Coverage Control for Mobile Sensing Networks

Jorge Cortés, *Member, IEEE*, Sonia Martínez, *Member, IEEE*, Timur Karataş, and
Francesco Bullo, *Senior Member, IEEE*

Abstract—This paper presents control and coordination algorithms for groups of vehicles. The focus is on autonomous vehicle networks performing distributed sensing tasks, where each vehicle plays the role of a mobile tunable sensor. The paper proposes gradient descent algorithms for a class of utility functions which encode optimal coverage and sensing policies. The resulting closed-loop behavior is adaptive, distributed, asynchronous, and verifiably correct.

Index Terms—Centroidal Voronoi partitions, coverage control, distributed and asynchronous algorithms, sensor networks.

I. INTRODUCTION

A. Mobile Sensing Networks

THE deployment of large groups of autonomous vehicles is rapidly becoming possible because of technological advances in networking and in miniaturization of electromechanical systems. In the near future, large numbers of robots will coordinate their actions through ad-hoc communication networks, and will perform challenging tasks, including search and recovery operations, manipulation in hazardous environments, exploration, surveillance, and environmental monitoring for pollution detection and estimation. The potential advantages of employing teams of agents are numerous. For instance, certain tasks are difficult, if not impossible, when performed by a single vehicle agent. Further, a group of vehicles inherently provides robustness to failures of single agents or communication links.

Working prototypes of active sensing networks have already been developed; see [1]–[4]. In [3], launchable miniature mobile robots communicate through a wireless network. The vehicles are equipped with sensors for vibrations, acoustic, magnetic, and infrared (IR) signals as well as an active video module (i.e., the camera or micro-radar is controlled via a pan-tilt unit). A second system is suggested in [4] under the name of Autonomous Oceanographic Sampling Network. In this case, underwater vehicles are envisioned measuring temperature, currents, and other distributed oceanographic signals. The vehicles communicate via an acoustic local area network and coordinate their motion in response to local sensing information and to evolving global data. This mobile sensing network is meant to provide the ability to sample the environment adaptively in space and time. By identifying evolving temperature and current gradients with higher accuracy and resolution than current static sensors, this technology could lead to the development and validation of improved oceanographic models.

B. Optimal Sensor Allocation and Coverage Problems

A fundamental prototype problem in this paper is that of characterizing and optimizing notions of quality-of-service (QoS) provided by an adaptive sensor network in a dynamic environment. To this goal, we introduce a notion of *sensor coverage* that formalizes an optimal sensor placement problem. This spatial resource-allocation problem is the subject of a discipline called locational optimization [5]–[9].

Locational optimization problems pervade a broad spectrum of scientific disciplines. Biologists rely on locational optimization tools to study how animals share territory and to characterize the behavior of animal groups obeying the following interaction rule: each animal establishes a region of dominance and moves toward its center. Locational optimization problems are spatial resource-allocation problems (e.g., where to place mailboxes in a city or cache servers on the internet) and play a central role in quantization and information theory (e.g., how to design a minimum-distortion fixed-rate vector quantizer). Other technologies affected by locational optimization include mesh and grid optimization methods, clustering analysis, data compression, and statistical pattern recognition.

Because locational optimization problems are so widely studied, it is not surprising that methods are indeed available to tackle coverage problems; see [5], and [8]–[10]. However, most currently available algorithms are not applicable to mobile sensing networks because they inherently assume a centralized computation for a limited-size problem in a known static environment. This is not the case in multivehicle networks which, instead, rely on a distributed communication and computation architecture. Although an ad-hoc wireless network provides the ability to share some information, no global omniscient leader might be present to coordinate the group. The inherent spatially distributed nature and limited communication capabilities of a mobile network invalidate classic approaches to algorithm design.

J. Cortés, T. Karatas, and F. Bullo are with the Coordinated Science Laboratory, University of Illinois at Urbana-Champaign, Urbana, IL 61801 USA (e-mail: jcortes@uiuc.edu; tkaratas@uiuc.edu; bullo@uiuc.edu).

