Coverage control with information aggregation

Wen Jiang and Miloš Žefran

Abstract—The aim of this paper is to incorporate information aggregation into coverage control for mobile sensor networks. In this scenario, the mobile sensor nodes serve a geographical region but in addition also communicate with a mobile sink node that aggregates the information. Finding the optimal sensor location for coverage with information aggregation is formalized by adding an appropriate term to the traditional coverage cost. We prove that the optimal partition of the space given locations of all sensor nodes is the power diagram and derive explicit expressions for the equilibrium location for all sensor nodes, including the sink node. We also design a gradient-descent motion control algorithm that drives all sensor nodes to an equilibrium configuration from arbitrary initial configuration. Numerical simulations that demonstrate the effectiveness of our proposed motion control algorithm are also provided.

I. INTRODUCTION

For mobile sensor networks, coverage is one of the most important tasks [1]–[3]. In coverage, each sensor node is responsible for sensing in its own region. Locational optimization has been identified as a convenient framework to address this problem [2], [4]–[8]. In their seminal paper [1], the authors show that optimal sensor coverage can be formulated as a minimization problem, where an appropriate cost function is minimized with respect to the partition of the space and the locations of the sensor nodes. The formulation naturally led to the Lloyd-type gradient-descent algorithm that achieves optimal sensor coverage. Several extensions of the original coverage control problem have been proposed [9]–[13].

Energy efficiency of coverage algorithms is another important concern. An energy-efficient deployment algorithm for the mobile sensors is proposed in [14]. In [15], agents with higher power are assigned to regions with larger area. In [16], the authors propose a distributed coverage control law that maximizes the joint detection probability of an event happening in the area while minimizing the energy consumed by the sensors sending the information from their detection range to a fixed sink via a wireless antenna. Further extensions are proposed in [17]. In the optimal network configuration, the perception areas of neighboring sensors overlap with each other and the sink node receives redundant information. In most coverage applications, each sensor dominates its unique subregion and there is no sensing overlap. The latter is more natural for facility location problems, where each point in an area needs to be served by at least one network node but the service quality does not improve when it is served by multiple nodes [1], [11]. For example, two charging stations that are equally far away from a robot do not improve the robot’s ability to recharge.

In our work, we consider a group of mobile sensors monitoring an area for events whose occurrence is governed by a probability density function $\phi$. The nodes send the information they collect to an aggregation (sink) node. The space is partitioned into subregions so that every point in the area is monitored by one sensor. Within its subregion, each sensor node collects the information about the occurrence of an event and sends the information to a mobile sink node. We try to minimize the total cost of both coverage and information aggregation for the network. Motivated by the cost of wireless communication in [16], we model the cost of sending the information from a sensor node to the sink node as a product of the amount of information within the subregion and the distance between the sensor node and the sink node. We minimize the combined cost of coverage and information aggregation with respect to both the partition of the space and the locations of all sensor nodes. We analytically determine the equilibrium configurations for all sensor nodes, including the mobile sink node. We also determine the optimal partition of the space given the locations of the sensor nodes. Using these results, we propose a gradient-descent algorithm that drives all the nodes, including the mobile sink node, to an equilibrium configuration from an arbitrary initial configuration.

II. PRELIMINARIES

In this section, we first review the power diagram following [5]. We then define the cost of information aggregation for mobile sensor networks in terms of the partition of the space, the density function over the space and the locations of all sensor nodes.

