Cooperative Pollution Supervising and Neutralization with Multi-actuator-sensor Network

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Abstract The present work considers a scenario that a multi-actuator-sensor network neutralizes poisonous gas and tracks the pollution sources in a bounded area. A novel algorithm is proposed to minimize the system information uncertainty while reaching balance on the workload of actuators. The method combines the centroidal Voronoi tessellations (CVT) with a consensus strategy. The CVT of the region insures a local optimal position configuration of the actuators, thus the sensing uncertainty can be minimized. The consensus algorithm utilizes the connection information among actuators, and helps them to reach a common workload. The consensus component will be terminated or suppressed when the workload is averaged. The consensus component may postpone the realization of CVT configuration. But it could be viewed as a perturbation that helps the actuators jump out of the local optimal CVT configuration. As a result, the information uncertainty may be further reduced. Comparison is drawn between the pure CVT algorithm and the method with consensus strategy. Simulations validated the proposed approach.

Key words Voronoi tessellation, position configuration, workload assignment, multi-agent system

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Multi-agent systems have drawn much attention in computer science and formed an important branch of distributed systems. The applications of multi-agent systems are expected to gain robustness, or to enhance the efficiency. A classic scenario is, a group of autonomous mobile robots cooperate with each other, without a centralized controller. In the present work, cooperative robots are implemented to track the pollution sources and spray neutralizer in a certain area. The environment information is obtained by wireless sensors which are distributed in the area. Such a system which consists of mobile actuators and wireless sensors is represented as multi-actuator-sensor network (MAS-net) in this paper.

The first challenge in MAS-net is to configure large amount of actuators on proper positions. The virtual rigid structure with a leader-follower style is one of the early solutions[1−5]. The weak point is the leader. The structure will collapse once the leader is lost. The artificial potential field is another solution[6−7]. Usually the positioning algorithm is based on virtual spring force and a potential filed. Such a solution could be totally distributed — no communication among agents at all. The equilibrium state of the virtual spring places the robots at the desired positions of the formation. But it has never been an easy job to design potential field functions for complicated locating solution. Game theory is a newly introduced solution[8]. The relative positions are achieved by exploiting the mechanism of non-cooperative games. References [9−10] formulated the formation control problem as a synchronization control problem. Reference [11] pointed out that the position control should be classified as formation regulation control and tracking control. In [12], the authors extended the concept of "formation control" to unfixed pattern. In fact, this is the general style of the problem. From their point of view, the important thing is to achieve some utility via formation control, rather than merely keeping the robots in a good-looking formation. Centroidal Voronoi tessellation (CVT) is utilized to solve the multi-robot cooperative problems[13−18]. Voronoi partitions and proximity graphs are used to solve the deployment and coverage of certain area[15]. In [16], the authors designed an adaptive algorithm for robots to move towards the mass centroid of their Voronoi regions. Its purpose is to record observations about the sensory environment with increasing resolution. The positions of sensors converge to a near-optimal sensing configuration. The estimation of sensory parameters are accelerated by introducing consensus scheme on estimation algorithm[17]. Reference [18] introduced a simultaneous coverage and tracking (SCAT) algorithm to solve the combined problem of area coverage and target tracking.

The secondary issue in MAS-net is to allocate the work load among the actuators. There are many algorithms on this issue, such as auctions[19] and game theory solution[8, 20]. The basic idea that attracts us is the concept of consensus. Many researchers discussed the consensus on robot movement, such as position and velocity, or even acceleration[4, 21−26]. But consensus on work load has not been discussed in the literature, to the best of the authors′ knowledge. The consensus algorithms guarantee the robots to reach a common place, or move in the same direction. However, the synchronization information is not limited to positions, errors or parameter estimations. It could be any variable that represents certain feature. The present work considers the scenario that a poisonous gas (or other material) is leaking from several unknown sources. The mission to neutralize the poisonous gas requires a reasonable division of the concerned area. Thus, the consensus information is chosen as the accumulated gas amount of each region. It is used to represent the workload of each actuator. The consensus on cumulated poisonous gas can be translated to a common workload that the actuators share.

