Team-based Coverage Control of Moving Sensor Networks with Uncertain Measurements*

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Abstract— **This paper addresses the problem of deploying teams of heterogeneous agents to cover a given environment, where individual agents have access to inaccurate position (measurement) of other agents. Due to their heterogeneity, different uncertainty regions are considered for the agents. A team-based approach is proposed here to minimize an objective function, defined with respect to the probability of events to occur in the environment. The main goal is to take into account inaccurate position information in the design of a control strategy, which is robust and can hence avoid a significant degradation in the coverage performance. To this end, the minimum of all possible distances between agents is considered as the modified distance measure. The immediate consequence of the uncertainty in the agent localization is that the environment is partitioned among teams to avoid overlapping of assigned regions to neighboring teams. The regions assigned to teams is then partitioned among members by implementing a control law with respect to the modified distance measure for avoiding collision. Finally, numerical simulation results examine the effectiveness of the proposed robust team-based partitioning method. Two examples are provided, each of which focuses on a different aspect of heterogeneity in the presence of uncertainty in the data available to the agents.**

I. Introduction

Numerous applications such as environmental monitoring, surveillance, search, data collection, and sensing require distributive deployment of a group of agents to perform an assigned task [1], [2], [3]. The main challenge in the deployment is a mindful distribution of the assigned workload among agents reliably and efficiently. A control strategy is designed by a gradient descent-based method to minimize the coverage cost function for the assigned environment [4]. This distributed control law calculates local optimal location of agents using Voronoi-based partitioning. This framework is extended to take into account more realistic constraints in deploying agents like collision avoidance, multiple regions of interest, non-convex environments, time-varying environments, and heterogeneous agents [5], [6], [7], [8], [9].

The present approaches in coverage control assume that the agents belong to a single team. However, this assumption may not hold in cases where the agents have different dynamics and communication capabilities. In fact, depending on the underlying task, deployment homogeneous or heterogeneous systems of agents may be essential. In addition, the availability of the position measurement of other agents may be limited due to communication deficiencies.

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A team-based design framework was proposed to take into account heterogeneous dynamics and differing capabilities of agents in coverage control [10], [11]. This framework suggests that teaming up each agent with others based on its dynamics, sensing capabilities, or embedded communication protocols can provide a more reliable approach to handle such scenarios. A gradient descent-based control law would locate the agents according to the positions of neighboring agents in the same or different teams. To execute the proposed algorithm, the control strategy strongly requires the precise location of neighboring agents that can be achieved under a number of impractical assumptions. Such assumptions hold true when all sensors measuring the location of agents are accurate and communication between the agents is healthy.

In practical applications, neighboring agents often receive inaccurate position of agents [12], [13]. Intermittent communications between agents can cause inaccurate position information and consequently affects the performance of the coverage control strategy that may increase the risk of collision [14], [15]. The self-triggered centroid algorithm is designed for an optimal deployment of multiple robots with outdated neighbor information according to the knowledge of the maximum speed of neighboring agents [16]. To that end, the guaranteed Voronoi diagram, which is introduced in [17], [18], is used to avoid collision in multi-agent systems. In a non-stationary uncertain environment, communication link may fail while delivering data packages between neighboring agents [19], [20], [21]. A coverage control strategy is designed to maximize area coverage based on optimizing the communication topology by taking into account the probability of events occurring in the environment [21].

The present work advances the previously proposed team-based coverage framework (see [10], [11]) by introducing a distributed control strategy that takes into account inaccurate position information of neighboring agents in deploying heterogeneous agents in a given environment. The main contribution is to consider uncertainty in the agent localization. The location of agents in the team-based coverage framework is considered as a disc-shaped region centered in the last known location of agents. The uncertainty of localization is modeled as the radii of the disc-shaped areas, which are varied for agents due to the heterogeneity of the agents, e.g., due to their dynamics or embedded communication capabilities. Each agent is teamed up with other agents according to their properties, capabilities, or assigned tasks. The environment is partitioned among the teams by taking into account the uncertainty in the locations of their member agents. To this end, the distance between an agent and a neighboring agent is defined as the infimum of all possible distances between the agent and the disc-shaped region associated with the agents belonging to the same team. Then, the Voronoi-based locational optimization framework is generalized to determine optimal partitioning in both team-level and agent-level by considering the modified distance technique.

