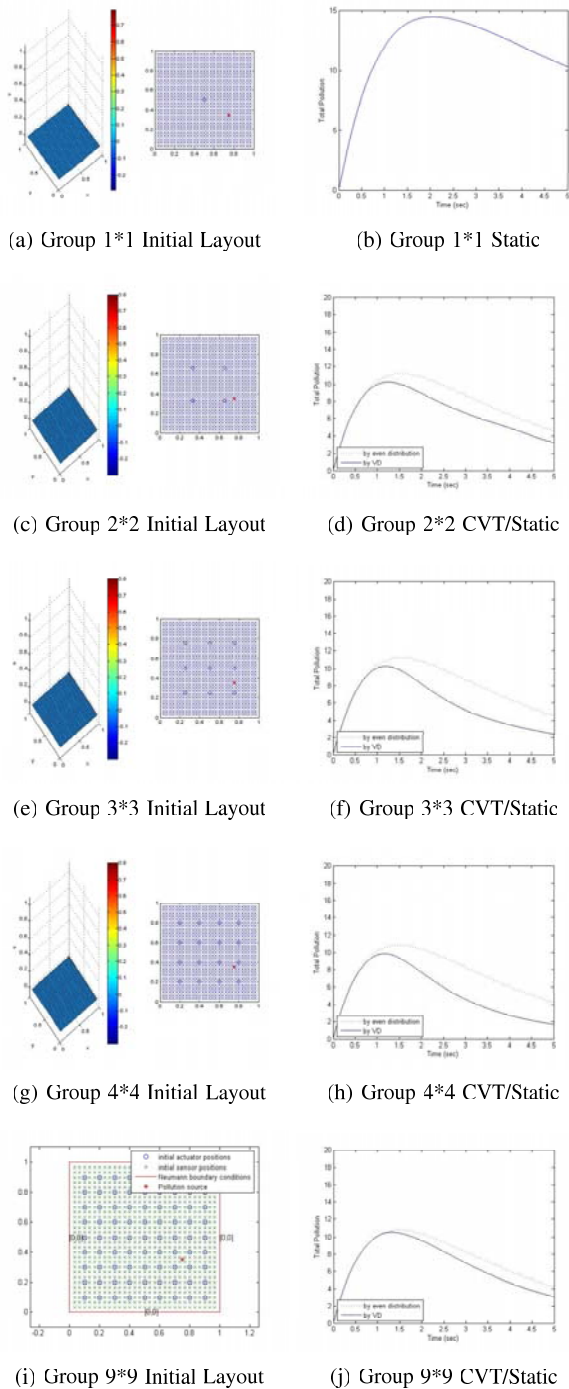


Fig. 5. Grouping Performance for mobile CVT/Static algorithm

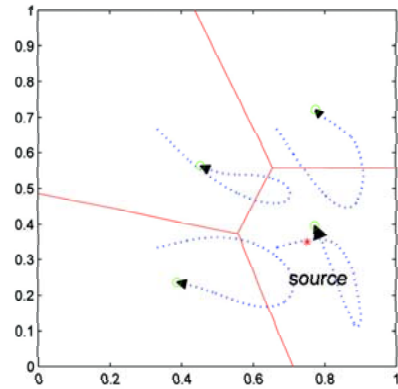


Fig. 6. Trajectories of 2*2 robots using CVT algorithm.

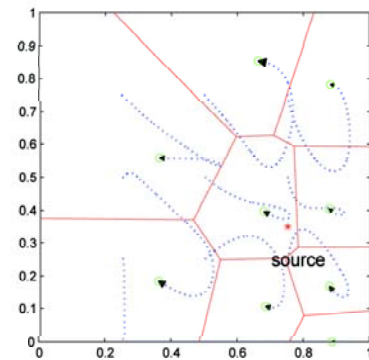


Fig. 7. Trajectory of 3*3 robots using CVT algorithm and the final Voronoi diagram.

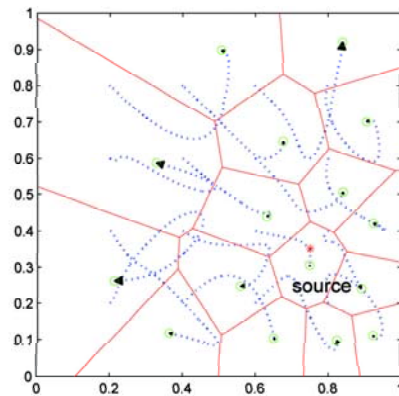


Fig. 8. Trajectory of 4*4 robots using CVT algorithm and the final Voronoi diagram.

From the above results, we can find out our CVT algorithm is distributed, scalable and with high performance. All the mobile CVT methods achieve better results than those of the static evenly distributed ones. However, the optimal grouping size for diffusion control is not always corresponding to the largest size. In other words, under the same total actuation

TABLE II
RUN TIME FOR SIMULATION AND CONTROL RESULTS

Grouping	Actuator Numbers	Neutralizing parameter
1*1 Actuator	1	320
2*2 Actuator	4	81
3*3 Actuator	9	36
4*4 Actuator	16	20.25
9*9 Actuator	81	4

TABLE III
COMPARISON OF PERFORMANCE FOR DIFFERENT GROUP SIZE

Grouping	P_{max}	t_{max}	P_{final}	P_{integ}
1*1 Static	100%	100%	100%	100%
2*2 (Static)	77.4%	74.9%	44.4%	68.5%
2*2 (Mobile)	71.0%	59.8%	32.0%	57.4%
3*3 (Static)	77.8%	74.3%	44.3%	68.5%
3*3 (Mobile)	71.1%	58.4%	23.5%	50.1%
4*4 (Static)	75.3%	72.3%	41.6%	65.9%
4*4 (Mobile)	68.2%	57.6%	16.7%	46.3%
9*9 (Static)	74.8%	73.1%	41.2%	65.5%
9*9 (Mobile)	72.3%	63.7%	30.2%	58.7%

resources, it is *not* definite to tell if the larger number of subgroups corresponds to a better performance. A mathematical model is needed for quantitative analysis of the effect of the grouping size on the efficiency in diffusion control.

VII. CONCLUSION

In this paper, we extended the application of Centroidal Voronoi Tessellation to the case of large number of mobile actuators for diffusion control. Computational complexity and distributed algorithm are discussed for scalability testing. Through our extensive simulation studies, we demonstrated the effect of the grouping size on the efficiency in diffusion control. Unfortunately, under the same total actuation resources, it is *not* definite to tell if the larger number of subgroups corresponds to a better performance.

In the future, we will investigate how to perform quantitative analysis of the effect of the grouping size on the efficiency in diffusion control. Furthermore, we will extend our research for pollution feedback control by using mobile sensors and take into account the sensor noise and unreliable communication induced uncertainties.

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