The paper endeavors to solve the combined problem of targets-tracking and task-allocation. The solution is composed by a CVT location configuration algorithm and a consensus protocol on actuators′ workload. This method can track the movement of the pollution sources, meanwhile balance the workload of actuators in real time. The proposed method may provide a local optimal configuration for the actuators.

1 Problem formulation

First of all, the scenario in which MAS-net cooperate is described in detail. There are several unknown sources from which the poisonous gas is leaking. A group of wireless sensors are scattered in the field. A sensor only sends information to its nearest actuator, in order to minimize the energy cost and prolong the battery life. The actuators search and track the pollution sources, using the information collected by the wireless sensors. At the same time, the actuators need to decide how to divide the region, so that each actuator shares a common workload on the neutralizing task. The mission for MAS-net brings in two major

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issues. The first issue is the uncertainty of the environment information, which is introduced by the communication between wireless sensors and actuators. The second one is the workload assignment, which is coupled with the pollution source tracking problem.

The information uncertainty can be modeled by the following equation:

$$H_1(P) = \sum_{i=1}^{n} H_1^i = \sum_{i=1}^{n} \int_{V_i} \|q - p_i\|^2 \phi(q) \mathrm{d}q \tag{1}$$

The symbol P indicates the positioning configuration of the actuators. Its elements are p_i, $i = 1, 2, \cdots, n$. Each agent i governs a region V_i which is generated by p_i. The sensors in region V_i only communicate and provide sensory information to the actuator on position p_i. A point in region $V = \cup_{i=1}^{n} V_i$ is denoted as q. The measurement on V is $\phi(q)$, $q \in V$. In fact, $\phi(q)$ is the measurement of the sensor at position q, rather than the diffusion function of poisonous sources. The information uncertainty defined in (1) is supposed to be minimized while the executing of the mission. Obviously, a discrete version of the above equation is necessary for real sensor networks. The sensory value cannot be obtained on every point in a region V_i, thanks to the limitation on the amount of sensors. Assume the sensors are scattered uniformly in the region V, then the system uncertainty can be expressed as

$$H_1(P) = \sum_{i=1}^{n} H_1^i = \sum_{i=1}^{n} \sum_{j \in V_i} \|q_j - p_i\|^2 \phi(q_j) \tag{2}$$

The symbol q_j is the position of the sensor j, and $\phi(q_j)$ is its reading.

According to the assumption that each sensor only communicates to its nearest actuator, a reasonable division of the region V is the Voronoi tessellation. Such a tessellation is generated from the positions of mobile actuators. Let q be a point on V, then the Voronoi tessellation can be defined as

$$V_i = \{q \in V \mid \|q - p_i\| \le \|q - p_j\|, \ \forall j \ne i\} \tag{3}$$

It follows from the definition that $V_i \cap V_j = \emptyset$, and $\cup_{i=1}^{n} V_i = V$. By the definition of Voronoi tessellation, the information uncertainty minimizing problem can be transformed to the position configuration problem of actuators.

The second issue concerns the workload of actuators. The balance of workload indicates that each actuator works at a common efficiency. This efficiency can be defined as the ratio between assigned gas amount and the neutralizer that an actuator carries. In the present work, it is assumed that actuators always carry enough neutralizer. Thus, the workload balance problem can be reduced to the case where each actuator has to neutralize a common amount of poisonous gas.

The reading of a sensor at position q is $\phi(q)$, which can be interpreted as the density of the poisonous gas at position q. For an actuator, the workload can be represented as the integral of density $\phi(q)$ on its corresponding Voronoi cell:

$$M_{V_i} = \int_{V_i} \phi(q) \mathrm{d}q$$

It could also be called the mass weight of a Voronoi cell. In case the sensors are static and spread uniformly in the environment, a discrete definition can replace the continuous one to simplify the realization:

$$M_{V_i} = \sum_{q_j \in V_i} \phi(q_j) \tag{4}$$

There are several ways to measure the workload difference among actuators. The variance of the workload is a good option. But it is a value related to the number of actuators. It is more important to find out how far away the present positioning configuration is from the average-workload configuration. Within the present work, the absolute error of measurement is