A. The power diagram

Partitioning a non-empty space $\Omega$ with $n$ generators located at $G = [g_1, g_2, \cdots, g_n]$ is equivalent to finding an assignment rule $\delta(q, g_i)$ for every point $q \in \Omega$ as a mapping from $\Omega \times G$ to $\{0, 1\}$, such that

$$
\delta(q, g_i) = \begin{cases} 
1 & \text{if } d(q - g_i) \leq d(q - g_j), j \neq i, \\
0 & j \in [1, 2, \cdots, n], \\
\text{otherwise.} & 
\end{cases}
\tag{1}
$$

where $d(\cdot)$ is a non-negative and non-decreasing function that measures the distance from $q$ to $g_i$. Under the assignment rule (1), the set of points assigned to $g_i$ is

$$
S(g_i) = \{ q \mid \delta(q, g_i) = 1, q \in \Omega \}.
$$

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W. Jiang and M. Žefran are with the Department of Electrical and Computer Engineering, University of Illinois at Chicago, Chicago, IL 60607, USA. Email: {wjiang9,mzefran}@uic.edu.
For the Voronoi diagram, the distance function is chosen to be \(d(\cdot) = ||\cdot||\), the Euclidean distance function:

\[
\delta_V(q, g_i) = \begin{cases} 
1 & \text{if } ||q - g_j|| \leq ||q - g_j||, j \neq i, \\
& j \in [1, 2, \cdots, n], \\
0 & \text{otherwise}. 
\end{cases}
\]

The set of points assigned to \(g_i\) is called the Voronoi cell generated by \(g_i\) and denoted by \(V(g_i)\).

The power diagram is a generalization of the Voronoi diagram where the Euclidean distance is generalized to the additively weighted power distance. Accordingly, the assignment rule becomes

\[
\delta_{PW}(q, g_i, w_i) = \begin{cases} 
1 & \text{if } ||q - g_j||^2 + w_i \leq ||q - g_j||^2 + w_j, j \neq i, \\
& j \in [1, 2, \cdots, n], \\
0 & \text{otherwise}. 
\end{cases}
\]

where \(w_i\) is the weight assigned to the \(i\)th generator. Under the assignment rule (2), the power cell generated by the \(i\)th generator is

\[
V_{PW}(g_i) = \{q \mid \delta_{PW}(q, g_i, w_i) = 1, q \in \Omega\}.
\]

Remark 1: Properties of the power diagram are different from those of the Voronoi diagram. A power cell \(V_{PW}(g_i)\) may be empty. But if the set \(V_{PW}(g_i)\) is not empty, it is a convex polygon. Also, under some choices of the weights \(w_i\), the generator of the set \(V_{PW}(g_i)\) might not be located in \(V_{PW}(g_i)\).

B. The cost of information aggregation

We study the case where in addition to coverage, nodes also need to send the measured information to a sink node, where the information is aggregated. For example, when a sensor network is used to monitor seismic activity over an area of interest, each node not only detects seismic waves within its region of interest but also sends the information about the seismic activity to a central sink node where data processing takes place.

We next model the cost of information aggregation from local nodes to the sink node. Suppose we have \(n\) nodes and one sink node performing a sensing task over a convex area \(\Omega\). We denote their locations by \(P = [p_0, p_1, p_2, \cdots, p_n]\), where \(p_0\) corresponds to the sink node. The probability density function describing how often an event happens over \(\Omega\) is \(\phi(q)\). Let \(W = [W_0, W_1, W_2, \cdots, W_n]\) be a partition of \(\Omega\) where \(W_i\) is the subregion monitored by the node \(i\). Suppose all sensor nodes communicate with the sink node directly. The cost of information aggregation from sensor nodes to the sink is thus,

\[
J_{agg}(P, W) = \sum_{i=0}^{n} \left( d(p_i - p_0) \cdot \int_{W_i} \phi(q) dq \right),
\]

where \(d(\cdot)\) is a non-negative and non-decreasing distance function. According to (3), the cost of information aggregation for the \(i\)th node is thus proportional to: (a) the cumulative probability of the subregion \(W_i\), which is \(\int_{W_i} \phi(q) dq\), and (b) the distance \(d(p_i - p_0)\) of the sensor node \(p_i\) from the sink node \(p_0\).