S. Martínez is with the Escola Universitària Politècnica de Vilanova i la Geltrú, Universidad Politécnica de Cataluña, Vilanova i la Geltrú 08800, Spain (e-mail: soniam@mat.upc.es).

C. Distributed Asynchronous Algorithms for Coverage Control

In this paper, we design coordination algorithms implementable by a multivehicle network with limited sensing and

communication capabilities. Our approach is related to the classic Lloyd algorithm from quantization theory; see [11] for a reprint of the original report and [12] for a historical overview. We present Lloyd descent algorithms that take into careful consideration all constraints on the mobile sensing network. In particular, we design coverage algorithms that are adaptive, distributed, asynchronous, and verifiably asymptotically correct.

Adaptive: Our coverage algorithms provide the network with the ability to address changing environments, sensing task, and network topology (due to agents' departures, arrivals, or failures).

Distributed: Our coverage algorithms are distributed in the sense that the behavior of each vehicle depends only on the location of its neighbors. Also, our algorithms do not require a fixed-topology communication graph, i.e., the neighborhood relationships do change as the network evolves. The advantages of distributed algorithms are scalability and robustness.

Asynchronous: Our coverage algorithms are amenable to asynchronous implementation. This means that the algorithms can be implemented in a network composed of agents evolving at different speeds, with different computation and communication capabilities. Furthermore, our algorithms do not require a global synchronization, and convergence properties are preserved, even if information about neighboring vehicles propagates with some delay. An advantage of asynchronism is a minimized communication overhead.

Verifiable Asymptotically Correct: Our algorithms guarantee monotonic descent of the cost function encoding the sensing task. Asymptotically, the evolution of the mobile sensing network is guaranteed to converge to so-called centroidal Voronoi configurations (i.e., configurations where the location of each generator coincides with the centroid of the corresponding Voronoi cell) that are critical points of the optimal sensor-coverage problem.

Let us describe the contributions of this paper in some detail. Section II reviews certain locational optimization problems and their solutions as centroidal Voronoi partitions. Section III provides a continuous-time version of the classic Lloyd algorithm from vector quantization and applies it to the setting of multivehicle networks. In discrete time, we propose a family of Lloyd algorithms. We carefully characterize convergence properties for both continuous and discrete-time versions (Appendix I collects some relevant facts on descent flows). We discuss a worst-case optimization problem, we investigate a simple uniform planar setting, and we present simulation results.

Section IV presents two asynchronous distributed implementations of Lloyd algorithm for ad-hoc networks with communication and sensing capabilities. Our treatment carefully accounts for the constraints imposed by the distributed nature of the vehicle network. We present two asynchronous implementations, one based on classic results on distributed gradient flows, the other based on the structure of the coverage problem. (Appendix II briefly reviews some known results on asynchronous gradient algorithms.)

Section V-A considers vehicle models with more realistic dynamics. We present two formal results on passive vehicle dynamics and on vehicles equipped with individual local controllers. We present numerical simulations of passive vehicle models and of unicycle mobile vehicles. Next, Section V-B describes density functions that lead the multivehicle network to predetermined geometric patterns. We present our conclusions and directions for future research in Section VI.

D. Review of Distributed Algorithms for Cooperative Control

Recent years have witnessed a large research effort focused on motion planning and coordination problems for multivehicle systems. Issues include geometric patterns [13]–[16], formation control [17], [18], gradient climbing [19], and conflict avoidance [20]. It is only recently, however, that truly distributed coordination laws for dynamic networks are being proposed; e.g., see [21]–[23].

Heuristic approaches to the design of interaction rules and emerging behaviors have been throughly investigated within the literature on behavior-based robotics; see [17], and [24]–[28]. An example of coverage control is discussed in [29]. Along this line of research, algorithms have been designed for sophisticated cooperative tasks. However, no formal results are currently available on how to design reactive control laws, ensure their correctness, and guarantee their optimality with respect to an aggregate objective.