The remainder of this paper is structured as follows. Section II discusses the problem statement. Section III outlines our two-level, team-based optimization problem. Section IV describes the proposed team-based partitioning in presence of uncertainty in data. A generalized version of the Voronoi partitioning is applied to calculate assigned subregions to teams and their agent members. This section also discusses the agents dynamics and presents the modeling of communication algorithm. Section V illustrates the numerical simulation results for the team-based partitioning with uncertainty in the agent localization. Finally, concluding remarks are presented in Section VI.

A. Notations

We use $\mathbb{N}$, $\mathbb{R}$ and $\mathbb{R}_+$ to denote the sets of positive natural, real, and nonnegative real numbers. The closed circle centered at $c \in \mathbb{R}^2$ with radius $r \in \mathbb{R}_+$ is defined by $B(c,r) := \{x \in \mathbb{R}^2 | \|x-c\| \leq r\}$. We define Q as a convex polytope in $\mathbb{R}^2$ and let $\mathscr{Q} = \{Q_1, Q_2, \ldots, Q_t\}$ be a *partition* of Q as a collection of t closed subsets with disjoint interiors. Moreover, the so-called *distribution density function* is denoted by φ where $\varphi : Q \to \mathbb{R}_+$ represents the probability of some phenomenon occurring over space Q. The function φ is assumed to be measurable and absolutely continuous. The Euclidean distance function is denoted by $\|\cdot\|$ and $|Q|$ represents the Lebesgue measure of convex subset Q. The vector set $\mathcal{P}_t = (p_{t1}, p_{t2}, \ldots, p_{tn_t})$ is the location of n_t agents belonging to t^{th} team moving in the space Q_t. As expected, the sensing performance of the agents decay as we move away from their location, and hence, sensing performance can be evaluated as a function of distance from the agent, i.e., $f(\|q - p_{tm}\|)$, where $q \in Q$.

II. Problem Statement

The traditional coverage control is based on partitioning of the space using Voronoi cells where each agent is separated from its neighbors using the bisector of lines connecting them. This type of partitioning relies on the availability of accurate data from other agents. As proposed in [10], a two step partitioning is defined to handle heterogeneity in deployment problems. The present work focuses on scenarios where for different reasons like missing or delayed communication, accurate data is not available to agents. A given polytope Q can be partitioned into a set of Voronoi cells of teams represented by their nucleus $\mathcal{L} = (l_1, \ldots, l_n)$. $\mathcal{V}(\mathcal{L}) = \{V_1, V_2, \ldots, V_n\}$ is considered as the optimal partitioning for a set of agents with fixed locations at a given space as

$$V_t = \{q \in Q | \; \|q - l_t\| \leq \|q - l_s\|\}. \tag{1}$$

We can take one more step towards handling heterogeneity by proposing a second level partitioning. The obtained Voronoi cells associated with the nuclei of the teams are then considered as the convex polytopes set to deploy their associated agents. Therefore, the sub-partitions are defined on the basis of the Voronoi cells V_t obtained from the team level partitioning. The Voronoi partitions $\mathcal{V}_t(\mathcal{P}_t) = \{V_{t1}, V_{t2}, \ldots, V_{tn_t}\}$ generated by the agents $(p_{t1}, p_{t2}, \ldots, p_{tn_t})$ belonging to t^{th} team are defined as

$$V_{tm} = \{q \in V_t | \; \|q - p_{tm}\| \leq \|q - p_{tr}\|\}, \tag{2}$$

where p_{tm} denotes the location of m^{th} agent in t^{th} team such that $m \in \{1, \ldots, n_t\}$.