Remark 2: According to the definition (3), the sink node also performs sensing. If the sink node only aggregates the information received from the other sensor nodes, the cost function (3) becomes

\[
J_{agg}(P, \tilde{W}) = \sum_{i=0}^{n} \left( d(p_i - p_0) \cdot \int_{\tilde{W}_i} \phi(q) dq \right),
\]

where \(\tilde{W} = [W_1, W_2, \cdots, W_n]\) is the partition of \(\Omega\). Since \(d(0) = 0\), the only difference between the two definitions is in the partition of the space, where in \(\tilde{W}\) the subregion monitored by the sink node is empty. In the rest of the paper we will use the cost function (3).

III. Equilibrium analysis of coverage with information aggregation

In [1], the coverage problem has been formulated as a minimization problem and the equilibrium configuration for this problem has been shown to be the centroidal Voronoi diagram. In this section, we consider the minimization problem that results when in addition to coverage, the sensor nodes communicate the information about their subregions to a mobile sink node. In this case, the natural cost to consider is a combination of coverage and information aggregation; both of these depend on the partition of the space and the locations of all sensor nodes. We compute the gradient of the cost function with respect to sensor locations and determine the optimal partition of the area \(\Omega\) as well as the equilibrium locations of the sensor nodes.

A. Minimization problem formulation

As noted above, we consider the task where mobile sensors monitor an area for the occurrence of an event and send the gathered information to a sink node that also moves. Regardless whether the sink node performs sensing or not, is mobile or fixed, the problem is to find the optimal partition of the space and the optimal locations of all the sensor nodes (including the sink node) that minimize a cost function that combines both coverage and information aggregation.

Problem statement: Assume \(n\) mobile sensors and a sink node are monitoring an area \(\Omega\) for the occurrence of an event governed by a positive density function \(\phi(q)\). Let \(p_i\) be the location of the \(i\)th mobile sensor, \(p_0\) the location of the sink node and \(W = [W_0, W_1, \cdots, W_n]\) be a partition of \(\Omega\). Let the coverage cost be

\[
J_{cov}(P, W) = \sum_{i=0}^{n} \int_{W_i} d(q - p_i) \phi(q) dq
\]

and the information aggregation cost be

\[
J_{agg}(P, W) = \sum_{i=0}^{n} \left( d(p_i - p_0) \cdot \int_{W_i} \phi(q) dq \right).
\]
The coverage control with information aggregation problem is then to determine a partition \( W = [W_0, W_1, \cdots, W_n] \) of \( \Omega \) and locations \( P = [p_0, p_1, \cdots, p_n] \) that minimize a cost function:

\[
\min_{P,W} J(P, W),
\]

where \( J = J_{cov} + \alpha J_{agg} \).

Remark 3: The coverage cost and the information aggregation cost do not necessarily have the same units of measurement. The constant \( \alpha \) in the combined cost function normalizes the aggregation cost with respect to the coverage cost. When the coverage cost dominates the combined cost, \( \alpha \) will be a small number, and vice versa. Note that if \( \alpha = 0 \), the problem turns into the regular coverage problem. If \( \alpha = \infty \), the optimal configuration corresponds to all sensor nodes located at the location of the sink node, i.e., \( p_i = p_0 \) for \( i = 1, 2, \cdots, n \).

B. Gradient of the cost with respect to sensor locations

First, we define two quantities for the \( i \)th subregion \( W_i \): the mass \( M_i = \int_{W_i} \phi(q) dq \), and the centroid \( C_i = \frac{1}{M_i} \int_{W_i} q \phi(q) dq \). Assuming that \( d(\cdot) = ||\cdot||^2 \), the combined cost function becomes

\[
J(P, W) = J_{cov}(P, W) + \alpha J_{agg}(P, W) = \sum_{i=0}^{n} \int_{W_i} \left( ||q - p_i||^2 + \alpha ||p_i - p_0||^2 \right) \phi(q) dq
\]

The partial derivative of (5) with respect to the location of all sensor nodes \( P \) is

\[
\nabla J = \left[ \frac{\partial J(P, W)}{\partial p_0}, \frac{\partial J(P, W)}{\partial p_1}, \cdots, \frac{\partial J(P, W)}{\partial p_n} \right].
\]

To compute the gradient, we thus need to compute the partial derivatives of (5) with respect to locations of both sensor nodes and the sink node when the partition of the space is fixed to be \( W \).