$$H_2(V) = \sum_{i=1}^{n} H_2^i = \sum_{i=1}^{n} \|M_{V_i} - \bar{M}\|^2 \tag{5}$$

where $\bar{M}$ is the average workload over the whole region V. Such value cannot be calculated by the actuators with the local information. It is observed globally and the averaged workload $\bar{M}$ is given as a known parameter. The variable H_2 is just a measurement on workload difference. It does not lead to a centralized controller on the behavior of agents. In fact, the MAS-net is fully distributed. The minimum of H_2 implies a preferable location configuration where the workload is balanced. It is a function of actuator positions, since the Voronoi tessellation is a function of these positions.

Both of the two issues are related to the position configuration of mobile actuators. The trade-off between two objectives is the key point of the solution. The present work proposes a combined solution for the combined problem of uncertainty minimizing and workload balancing, taking advantage of the MAS-net system.

2 Centroidal Voronoi tessellation

This section deals with the minimization of information uncertainty. The mass weight of a Voronoi cell is calculated with the poisonous gas density $\phi(q)$. It is proved that the centroidal Voronoi tessellation (CVT) can provide local optimal configurations of the actuator positions. The MAS-net constructs CVT and obtains the centroid information, without explicitly calculating the boundaries of each Voronoi cell.

2.1 The minimum of H_1

The mass centroid of region V_i is defined as

$$p_i^* = \frac{\int_{V_i} q\phi(q) \mathrm{d}q}{\int_{V_i} \phi(q) \mathrm{d}q}, \quad i = 1, \cdots, n \tag{6}$$

The corresponding discrete definition is

$$p_i^* = \frac{\sum\limits_{q_j \in V_i} q_j \phi(q_j)}{\sum\limits_{q_j \in V_i} \phi(q_j)}, \quad i = 1, \cdots, n \tag{7}$$

By the definition of Voronoi tessellation in (3), the positions P are the generators of the cells. Centroidal Voronoi tessellation indicates the Voronoi tessellation in which the generators are exactly the mass centroids of corresponding cells. Let $P^* = \{p_1^*, p_2^*, \cdots, p_n^*\}$ be the mass centroids, then CVT means $P = P^*$.

It follows from (1) that $H_1(P) > 0$. A local minimum can be reached when $\frac{\partial H_1}{\partial P} = 0$. The solution of this equation is

$$\frac{\partial H_1}{\partial p_i} = \frac{\partial H_1^i}{\partial p_i} = \frac{\partial \int_{V_i} (q^2 - 2p_i q + p_i^2) \phi(q) \mathrm{d}q}{\partial p_i} = \\ -2\int_{V_i} q\phi(q) \mathrm{d}q + 2p_i \int_{V_i} \phi(q) \mathrm{d}q =$$

$$2\int_{V_i}\phi(q)\mathrm{d}q\left(p_i-\frac{\int_{V_i}q\phi(q)\mathrm{d}q}{\int_{V_i}\phi(q)\mathrm{d}q}\right)=2M_{v_i}(p_i-p_i^*)$$

Thus, the CVT positioning configuration provides local optimum of information uncertainty. It is a necessary condition for the actuators to locally minimize the uncertainty happened in the communication with sensors.

2.2 Construction of CVT

The most common and basic algorithm to construct discrete CVT is Lloyd′s algorithm. It has a clear-cut iteration between building Voronoi tessellations and computing their centroids. Lloyd′s method requires fewer iterations, but each iteration is expensive thanks to the precise calculation on the Voronoi tessellation boundaries and mass centroids. A substitute is the MacQueen algorithm. It does not require precise construction of Voronoi tessellations or mass centroid. But each iteration in MacQueen′s algorithm only moves one generator. The evolution would be extremely slow if there are many actuators.

As a matter of fact, it is the information in a Voronoi cell that drives an actuator to move, rather than the boundaries or the intersections. The MAS-net ignores the calculation on boundaries, and focuses on the sensor information. It is based on MacQueen′s algorithm. The centroids are calculated directly and the actuators are driven towards them.