In coverage control, reliability of communication algorithm plays an important role in providing agents with accurate position information. An immediate consequence of inaccuracy in data is that the calculated partitioning of the space may not reflect the true position of the agents. In traditional Voronoi partitioning, this would result in the risk of collision since the boundaries of Voronoi cells may not confine the agents. Therefore, such uncertainties cause agents to pass from a close vicinity of each other resulting in possibility of collision. In addition, the differences in agents communication may not allow us to deploy all the agents together where different delays in communication may cause existing robust frameworks (e.g., [16]) to fail. We address this issue by proposing a team-based framework, where agents can be deployed in teams that differ from communication capability point of view.

III. Team-based Optimization Framework

The main objective of this work is to adopt the proposed team-based deployment method for the case where various types of uncertainties such as lost or delayed communications exist. To do so, we first need to define an optimization problem that can handle not only the deployment and partitioning tasks inside teams but also the overall partitioning inside the main polytope Q. This can be done by breaking the optimization problem into two functions in a way that the solution to each problem represents the optimum configuration of the teams and their associated agents. Therefore, the deployment task in the presented team-based framework can be addressed by solving a two-level optimization problem. According to the definition of teams, the sensing performance measure can be calculated using the following two-level sensing performance measures

$$\mathcal{G}(\mathcal{L}, \mathscr{Q}) = \sum_{t=1}^{n} \int_{Q_t} \|q - l_t\|^2 \varphi_t(q) \mathrm{d}q, \tag{3}$$

$$\mathcal{G}_t(\mathcal{P}_t, \mathscr{Q}_t) = \sum_{m=1}^{n_t} \int_{Q_{tm}} \|q - p_{tm}\|^2 \varphi_t(q) \mathrm{d}q, \tag{4}$$

where l_t and φ_t respectively denote the nucleus and density function of t^{th} team as a representative of its team members, and $\mathscr{Q} = (Q_1, \ldots, Q_n)$, $\mathcal{P}_t = (p_{t1}, \ldots, p_{tn_t})$ and $\mathscr{Q}_t = \{Q_{t1}, \ldots, Q_{tn_t}\}$. In other words, the objective is to develop two appropriate deployment algorithms to collectively deploy heterogeneous agents. The first step is to solve the team-level optimization problem with the cost function (3) to guarantee a locally optimum configuration and partitioning of the convex polytope $\mathcal{Q}$, while applying the nuclei of teams as a representative of the locations of team members. The given region is divided into subregions and assigned to teams with respect to their density functions φ_t, for $t = 1, ..., n$. The solution to the problem of minimizing the sensing cost (3) gives a team-level partitioning, where members of t^{th} team are in charge of covering subregion $\mathcal{Q}_t$. Once regions are assigned to teams, solving the second optimization problem with the cost function (4) divides the region assigned to each team among agent members, such that polygons $\mathcal{Q}_{t1}, \ldots, \mathcal{Q}_{tn_t}$ are pairwise disjoint interiors whose union covers $\mathcal{Q}_t$.

It is proven that among different partitioning schemes the Voronoi partitions are optimum in the sense of minimizing both individually defined cost functions (3) and (4) [4]. Hence, for a given set of nuclei $\mathcal{L} \in \mathcal{Q}$, agents position $\mathcal{P}_t \in V_t$, a *partition* $\mathscr{Q}$ of $\mathcal{Q}$ and a *partition* $\mathscr{Q}_t$ of V_t, it satisfies

$$\mathcal{G}(\mathcal{L}, \mathcal{V}(\mathcal{L})) \leq \mathcal{G}(\mathcal{L}, \mathscr{Q}), \tag{5}$$

$$\mathcal{G}_t(\mathcal{P}_t, \mathcal{V}_t(\mathcal{P}_t)) \leq \mathcal{G}_t(\mathcal{P}_t, \mathscr{Q}_t). \tag{6}$$