The partial derivative of (5) with respect to the location of the sink node \( p_0 \) is

\[
\frac{\partial J(P, W)}{\partial p_0} = \sum_{i=0}^{n} \int_{W_i} \frac{\partial}{\partial p_0} \left( ||q - p_i||^2 + \alpha ||p_i - p_0||^2 \right) \phi(q) dq
\]

\[
= \int_{W_0} 2(p_0 - q)\phi(q) dq + \sum_{i=1}^{n} \int_{W_i} 2\alpha(p_0 - p_i)\phi(q) dq
\]

\[
= 2p_0M_0 - 2C_1M_1 + \sum_{i=1}^{n} 2\alpha(p_0 - p_i)M_i
\]

\[
= 2p_0 \left( M_0 + \alpha \sum_{i=1}^{n} M_i \right) - 2 \left( C_0M_0 + \alpha \sum_{i=1}^{n} p_iM_i \right).
\]

The partial derivative of (5) with respect to the location of the \( i \)th sensor node \( p_i \) is

\[
\frac{\partial J(P, W)}{\partial p_i} = \sum_{i=0}^{n} \int_{W_i} \frac{\partial}{\partial p_i} \left( ||q - p_i||^2 + \alpha ||p_i - p_0||^2 \right) \phi(q) dq
\]

\[
= \int_{W_i} 2(p_i - q)\phi(q) dq + \sum_{j=1}^{n} \int_{W_j} 2\alpha(p_i - p_j)\phi(q) dq
\]

\[
= 2p_iM_i - 2C_iM_i + \sum_{j=1}^{n} 2\alpha(p_i - p_j)M_j
\]

\[
= 2p_i \left( \sum_{i=1}^{n} M_i \right) - 2 \left( C_iM_i + \alpha \sum_{j=1}^{n} p_jM_j \right).
\]

C. Optimizing coverage and information aggregation

In order to minimize the combined cost function \( J(P, W) \) over the space \( \Omega \), we need to determine both the optimal partition of the space \( W^* \), and the optimal locations of all sensor nodes \( P^* \).

First, we derive the optimal partition of the space given the locations of all sensor nodes \( P = [p_0, p_1, \cdots, p_n] \). Solving the minimization problem

\[
\min_{P} J(P, W)
\]

given \( P = [p_0, p_1, \cdots, p_n] \) is equivalent to finding an assignment rule (1) associated with a proper distance function for \( \forall q \in \Omega \). Note that the combined cost function (5) integrates the quantity

\[
\left( ||q - p_i||^2 + \alpha ||p_i - p_0||^2 \right) \phi(q)
\]

over \( \Omega \) and the density function \( \phi(q) \) is given. By denoting \( \alpha||p_i - p_0||^2 \) by \( \omega_i \), the partition minimizing the combined cost function (5) when the locations of all sensors nodes \( P \) are given is given by the assignment rule

\[
\delta(q, p_i) = \begin{cases} 1 & \text{if } i = \text{arg min}_j ||q - p_j||^2 + \omega_j, \\ 0 & \text{otherwise}. \end{cases}
\]

Comparing to the assignment rule (2), we conclude that the partition that minimizes the combined cost function when the locations of all sensor nodes are given is precisely the power diagram, \( W_i^* = \{ q \in \Omega | ||q - p_i||^2 + \omega_i \leq ||q - p_j||^2 + \omega_j, j \neq i \} \).