In MAS-net, both of the actuators and the sensors are discretely distributed in the region of interest. As is stated in the previous sections, a sensor only communicates with its nearest actuator. To find the nearest actuator, a sensor increases its communication range from 0. The first found actuator must be the nearest. Such method can be used at the first round of search. Once a sensor has already connected to a certain actuator, it could adjust the communication range corresponding to the movement to the actuator. If a sensor detects 2 actuators within its communication range, it could reduce the range so that it only sends information to the nearest one. The consequence is that the sensors divide themselves into several groups, which represent different Voronoi cells. There is only one actuator in each cell, which is located at the generator point of the Voronoi tessellation.

An actuator can calculate the centroid with the sensor readings in its corresponding Voronoi cell, and then drives towards it. Assume the sensors are uniformly scattered in the region V, the centroid can be calculated with (7). Given region V, sensor positions $q_i \in V$, actuator positions $p_i(k)$, the algorithm to build CVT can be represented as Algorithm 1.

Algorithm 1 (Discrete CVT algorithm).
Load the initial actuator positions $p_i(0) \in V$;
Load the initial sensor positions $q_j \in V$;
While convergence criterion not satisfied **do**
  For every sensor q_j **do**
    find the nearest actuator $p_i(k)$;
    send signal to p_i to indicate $q_j \in V_i$;
  End for
  Each robot calculate the mass centroid $p_i^*(k)$;
  Each robot drives to $p_i^*(k)$;
  $k = k + 1$
End while

The actuators do not maintain a diffusion function locally. All the sensory information about the region V_i is obtained from the wireless sensors in V_i. The Voronoi tessellation and the sensor-actuator connections update dynamically. The algorithm do not give the Voronoi tessellation explicitly, but every actuator is capable to calculate the mass centroid, with the local information inside its Voronoi cell.

Given the centroid of a Voronoi cell as p_i^*, the error is defined as $e_i = p_i^* - p_i$. The actuator is driven by a PD controller

$$u_i(t) = k_p e_i(t) + k_d \dot{e}_i(t) \tag{8}$$

The actuators are modeled by the ordinary second-order dynamics. The initial acceleration and velocity are both set to 0. The control input will be the acceleration of the actuators. The CVT position configuration can help the actuators explore the polluted region. However, it cannot guarantee the actuators to share a common workload in large scale (see Section 4). The following section will discuss how to utilize the network connection information to achieve a consensus on actuators′ workload.

3 Workload balancing

This section focuses on how to balance the actuators′ workload and how to resolve the conflict between uncertainty minimizing and workload assignment. The basic idea is to share information among actuators through connection between them.

The MAS-net includes both eternal and temporary connections among agents. The connection between a sensor and its nearest actuator is a temporary one. There exists a network among actuators which will be hold during the execution of the task. It guarantees a spanning tree, which is an necessary condition for a network to reach consensus. It also provides a few long range connections even when two actuators are far away from each other. These links are eternal ones. Temporary connections between actuators could be built when two of them are neighbors according to the CVT.

The sensor network can provide information about the polluted field. The density (sensor reading) is larger when it is nearer to the pollution sources, smaller when it is further from the sources. The mass weight of a Voronoi cell may represent the workload of an actuator. The consensus on weight indicates that the actuators in system share a common workload.

The basic strategy to reach consensus is to let one actuator "encroach upon" its neighbor actuator′s Voronoi region, if its workload is smaller than its neighbor′s. The action is simple — drive towards it. The neighbor information is obtained through the connection between actuators, including eternal links and temporary ones. There are two essential problems: when to encroach and what to do if it interrupts the CVT positioning configuration. The proposed method invokes the consensus procedure with a probability. This probability converges to zero as the workload approaches consensus. Given the graph $A = \{a_{ij}\}_{n\times n}$ which underlays the actuator network, $a_{ij} = 1$ if actuator i and j are connected. $a_{ii} = 1$. Let N_i denote the neighbors of actuator i, $j \in N_i$ if $a_{ij} > 0$. Thus, actuator i is a neighbor of itself. The position of actuator i is denoted by p_i. The consensus procedure can be represented as Algorithm 2.