This concludes that the Voronoi cells represent the optimum partitioning. Furthermore, for any $\mathcal{L}' = (l'_1, l'_2, \ldots, l'_n) \in \mathcal{Q}$ and $\mathcal{P}'_t = (p'_{t1}, p'_{t2}, \ldots, p'_{tn_t}) \in V_t$ satisfying $\|l'_t - C_{V_t}\| \leq \|l_t - C_{V_t}\|$ and $\|p'_{tm} - C_{V_{tm}}\| \leq \|p_{tm} - C_{V_{tm}}\|$, respectively, we have

$$\mathcal{G}(\mathcal{L}', \mathscr{Q}) \leq \mathcal{G}(\mathcal{L}, \mathscr{Q}), \tag{7}$$

$$\mathcal{G}_t(\mathcal{P}'_t, \mathscr{Q}_t) \leq \mathcal{G}_t(\mathcal{P}_t, \mathscr{Q}_t). \tag{8}$$

In other words, the given cost function is minimized when agents are at the centroids of their corresponding Voronoi cells. Our objective in the present work is to come up with an efficient coordination strategy that can deploy the agents based on sensing cost functions (3) and (4) where there is an imperfect communication resulting in inaccurate position data.

IV. Team-based Partitioning in Presence of Uncertainty in Agents' Position

A. Guaranteed Voronoi partitions

We define the set of teams by $\mathcal{L} = (l_1, l_2, \ldots, l_n)$, where each $l_t, t = 1 : n$, represents the nucleus of team t that is a function of the agents' position in the associated team $l_t = g(p_{t1}, p_{t2}, \ldots, p_{tn_t})$. The function dependency of l_t on the position of the agents is discussed later. Now, we can partition the polytope $\mathcal{Q}$ into a set of so called guaranteed Voronoi cells $g\mathcal{V}(\mathcal{L}) = \{gV_1, gV_2, \ldots, gV_n\}$ to handle the case where the nucleus of teams is prone to uncertainty. It is assumed that there is a set of uncertainty regions associated with nuclei $\mathcal{B} = \{\mathcal{B}_1, \ldots, \mathcal{B}_n\}$ as

$$gV_t = \{q \in \mathcal{Q} | \max_{q \in \mathcal{Q}_t} \|q - l_t\| \leq \min_{q \in \mathcal{Q}_s} \|q - l_s\|\}, \tag{9}$$

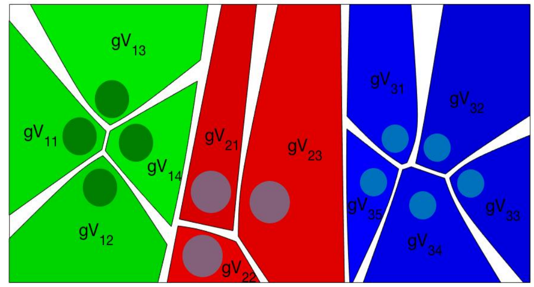

Fig. 1. Guaranteed Voronoi cells for three teams consisting of three, four and five agents.

where $l_t \in \mathcal{B}_t$, $l_s \in \mathcal{B}_s$ and gV_t represents the guaranteed Voronoi cell associated with nucleus l_t. The inequality (9) implies that all the points inside gV_t are closer to l_t than any other nucleus in the region, l_s, $s \neq t$. The area between teams is considered as unassigned region due to the uncertainty in nucleus of the teams which means these points would not belong to any of the regions defined by (9). It should be noted that the inequality (9) defines the boundaries of each guaranteed Voronoi cell. Each agent's position is recognized by an uncertainty disk that is calculated by its position and a radius, $r_i, i \in \{1, \ldots, N\}$. The edges of the guaranteed Voronoi cells are obtained by

$$\delta^g_{ij} = \{q \in \mathcal{Q} | \|q - p_i\| + r_i = \|q - p_j\| + r_j\}, \tag{10}$$