Second, we derive the optimality conditions for the locations of all sensor nodes when the partition of the space \( W = [W_0, W_1, \cdots, W_n] \) is fixed. The optimization problem is

\[
\min_{P} J(P, W)
\]

given \( W = [W_0, W_1, \cdots, W_n] \). The first order necessary condition for the locations to minimize \( J(P, W) \) is \( \nabla J = 0 \). Based on the partial derivatives computed in equations (6) and (7), we compute the equilibrium locations by setting partial derivatives to zero. Moreover, the second order sufficient optimality condition is that the Hessian matrix \( \nabla^2 J \) is positive definite. Given \( W = [W_0, W_1, \cdots, W_n] \), the
Hessian matrix $\nabla^2 J$ is
\[
2 \begin{pmatrix}
M_0 + \alpha \sum_{i=1}^{n} M_i & -\alpha M_1 & \cdots & -\alpha M_n \\
-\alpha M_1 & (1 + \alpha) M_1 & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
-\alpha M_n & 0 & \cdots & (1 + \alpha) M_n
\end{pmatrix}
\]
We check the $k^{th}$ leading principal minor of $\nabla^2 J$
\[
2^k \left( M_0 + \alpha \sum_{i=1}^{k} M_i \right) \prod_{i=1}^{k} \left( \frac{(M_0 + \alpha \sum_{i=1}^{k} M_i)^2 - \alpha^2 M_i^2}{M_0 + \alpha \sum_{i=1}^{k} M_i} \right)
\]
which is clearly positive since $M_i > 0, \forall i \in \{0, 1, \cdots, n\}$.
Therefore, the Hessian matrix is positive definite which guarantees that the critical locations are minima. By setting the gradient $\nabla J = 0$, we get that the locations of the sink node and the mobile nodes that minimize the cost function $J(P, W)$ are
\[
p_0 = \frac{C_0 M_0 + \alpha \sum_{i=0}^{n} C_i M_i}{M_0 + \alpha \sum_{i=1}^{n} M_i}
\]  
(9)
and
\[
p_i = \frac{C_i + \alpha p_{0}^*}{1 + \alpha}
\]  
(10)

**Remark 4:** The constant $\alpha$ in the cost function reflects how important the cost of information aggregation is compared with the cost of coverage. In the optimal solution (10), the constant $\alpha$ affects $p_i^*$ in a straightforward way. A small $\alpha$ means that the coverage cost dominates the combined cost. Thus, the optimal solution will be close to the regular coverage solution in [1]. Conversely, a large $\alpha$ means that the information aggregation cost dominates the combined cost. As a result, the optimal solutions will be close to the sink node.

Note that equations (9) and (10) are coupled. However, we can get the decoupled solutions by solving equations (10) and (9) to obtain
\[
p_0^* = \frac{C_0 M_0 + \alpha \sum_{i=0}^{n} C_i M_i}{M_0 + \alpha \sum_{i=0}^{n} M_i}
\]  
(11)
and
\[
p_i^* = \frac{M_0(C_i + \alpha C_0)}{1 + \alpha}
\]  
(12)

**IV. Motion Control for Optimizing Coverage and Information Aggregation**

In this section, we describe a discrete-time Lloyd-like iterative motion algorithm that drives all sensor nodes from arbitrary initial locations to the optimal locations that minimize the combined cost function $J(P, W)$. We prove that under our motion control algorithm, the combined cost function decreases iteration by iteration and converges to a local minimum.

**Remark 5:** Given locations of all sensor nodes, the partition that minimizes the combined cost is the power diagram generated by the sensor nodes, while given the partition of the space, the locations of all sensor nodes that minimize the combined cost are given by equations (11) and (12). Therefore, when we say the partition, $W^*$, and the locations, $P^*$ are optimal, it means the partition generated by the current locations of all sensor nodes is the power diagram and the current locations satisfy optimality conditions (9) and (10). Under the optimal $W^*$ and $P^*$, the combined cost function $J(P^*, W^*)$ reaches a local minimum. The optimal partition and locations are not unique. There may be other power diagram $W'$ and locations $P'$ satisfying optimality conditions (9) and (10). How to reach the global minimum is a known open problem, see Remark 3.2 in [1] and also [2].