Algorithm 2 (Workload consensus algorithm).
For each actuator i **do**
  Find the neighboring cell with maximal workload in N_i;
  Mark it as $p_{\max}$, and set $V_m = V_{p_{\max}}$;
  Randomly generate a positive number $\rho^i \in (0, 1)$;
  If $\rho^i > \rho_0^i$ **then**
    $u_i(t) = k_p e_i(t) + k_d \dot{e}_i(t)$;

Else

$$u_i(t) = k_p(p_m(t) - p_i(t)) + k_d \frac{\mathrm{d}(p_m(t) - p_i(t))}{\mathrm{d}t};$$

End if

End for

The symbol $\rho_0^i \in (0,1)$ is the threshold for an actuator to choose its action. It is determined by the following equation:

$$\rho_0^i = \frac{|\Delta M|}{M_{V_i}} = \frac{|M_{V_m} - M_{V_i}|}{M_{V_i}} \tag{9}$$

If $\rho^i > \rho_0^i$, the actuator will handle the CVT driven movement. Otherwise it will move towards the neighbor with the maximal workload. Obviously, when the neighboring actuators are of the same weight, $\rho_0^i = 0$. The consensus algorithm will stop driving any actuator towards another. The workload balance strategy is a perturbation on the CVT algorithm. It drives the actuator away from the CVT configuration. Therefore, the encroach movement cannot be too fast. In fact, Algorithm 2 only determines the direction that actuator moves. The control will be terminated when the workload of actuators are the same. Such perturbation effect helps the CVT configuration to jump out of the local optimal, heading to a lower value of uncertainty.

4 Simulations

Numerical simulations are conducted to validate the proposed methods. A group of actuators will search the square area, and configure themselves onto positions which minimize the information uncertainty. An exponential function is employed as the density function describing the pollution sources. For a pollution resource located at μ_j, the density is

$$\phi_j(q) = 0.6 \exp\left\{-10(q - \mu_j)^2\right\}$$

Then, the density function over the whole field V with 4 pollution sources is

$$\phi(q) = \sum_{j=1}^{4} \phi_j(q)$$

In the real world applications, sensors may not detect a signal smaller than a certain value. Let s_0 denote such threshold. In the following simulations, s_0 is set to 0.1.

The simulation initial positions can be seen in Fig. 1. The stars indicate the pollution sources. Four sources are located in the environment. They can move within the region $V : (0,1) \times (0,1)$. Their initial positions are $\{(0.3, 0.3), (0.3, 0.7), (0.7, 0.3), (0.7, 0.7)\}$. There are 12 robots executing the tracking and neutralizing task, which are initially located in the region of $(0, 0.2) \times (0, 0.2)$, and indicated by circles. In the simulations, the initial conditions in each run are set the same as is shown.

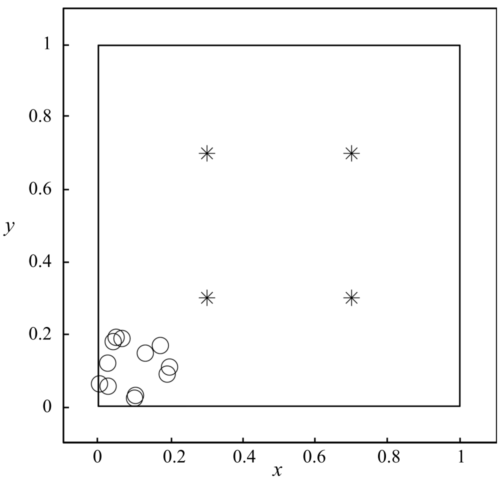

Fig. 1 The initial settings of simulations

4.1 CVT positioning configuration

The pollution sources are first set to be static to test the construction process of CVT. They are located at the initial positions.