The study of distributed algorithms is concerned with providing mathematical models, devising precise specifications for their behavior, and formally proving their correctness and complexity. Via an automata-theoretic approach, the references [30] and [31] treat distributed consensus, resource allocation, communication, and data consistency problems. From a numerical optimization viewpoint, the works in [32] and [33] discuss distributed asynchronous algorithms as networking algorithms, rate and flow control, and gradient descent flows. Typically, both these sets of references consider networks with fixed topology, and do not address algorithms over ad-hoc dynamically changing networks. Another common assumption is that any time an agent communicates its location, it broadcasts it to every other agent in the network. In our setting, this would require a nondistributed communication setup.

Finally, we note that the terminology "coverage" is also used in [34] and [35] and references therein to refer to a different problem called the *coverage path-planning problem*, where a single robot equipped with a limited footprint sensor needs to visit all points in its environment.

II. FROM LOCATION OPTIMIZATION TO CENTROIDAL VORONOI PARTITIONS

A. Locational Optimization

In this section, we describe a collection of known facts about a meaningful optimization problem. References include the theory and applications of centroidal Voronoi partitions, see [10], and the discipline of facility location, see [6]. In the paper, we interchangeably refer to the elements of the network as sensors, agents, vehicles, or robots. We let $\mathbb{R}_+$ be the set
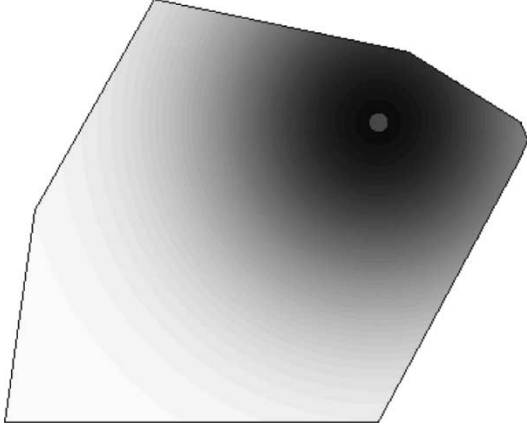
Fig. 1.   Contour plot on a polygonal environment of the Gaussian density function $\phi = \exp(-x^2 - y^2)$.

of nonnegative real numbers, $\mathbb{N}$ be the set of positive natural numbers, and $\mathbb{N}_0 = \mathbb{N} \cup \{0\}$.

Let Q be a convex polytope in $\mathbb{R}^N$, including its interior, and let $\| \cdot \|$ denote the Euclidean distance function. We call a map $\phi \colon Q \rightarrow \mathbb{R}_+$ a *distribution density function* if it represents a measure of information or probability that some event takes place over Q. In equivalent words, we can consider Q to be the bounded support of the function ϕ. Let $P = (p_1, \ldots, p_n)$ be the *location of n sensors*, each moving in the space Q. Because of noise and loss of resolution, the *sensing performance* at point q taken from ith sensor at the position p_i degrades with the distance $\|q - p_i\|$ between q and p_i; we describe this degradation with a nondecreasing differentiable function $f \colon \mathbb{R}_+ \rightarrow \mathbb{R}_+$. Accordingly, $f(\|q - p_i\|)$ provides a quantitative assessment of how poor the sensing performance is (see Fig. 1).

Remark 2.1: As an example, consider n mobile robots equipped with microphones attempting to detect, identify, and localize a sound source. *How should we plan the robots' motion in order to maximize the detection probability?* Assuming the source emits a known signal, the optimal detection algorithm is a matched filter (i.e., convolve the known waveform with the received signal and threshold). The source is detected depending on the signal-to-noise-ratio (SNR), which is inversely proportional to the distance between the microphone and the source. Various electromagnetic and sound sensors have SNRs inversely proportional to distance.