The discrete-time motion algorithm is a Lloyd-like iterative algorithm. In the $k^{th}$ iteration, all sensor nodes maintain their power diagrams $W_i^k$ first. Then, all sensor nodes compute $C_i^k$ and $M_i^k$ and report them to the sink node. The sink node moves to a new location computed by (11) and broadcasts the new location to all sensor nodes. Finally, all sensor nodes move to the new locations computed by equation (10).

**Remark 6:** Though we have a decoupled solution to $p_i^*$ in (12), we still use equation (10) to compute the optimal location of $p_i^*$ because the solution (10) requires the mass and the center of mass of all other nodes in the network. Instead, if solution (10) is used to compute $p_i^*$, the node just needs to get $p_0^*$ from the sink to finish the computation, which is more efficient.

**Algorithm 1** The iterative motion algorithm for coverage and information aggregation control in mobile sensor networks

**Require:** Iteration $k$, mobile sensor $i$, location $p_i^k$, $i \in [0, 1, \cdots, n]$

1: Maintain power diagram cells $W_i^k$
2: All sensor nodes and the sink compute $C_i^k$ and $M_i^k$
3: All sensor nodes report $p_i^k$ and $M_i^k$ to the sink
4: The sink moves to $p_{0}^{k+1}$ computed by (11)
5: The sink broadcasts $p_{0}^{k+1}$ to all sensor nodes
6: All sensor nodes move to $p_{i}^{k+1}$ computed by equation (10)
7: $k = k + 1$

**Theorem 1:** If the motion of all sensor nodes follows Algorithm 1, the combined cost function $J(P, W)$ decreases in every iteration and converges to a local minimum.
Proof: Denote the partition and the locations of all sensors nodes at the beginning of the $k$th iteration by $W^{k-1} = [W_0^{k-1}, W_1^{k-1}, \ldots, W_n^{k-1}]$ and $P^{k-1} = [p_0^{k-1}, p_1^{k-1}, \ldots, p_n^{k-1}]$ respectively, where $W_0$ and $p_0$ are associated with the sink node. Accordingly, the cost function at the beginning of the $k$th iteration is $J(W^{k-1}, W^{k-1})$.

First, we prove the convergence. In the $k$th iteration, the algorithm first determines the power diagram $W^k = [W_0^k, W_1^k, \ldots, W_n^k]$ by the assignment rule (2) that minimizes $J(P^{k-1}, W^k)$. Hence, $J(P^{k-1}, W^k) < J(P^{k-1}, W^{k-1})$. Then, the algorithm drives all sensor nodes to the new locations $P^k$ computed by equations (11) and (10). During the motion, the partition of the space remains unchanged. Hence, according to the optimality conditions, $J(P^k, W^k) < J(P^{k-1}, W^k)$. We conclude that the cost function decreases in each iteration, $J(P^k, W^k) < J(P^{k-1}, W^{k-1})$.

Note that the cost function integrates quantity (8) for all $q \in \Omega$. Since the density function $\phi(q) > 0$, the quantity (8) is positive everywhere except at the location of the sink node $p_0$. Hence, the cost function $J(P, W)$ is also positive over the non-empty area $\Omega$. Therefore, the cost function converges based on the fact that it is positive and it decreases iteration by iteration.