The CVT configuration is satisfied, although workload of actuators are not balanced yet. Fig. 2 shows that the actuators′ distance from the centroids converges to 0. That means the CVT positioning configuration is achieved. The final actuator positions generated by the proposed CVT algorithm can be seen in Fig. 3. The actuators gathered to several groups due to Fig. 4, which represents the projection of agent positions on unit square. The dashed lines indicate the boundary of Voronoi cells. The left-bottom source (denoted by a star) attracted 6 actuators around it. Meanwhile, there are only 1 or 2 actuators tracking the other pollution sources. The actuator close to the left boundary does not supervise any of the sources. In fact, its workload is 0, which means the sensor readings in its Voronoi cell all equal 0.

As shown in Figs. 5 and 6, the sensing uncertainty H_1 and the workload difference H_2 both hold pretty high values for pure CVT position configuration.

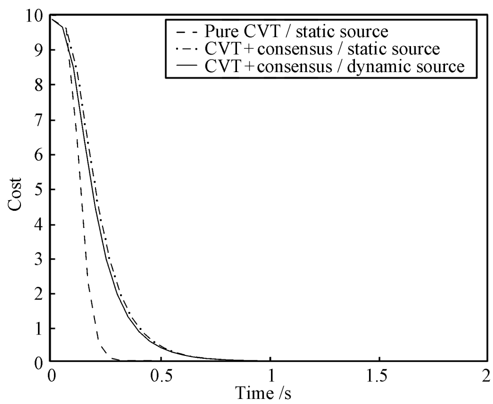

Fig. 2 The distance between actuators and centroids

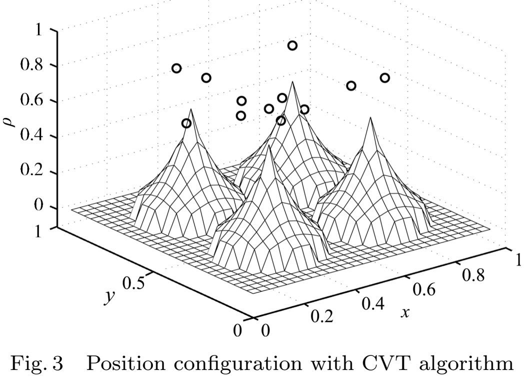

Fig. 3 Position configuration with CVT algorithm

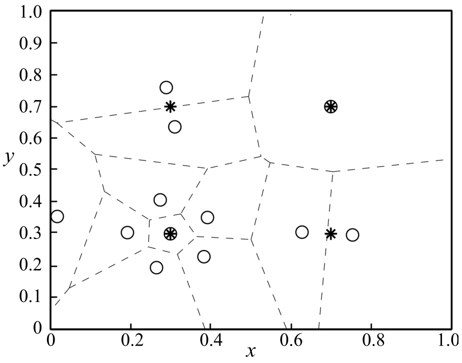

Fig. 4 The 2D projection of CVT configuration

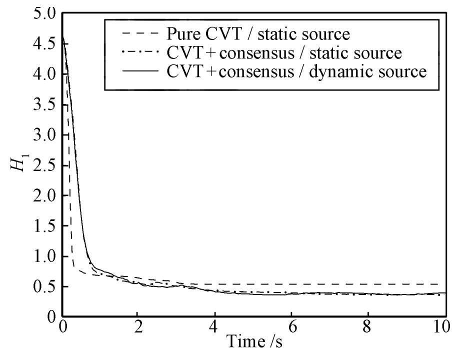

Fig. 5 The information uncertainty

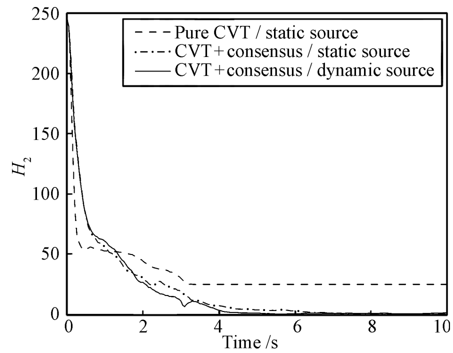

Fig. 6 The workload divergence

A simulation on the CVT construction scheme of [18] is also conducted. The control law over actuators is modified, in order to set the comparison under the same scale. The initial conditions and the Simulink setting are inherited from the MAS-net platform. The position configuration, as is expected, is exactly the same as the result of the proposed CVT construction. The interpretation is simple: both algorithms are driven by the centroids of Voronoi cells. The only difference is time cost on the simulation. The method in [18] takes roughly 10 % more time to finish the simulation. The calculation on Voronoi boundaries leads this difference. The test on the algorithm in [18] is conducted under the assumption that the actuators know the density distribution in its Voronoi cell, or it can obtain the sensor readings with in its Voronoi cell.

4.2 CVT with balanced workload

Both static and dynamic pollution sources are discussed. Algorithm 2 provides the control law of actuators. The workload of actuators reaches consensus while the CVT configuration is satisfied. In Fig. 5, the information uncertainty reaches lower value than the pure CVT algorithm. The same is the conclusion on the workload difference.