Within the context of this paper, a *partition* of Q is a collection of n polytopes $\mathcal{W} = \{W_1, \ldots, W_n\}$ with disjoint interiors, whose union is Q. We say that two partitions $\mathcal{W}$ and $\mathcal{W}'$ are equal if W_i and W_i' only differ by a set of ϕ-measure zero, for all $i \in \{1, \ldots, n\}$.

We consider the task of minimizing the locational optimization function

$$\mathcal{H}(P, \mathcal{W}) = \sum_{i=1}^{n} \int_{W_i} f(\|q - p_i\|)\phi(q)dq \qquad (1)$$

where we assume that the ith sensor is responsible for measurements over its "dominance region" W_i. Note that the function $\mathcal{H}$ is to be minimized with respect to both 1) the sensors location P, and 2) the assignment of the dominance regions $\mathcal{W}$. The optimization is, therefore, to be performed with respect to

the position of the sensors and the partition of the space. This problem is referred to as a facility location problem and, in particular, as a continuous p-median problem in [6].

Remark 2.2: Note that if we interchange the positions of any two agents, along with their associated regions of dominance, the value of the locational optimization function $\mathcal{H}$ is not affected. Equivalently, if Σ_n denotes the discrete group of permutations of n elements, then $\mathcal{H}(p_1, \ldots, p_n, W_1, \ldots, W_n) = \mathcal{H}(p_{\sigma(1)}, \ldots, p_{\sigma(n)}, W_{\sigma(1)}, \ldots, W_{\sigma(n)})$ for all $\sigma \in \Sigma_n$. To eliminate this discrete redundancy, one could take natural action of Σ_n on Q^n, and consider Q^n / Σ_n as the configuration space for the position P of the n vehicles.

B. Voronoi Partitions

One can easily see that, at a fixed-sensors location, the optimal partition of Q is the *Voronoi partition* $\mathcal{V}(P) = \{V_1, \ldots, V_n\}$ generated by the points $(p_1, \ldots, p_n)$

$$V_i = \{q \in Q | \ \|q - p_i\| \leq \|q - p_j\|, \ \forall \ j \neq i\}.$$

We refer to [9] for a comprehensive treatment on Voronoi diagrams, and briefly present some relevant concepts. The set of regions $\{V_1, \ldots, V_n\}$ is called the Voronoi diagram for the generators $\{p_1, \ldots, p_n\}$. When the two Voronoi regions V_i and V_j are adjacent (i.e., they share an edge), p_i is called a *(Voronoi) neighbor* of p_j (and vice versa). The set of indexes of the Voronoi neighbors of p_i is denoted by $\mathcal{N}(i)$. Clearly, $j \in \mathcal{N}(i)$ if and only if $i \in \mathcal{N}(j)$. We also define the (i, j) face as $\Delta_{ij} = V_i \cap V_j$. Voronoi diagrams can be defined with respect to various distance functions, e.g., the 1-, 2-, $s-$, and ∞-norm over $Q = \mathbb{R}^m$, see [36]. Some useful facts about the Euclidean setting are the following: if Q is a convex polytope in an N-dimensional Euclidean space, the boundary of each V_i is the union of $(N - 1)$-dimensional convex polytopes.

In what follows, we shall write

$$\mathcal{H}_\mathcal{V}(P) = \mathcal{H}(P, \mathcal{V}(P)).$$

Note that using the definition of the Voronoi partition, we have $\min_{i \in \{1, \ldots, n\}} f(\|q - p_i\|) = f(\|q - p_j\|)$ for all $q \in V_j$. Therefore

$$\mathcal{H}_\mathcal{V}(P) = \int_Q \min_{i \in \{1, \ldots, n\}} f(\|q - p_i\|)\phi(q)dq,$$

$$= E_{(Q, \phi)}\left[\min_{i \in \{1, \ldots, n\}} f(\|q - p_i\|)\right] \qquad (2)$$