where δ^g_{ij} represents hyperbolas with foci p_i and p_j that is closer to p_i and semimajor axis $\frac{1}{2}(r_i + r_j)$. Given the shape of these boundaries, one can conclude the convexity of the guaranteed Voronoi. The obtained guaranteed Voronoi cells associated with the nuclei of the teams are then considered as the convex polytopes. This will divide cell gV_t into smaller pieces that form guaranteed Voronoi cells associated with agents belonging to each cluster. Given the uncertainty disks of agents $\mathcal{B}'_t = \{\mathcal{B}_{t1}, \ldots, \mathcal{B}_{tn_t}\}$, the obtained guaranteed Voronoi cells are defined by $g\mathcal{V}_t(\mathcal{P}_t) = \{gV_{t1}, gV_{t2}, \ldots, gV_{tn_t}\}$ that are generated by the agents $(p_{t1}, p_{t2}, \ldots, p_{tn_t})$ belonging to t^{th} team as

$$gV_{tm} = \{q \in gV_t | \max_{q \in gV_t} \|q - p_{tm}\| \leq \min_{q \in gV_t} \|q - p_{tr}\|\}, \tag{11}$$

where $p_{t1} \in \mathcal{B}_{t1}$, $p_{tr} \in \mathcal{B}_{tr}$ and p_{tm} denotes the location of m^{th} agent in t^{th} team such that $m \in \{1, \ldots, n_t\}$. Refer to Figure 1 for an illustrative example.

We recall the basic characteristics of the Voronoi partitions including their associated mass, centroid and polar moment of inertia as [4]

$$M_{gV_{tm}} = \int_{gV_{tm}} \varphi(q) \mathrm{d}q, \; C_{gV_{tm}} = \frac{1}{M_{gV_{tm}}} \int_{gV_{tm}} q \, \varphi(q) \mathrm{d}q. \tag{12}$$

Furthermore, we also define the characteristics of the teams's guaranteed Voronoi cells as

$$M_{gV_t} = \int_{gV_t} \varphi(q)\mathrm{d}q,\ C_{gV_t} = \frac{1}{M_{gV_t}} \int_{gV_t} q\ \varphi(q)\mathrm{d}q. \quad (13)$$

It should be mentioned that the nucleus is not representative of any real agent at that position. Instead, it can be considered as the imaginary point that imposes the dynamics of teams of agents and their associated cells.

B. Data structure of teams and agents

The two-level optimization problem requires a proper data structure and flow among the agents in the presence of uncertainty. To this end, the structure needs to be clarified to make sure that even if agents receive outdated information, they can still maintain their optimal configuration. In addition, given that the distance between agents may increase during deployment, they should be able to balance the necessity of receiving new information and spending the available onboard energy.

In the proposed team-based partitioning, it is assumed that the agents in t^{th} team in elapsed time τ_{ti}^{j} have access to the position of their teammates $j \in \{1, 2, \ldots, n_t\}$. From i^{th} agent view, it can calculate the maximum possible distance that each agent in the same team can travel in a given time. The maximum traversed distance is calculated using the maximum possible speed of the agents in the same team by $r_{ti}^{j} = v_{max}\tau_{ti}^{j}$. Therefore, i^{th} agent can calculate the disk $\mathcal{B}_{ti}^{j} = \bar{B}(p_{ti}^{j}, r_{ti}^{j})$ that contains agent j. It should be mentioned that value of r_{ti}^{j} needs to be updated until r_{ti}^{j} gets larger than the diameter of Q_t. Two-level optimization imposes uncertainty on the position and partitioning of the teams. Therefore, the uncertainty radius needs to be defined in the teams level. The uncertainty radius of the teams is calculated as the average of uncertainty disks of each agent in the same team.

Remark 1: Since maximum uncertainty radius of each agent does not exceed $\text{diam}(Q_t)$, hence the maximum uncertainty radius of each team will be smaller that $\text{diam}(Q)$.