The final positions of actuators chasing dynamic pollution sources are represented in Figs. 7 and 8. Every three actuators form a triangle around a pollution source. All the actuators participate in the tracking task and share a balanced workload (Fig. 6). Although the pollution sources tried actively to escape, the actuators still organized a circle-like formation around them. The point is, the workload is shared equally by all the actuators. The edges between actuators in Fig. 8 represent the topology of the initial network. The network is built by B-A model[27] based on a complete graph with three nodes. According to the observations, a non-complete graph provides better performance on the consensus scheme. A complete graph of 12 actuators introduces oscillation. Another reason for oscillation is the switching strategy between CVT positioning algorithm and the workload consensus scheme. By following the consensus algorithm, the actuator may deviate from the CVT configuration. However, such behavior turned out to be a perturbation on local optimal, and further reduced the information uncertainty. Such deviation can be eliminated by CVT algorithm after the consensus on workload is constructed. Of course, there will be several actuators moving back and forth between sources if the actuator number cannot be exactly divided by the number of pollution sources.

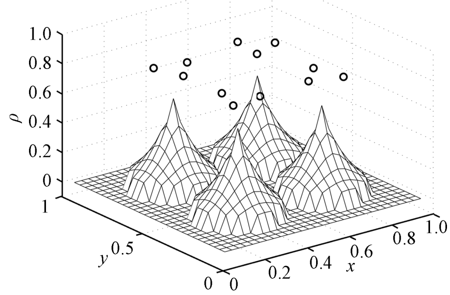

Fig. 7 Position configuration with CVT and consensus scheme

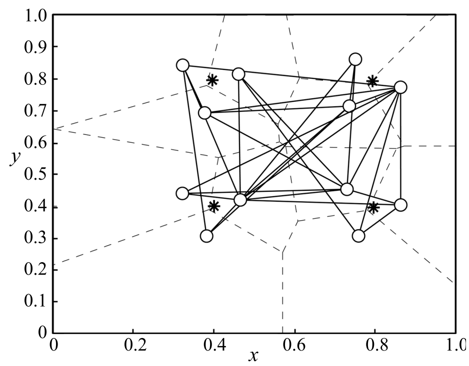

Fig. 8 The 2D projection of CVT + consensus configuration. The solid edges represent the connection between actuators.

Figs. 5 and 6 show that the information uncertainty H_1 and workload difference H_2 can both be further reduced by combining consensus protocol with CVT positioning algorithm.

5 Conclusions

The paper discusses the application of MAS-net on poisonous gas tracking and neutralizing mission. A CVT algorithm combined with consensus strategy is introduced to minimize information uncertainty while balancing the workload among actuators. CVT positioning algorithm configures the actuators on the local optimum of information uncertainty, but cannot balance their workload. It does not calculate the boundaries explicitly. The sensor information is extracted to the centroid position of the Voronoi cell directly. The consensus on the weight of Voronoi cells offers a path to a common workload among actuators. The proposed method utilizes the connections among actuators. It has much better performance on workload assignment, and can further reduce the information uncertainty than the pure CVT algorithm.

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