that is, the locational optimization function can be interpreted as an expected value composed with a "min" operation. This is the usual way in which the problem is presented in the facility location and operations research literature [6]. Remarkably, one can show [10] that

$$\frac{\partial \mathcal{H}_\mathcal{V}}{\partial p_i}(P) = \frac{\partial \mathcal{H}}{\partial p_i}(P, \mathcal{V}(P))$$

$$= \int_{V_i} \frac{\partial}{\partial p_i} f(\|q - p_i\|)\phi(q)dq \qquad (3)$$

i.e., the partial derivative of $\mathcal{H}_\mathcal{V}$ with respect to the ith sensor only depends on its own position and the position of its Voronoi neighbors. Therefore, the computation of the derivative of $\mathcal{H}_\mathcal{V}$ with respect to the sensors' location is decentralized *in the sense*

of Voronoi. Moreover, one can deduce some smoothness properties of $\mathcal{H}_\mathcal{V}$: since the Voronoi partition $\mathcal{V}$ depends at least continuously on $P = (p_1, \ldots, p_n)$, for all $p_i \neq p_j$, the function $\mathcal{H}_\mathcal{V}$ is at least continuously differentiable on $Q^n \setminus \{P \in Q^n \mid p_i = p_j$ for some $i, j \in \{1, \ldots, n\}, i \neq j\}$.

C. Centroidal Voronoi Partitions

Let us recall some basic quantities associated with a region $V \subset \mathbb{R}^N$ and a mass density function ρ. The (generalized) mass, centroid (or center of mass), and polar moment of inertia are defined as

$$M_V = \int_V \rho(q)dq, \quad C_V = \frac{1}{M_V}\int_V q\rho(q)dq$$
$$J_{V,p} = \int_V \|q - p\|^2 \rho(q)dq.$$

Additionally, by the parallel axis theorem, one can write

$$J_{V,p} = J_{V,C_V} + M_V\|p - C_V\|^2 \tag{4}$$

where $J_{V,C_V} \in \mathbb{R}_+$ is defined as the polar moment of inertia of the region V about its centroid C_V.

Let us consider again the locational optimization problem (1), and suppose now we are strictly interested in the setting

$$\mathcal{H}(P, \mathcal{W}) = \sum_{i=1}^n \int_{W_i} \|q - p_i\|^2 \phi(q)dq \tag{5}$$

that is, we assume $f(\|q - p_i\|) = \|q - p_i\|^2$. The parallel axis theorem leads to simplifications for both the function $\mathcal{H}_\mathcal{V}$ and its partial derivative

$$\mathcal{H}_\mathcal{V}(P) = \sum_{i=1}^n J_{V_i,C_{V_i}} + \sum_{i=1}^n M_{V_i}\|p_i - C_{V_i}\|^2$$
$$\frac{\partial \mathcal{H}_\mathcal{V}}{\partial p_i}(P) = 2M_{V_i}(p_i - C_{V_i}).$$

Here, the mass density function is $\rho = \phi$. It is convenient to define

$$\mathcal{H}_{\mathcal{V},1} = \sum_{i=1}^n J_{V_i,C_{V_i}}, \quad \mathcal{H}_{\mathcal{V},2} = \sum_{i=1}^n M_{V_i}\|p_i - C_{V_i}\|^2.$$

Therefore, the (not necessarily unique) local minimum points for the location optimization function $\mathcal{H}_\mathcal{V}$ are *centroids* of their Voronoi cells, i.e., each location p_i satisfies two properties simultaneously: it is the generator for the Voronoi cell V_i, and it is its centroid

$$C_{V_i} = \arg\min_{p_i} \mathcal{H}_\mathcal{V}(P).$$

Accordingly, the critical partitions and points for $\mathcal{H}$ are called *centroidal Voronoi partitions*. We will refer to a sensors' configuration as a *centroidal Voronoi configuration* if it gives rise to a centroidal Voronoi partition. Of course, centroidal Voronoi configurations depend on the specific distribution density function ϕ, and an arbitrary pair (Q, ϕ) admits, in general, multiple centroidal Voronoi configurations. This discussion provides a proof alternative to the one given in [10] for the necessity of centroidal Voronoi partitions as solutions to the continuous p-median location problem.