C. Agents dynamics

The deployment problem of teams of agents is decomposed into two optimization problems. We assume that both functions $\mathcal{G}$ and $\mathcal{G}_t$ in (3) and (4) are smooth and continuous over their regions. The defined cost functions are used to obtain the optimal dynamics on the agents and nucleus of teams. We assume that the following single integrator dynamics are imposed on the agents and nucleus of teams:

$$\dot{l}_t = u_t, \quad (14)$$
$$\dot{p}_{tm} = u_{tm}, \quad (15)$$

where u_t and u_{tm} are the inputs in teams and agents level, respectively. It is assumed that the inputs are bounded by the maximum velocity of the agents, $\|u_{tm}\| \leq v_{max}$ and $\|u_t\| \leq v'_{max}$ for $t \in \{1, \ldots, n_t\}$. The teams are considered to move in a slower rate than agents, therefore, $v'_{max} \leq v_{max}$. Then, the derivatives of the cost functions are obtained to implement the gradient descent-based controllers as

$$u_t = \begin{cases} M_{V_t}(l_t - C_{V_t}) & \text{if} \quad \|u_t\| < v'_{max} \\ \frac{v'_{max}}{\|M_{V_t}(l_t - C_{V_t})\|} M_{V_t}(l_t - C_{V_t}) & \text{else} \end{cases}$$

$$u_{tm} = \begin{cases} M_{V_{tm}}(p_{tm} - C_{V_{tm}}) & \text{if} \quad \|u_{tm}\| < v_{max} \\ \frac{v_{max}}{\|M_{V_{tm}}(p_{tm} - C_{V_{tm}})\|} M_{V_{tm}}(p_{tm} - C_{V_{tm}}) & \text{else} \end{cases}$$

It can be seen that if the teams nucleus and agents position move to the centroid of their Voronoi cells, the local minimum is achieved. Accordingly, the critical partitions and points for $\mathcal{G}$ and $\mathcal{G}_t$ are the centroidal Voronoi partitions.

D. Modeling a distributed network of agents

The agents need to be modeled with respect to their actions including sensing, communication, computation and control. The behavior of agents in a given network is then describable as how they interact to perform the assigned task(s). In essence, the communication network and the data flow in a system of agents need to be investigated. The characteristics and structure of agents communication are discussed next.

Characteristics of the agents communication: An agent in the given framework is introduced here as the m^{th} element of the t^{th} team. Each agent is capable of allocating the state of the system and performing the required operations. The agent that is located at p_{tm} can move over the space at any time for any period of time $\delta t_{tm} \in \mathbb{R}_+$ following the enforced first order dynamics (15). Any agent has access to both its position p_{tm} and associated team nucleus l_t that are received through the communication with the neighboring agents. Each agent also computes the control pair $(\delta t_{tm}, u_{tm})$ and r_{tm} for the agent at p_{tm}. The agents on the borders of teams also receive the information on the nucleus of the neighboring teams. This information is provided through communicating with the neighboring agents belonging to the neighboring teams. Furthermore, it can detect the neighboring agents within the radius R_{tm} of the agent at p_{tm}. Each agent is able to send/receive information to/from the other agents within the communication radius $R_{tm} \in \mathbb{R}_+$. It is also assumed that the agent can adjust the radius R_{tm} to ensure the minimum communication, especially in the presence of a limited communication bandwidth [10].

V. Simulation Results and Discussion

In this section, the proposed method of this paper is investigated via two numerical examples.

Example 1

In the first example, 15 agents are deployed on a 5×10 rectangular shape area in five teams with equal number of agents. A Gaussian function with 3 picks is used to represent the importance region which is defined by following density function

$$\varphi(x, y) = \sum_{i=1}^{n_p} \exp(-\frac{(x - a_i)^2 + (y - b_i)^2}{2\sigma^2}), \quad (16)$$

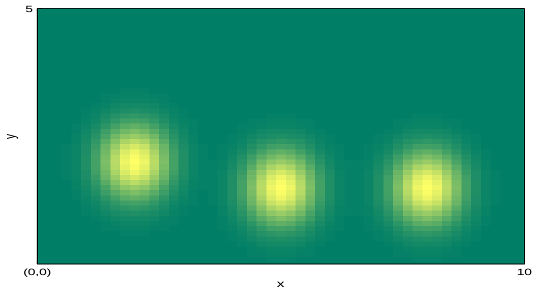

Fig. 2. Gaussian density function with the centers chosen at $(2,2)$, $(5,1.5)$ and $(8,1.5)$.