Second, we prove that under the motion algorithm 1, the cost function converges to a local minimum. Suppose the cost function converges to $J(P^*, W^*)$. Due to the convergence, for an arbitrary small number $\epsilon$, we have a positive number $N$ such that when $t > N$, $||J(P^k, W^k) - J(P^*, W^*)|| < \epsilon$. If $J(P^*, W^*)$ is not a local minimum, then there exists $M > N$ such that for the same $\epsilon$ we choose, $||J(P^M, W^M) - J(P^N, W^N)|| > \epsilon$, which contradicts the convergence itself. Therefore, the cost function converges to a local minimum.

V. Simulations

In this section, we provide a simulation for nine sensor nodes (including one sink node) to achieve an optimal sensing configuration in a unit square $\Omega = [0, 1] \times [0, 1]$. The initial locations of all sensor nodes are randomly chosen in the bottom left corner $[0, 0.4] \times [0, 0.4]$. The sink node performs sensing and is free to move. We run 50 iterations to show that under our motion algorithm, all sensor nodes reach an optimal partition and the locations that minimize the cost function $J(P, W)$. We also show that the cost function $J(P, W)$ monotonically decreases and converges to a local minimum. The density function we use in the simulation is a constant plus a Gaussian distribution, $\phi(x, y) = 0.1 + 2e^{-0.75[(x-3)^2+0.75(y-3)^2]}$. The constant $\alpha$ in the cost function is 0.2 during the simulation. We limit the maximum step for each node within a single iteration to 0.05, which is $1/20$ of the length of the side.

Fig. 1 shows the initial locations of all sensors nodes. The red pentagram and colored dots represent the locations of the sink node and other mobile sensor nodes, respectively. Fig. 2 shows the optimal sensing configuration and how sensor nodes achieve it starting from their initial locations. Black lines are boundaries of neighboring power diagram cells. Blue lines show the trajectories of all sensor nodes before they reach optimal locations. The dark area in the background shows the contour of the density function. The cost function decreases monotonically in each step. After 25 iterations, the decrease falls below $10^{-4}$ and the cost function converges to $1.416 \times 10^{-2}$.

We compare different optimal sensing configurations achieved by the network given different values of the constant $\alpha$. As we discussed in Remark 4, a small $\alpha$ results in more Voronoi-like partition and a large $\alpha$ forces the sensor nodes to be deployed much closer to the sink node. Sometimes the sink may go out of the subregion it dominates. Figures 3 and 4 show the final partition and locations of all sensor nodes when the information aggregation cost is weighed heavily, $\alpha = 0.5$ and 0.8 respectively. In Figure 3, the yellow and cyan nodes are almost on the boundary of their dominant subregions. While in Figure 4, the yellow and cyan nodes tend to be closer to the sink node and even leave their dominant subregions.

VI. Conclusion

In this paper, we study the problem where in addition to coverage, a sensor network needs to aggregate the gathered information. First, we formally model the cost of information aggregation in mobile sensor networks. We then consider the problem where the network needs to minimize a linear combination of the coverage cost and the information aggregation cost. We show that under fixed locations of all sensor nodes, the power diagram is the optimal partition of the space that minimizes the combined cost function. We derive explicit expressions for optimal sensor and sink locations given the partition of the space. Also, we present a Lloyd-like discrete-time motion control algorithm that drives all sensor nodes to an optimal sensing configuration starting from any initial location. We also prove that the proposed motion control algorithm drives the combined cost function to a local minimum. A problem that remains unsolved is how to reach a globally optimal solution. Another issue with the proposed approach is that for larger values of $\alpha$, sensors may not be located in their corresponding subregions. While this may not be a problem in facility location problems, it could be problematic in sensing applications. This phenomenon thus also warrants additional research.

REFERENCES

Fig. 1. The initial locations of all sensor nodes.

Fig. 2. Evolution of the sensor locations and the optimal sensing configuration when $\alpha = 0.2$.

Fig. 3. Evolution of the locations of all sensor nodes and the optimal sensing configuration when $\alpha = 0.5$.

Fig. 4. Evolution of the locations of all sensor nodes and the optimal sensing configuration when $\alpha = 0.8$.