III. CONTINUOUS AND DISCRETE-TIME LLOYD DESCENT FOR COVERAGE CONTROL

In this section, we describe algorithms to compute the location of sensors that minimize the cost $\mathcal{H}$, both in continuous and in discrete time. In Section III-A, we propose a continuous-time version of the classic Lloyd algorithm. Here, both the positions and partitions evolve in continuous time, whereas the Lloyd algorithm for vector quantization is designed in discrete time. In Section III-B, we develop a family of variations of Lloyd algorithm in discrete time. In both settings, we prove that the proposed algorithms are *gradient descent flows*.

A. A Continuous-Time Lloyd Algorithm

Assume the sensors location obeys a first-order dynamical behavior described by

$$\dot{p}_i = u_i.$$

Consider $\mathcal{H}_\mathcal{V}$ a cost function to be minimized and impose that the location p_i follows a gradient descent. In equivalent control theoretical terms, consider $\mathcal{H}_\mathcal{V}$ a Lyapunov function, and stabilize the multivehicle system to one of its local minima via dissipative control. Formally, we set

$$u_i = -k_{\text{prop}}(p_i - C_{V_i}) \tag{6}$$

where k_{prop} is a positive gain, and where we assume that the partition $\mathcal{V}(P) = \{V_1, \ldots, V_n\}$ is continuously updated.

Proposition 3.1 (Continuous-Time Lloyd Descent): For the closed-loop system induced by (6), the sensors location converges asymptotically to the set of critical points of $\mathcal{H}_\mathcal{V}$, i.e., the set of centroidal Voronoi configurations on Q. Assuming this set is finite, the sensors location converges to a centroidal Voronoi configuration.

Proof: Under the control law (6), we have

$$\frac{d}{dt}\mathcal{H}_\mathcal{V}(P(t)) = \sum_{i=1}^n \frac{\partial \mathcal{H}_\mathcal{V}}{\partial p_i}\dot{p}_i$$
$$= -2k_{\text{prop}}\sum_{i=1}^n M_{V_i}\|p_i - C_{V_i}\|^2$$
$$= -2k_{\text{prop}}\mathcal{H}_{\mathcal{V},2}(P(t)).$$

By LaSalle's principle, the sensors location converges to the largest invariant set contained in $\mathcal{H}_{\mathcal{V},2}^{-1}(0)$, which is precisely the set of centroidal Voronoi configurations. Since this set is clearly invariant for (6), we get the stated result. If $\mathcal{H}_{\mathcal{V},2}^{-1}(0)$ consists of a finite collection of points, then $P(t)$ converges to one of them (see *Corollary 1.2*). ∎

Remark 3.2: If $\mathcal{H}_{\mathcal{V},2}^{-1}(0)$ is finite, and $P(t) \rightarrow C$, then a sufficient condition that guarantees exponential convergence is that the Hessian of $\mathcal{H}_\mathcal{V}$ be positive definite at C. Establishing this property is a known open problem, see [10]. Note that this gradient descent is not guaranteed to find the global minimum. For example, in the vector quantization and signal processing literature [12], it is known that for bimodal distribution density functions, the solution to the gradient flow reaches local minima where the number of generators allocated to the two region of maxima are not optimally partitioned.

B. A Family of Discrete-Time Lloyd Algorithms

Let us consider the following variations of Lloyd algorithm. Let T be a continuous mapping $T: Q^n \rightarrow Q^n$ verifying the following two properties:

1) for all $i \in \{1, \ldots, n\}$, $\|T_i(P) - C_{V_i(P)}\| \leq \|p_i - C_{V_i(P)}\|$, where T_i denotes the ith component of T;
2) if P is not centroidal, then there exists a j such that $\|T_j(P) - C_{V_j(P)}\| < \|p_j - C_{V_j(P)}\|$.