where n_p is the number of centers, (a_i, b_i) represents the coordinate of the centers and σ is the variance. In this example, we assume $n_p = 3$ and $\sigma = 0.25$. Figure 2 illustrates the density function over the given space. The agents are deployed as clusters or teams at a random initial configuration where each agent starts from an initial point inside its team. The implemented single integrator control law moves the agents towards their centroid while being prone to communication or data packet loss. To simulate and represent uncertainty in both agents and teams level, we have assigned uncertainty disks based on maximum speed of the agents. In this example, we assume the maximum speed of the agents is 0.8 m/s. The maximum speed and the time step for data transfer $\tau_{ti} = 0.04$ sec can give us the radius of uncertainty disk $r_{ti} = 0.032$ m. The proposed approach deploys agents using calculated uncertainty disks via computing the guaranteed Voronoi cells in both agents and teams level. In fact, the accumulated uncertainties in agents level are used to obtain the team guaranteed Voronoi cells and then, the agent cells are computed based on their individual uncertainty disks. It is shown that the agents can be assigned to different teams while taking the individual uncertainties into account. This example demonstrates the deployment of agents in multiple teams while they only require the position information from the agents in the same team and only the nucleus of other teams in their neighborhood. Figure 3 shows the initial through final configuration of the agents under uncertain communication.

Example 2

Second example represents a case with three teams consisting of three, four and five agents. In this case, it is assumed that the agents are equipped with heterogeneous communication systems where the time τ_{ti} can be different from one agent to another. This results in uncertainty disks with different radii. In this example, it is assumed that the agents have time steps of 0.02, 0.03 and 0.05 with different maximum speeds of 0.7, 0.8 and 1 m/s. Figure 4 illustrates the simulation results associated with this case. Agents with heterogeneous dynamics start from shown initial configuration and converge to the final configuration in the presence of uncertainty. This example illustrates the case where due to the requirements of the underlying task, the agents need to start from different parts of the region. As a result, their relative distance is large that can negatively impact the possibility of communication with agents in other parts of the region. As shown in the results, the proposed approach successfully deploys the agents while assuming that the uncertainty disks associated with agents belonging to each team may have different radii. It is shown how the agents are deployed in teams of agents according to their different dynamics. This example illustrates that the proposed approach can be used to deploy agents with different communication intervals and dynamics. As shown, the agents move towards their final configuration according to their importance functions in both teams and agents level.

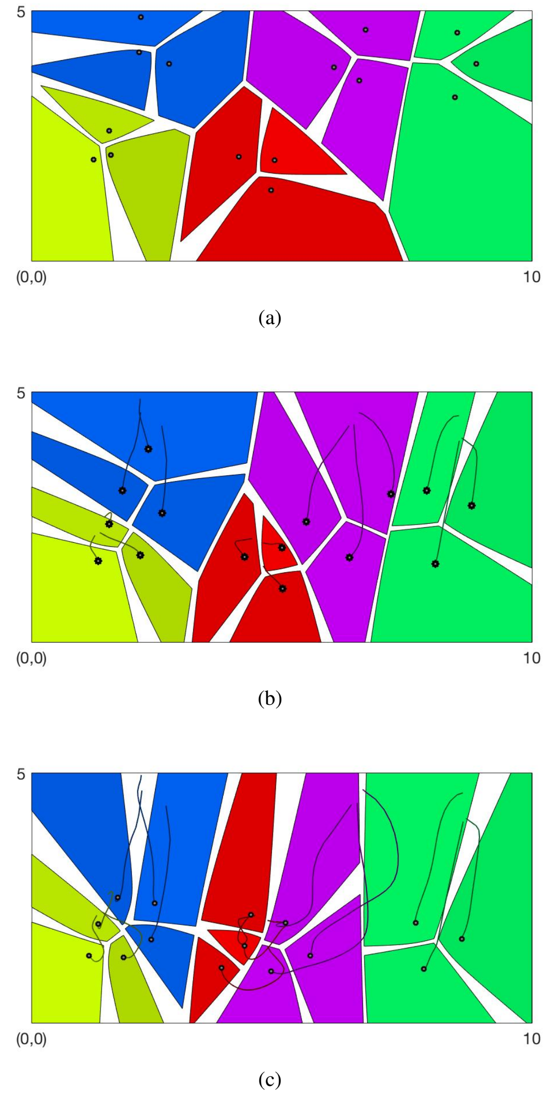

Fig. 3. Change from the initial to the final configuration is shown for: (a) first iteration, (b) 50^{th} iteration, and (c) 100^{th} iteration in Example 1.

VI. Concluding Remarks

In this paper, a team-based coverage control approach is proposed in the presence of uncertainty in the agent localization. The proposed control strategy does not require the precise location of agents. Instead, agents need access to an approximate location of neighboring agents, which is

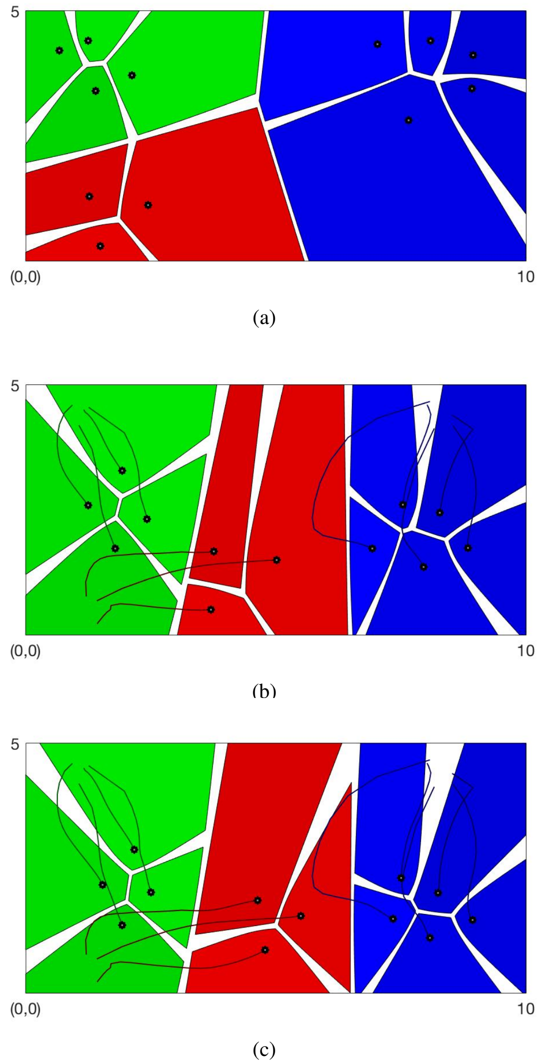

Fig. 4. Change from the initial to the final configuration is shown for: (a) first iteration, (b) 50^{th} iteration, and (c) 100^{th} iteration in Example 2.

located inside a disc-shaped region. Center of the uncertain region is the last precise location of agents and its radius is determined by heterogeneous capabilities of agents like dynamics or communication system. The modified distance between each agent and its neighboring agents is calculated as the distance between location of the agent and the farthest possible location of the neighboring agent. The assigned regions to teams are calculated by guaranteed Voronoi partitioning according to the modified distance measure in order to guarantee collision avoidance between agents in neighboring teams. Then, the assigned region to each team is partitioned among members to avoid overlapping among assigned regions to agents inside each team. The distributed control law determines the local optimal locations of agents in their assigned regions. Simulations have illustrated effects of the uncertainty in the agent localization on the coverage control while avoiding collisions in both teams and agents level. The results indicate that agents can be deployed in various teams in different numbers while they have heterogeneous dynamics and different communication intervals.

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