Property 1) guarantees that, if moved according to T, the agents of the network do not increase their distance to its corresponding centroid. Property 2) ensures that at least one robot moves at each iteration and strictly approaches the centroid of its Voronoi region. Because of this property, the fixed points of T are the set of centroidal Voronoi configurations.

Proposition 3.3 (Discrete-Time Lloyd Descent): Let $T: Q^n \rightarrow Q^n$ be a continuous mapping satisfying properties 1) and 2). Let $P_0 \in Q^n$ denote the initial sensors' location. Then, the sequence $\{T^m(P_0)| \ m \in \mathbb{N}\}$ converges to the set of centroidal Voronoi configurations. If this set is finite, then the sequence $\{T^m(P_0)| \ m \in \mathbb{N}\}$ converges to a centroidal Voronoi configuration.

Proof: Consider $\mathcal{H}_{\mathcal{V}}: Q^n \rightarrow \mathbb{R}_+$ as an objective function for the algorithm T. Using the parallel axis theorem, $\mathcal{H}(P, \mathcal{W}) = \sum_{i=1}^n J_{W_i, C_{W_i}} + \sum_{i=1}^n M_{W_i}\|p_i - C_{W_i}\|^2$, and therefore

$$\mathcal{H}(P', \mathcal{W}) \leq \mathcal{H}(P, \mathcal{W}) \tag{7}$$

as long as $\|p_i' - C_{W_i}\| \leq \|p_i - C_{W_i}\|$ for all $i \in \{1, \ldots, n\}$, with strict inequality if for any i, $\|p_i' - C_{W_i}\| < \|p_i - C_{W_i}\|$. In particular, $\mathcal{H}(C_{\mathcal{W}}, \mathcal{W}) \leq \mathcal{H}(P, \mathcal{W})$, with strict inequality if $P \neq C_{\mathcal{W}}$, where $C_{\mathcal{W}}$ denotes the set of centroids of the partition $\mathcal{W}$. Moreover, since the Voronoi partition is the optimal one for fixed P, we also have

$$\mathcal{H}(P, \mathcal{V}(P)) \leq \mathcal{H}(P, \mathcal{W}) \tag{8}$$

with strict inequality if $\mathcal{W} \neq \mathcal{V}(P)$.

Now, because of property 1) of T, inequality (7) yields

$$\mathcal{H}(T(P), \mathcal{V}(P)) \leq \mathcal{H}(P, \mathcal{V}(P)) = \mathcal{H}_{\mathcal{V}}(P)$$

and the inequality is strict if P is not centroidal by property 2) of T. In addition

$$\mathcal{H}_{\mathcal{V}}(T(P)) = \mathcal{H}(T(P), \mathcal{V}(T(P))) \leq \mathcal{H}(T(P), \mathcal{V}(P))$$

because of (8). Hence, $\mathcal{H}_{\mathcal{V}}(T(P)) \leq \mathcal{H}_{\mathcal{V}}(P)$, and the inequality is strict if P is not centroidal. We then conclude that $\mathcal{H}_{\mathcal{V}}$ is a descent function for the algorithm T. The result now follows from the global convergence *Theorem 1.3* and *Proposition 1.4* in Appendix I. ∎

Remark 3.4: Lloyd algorithm in quantization theory [11], [12] is usually presented as follows. Given the location of n agents, $p_1, \ldots, p_n$: 1) construct the Voronoi partition corresponding to $P = (p_1, \ldots, p_n)$; 2) compute the mass centroids of the Voronoi regions found in step 1). Set the new location of the agents to these centroids, and return to step 1). Lloyd

algorithm can also be seen as a fixed-point iteration. Consider the mappings $LL_i: Q^n \rightarrow Q$ for $i \in \{1, \ldots, n\}$

$$LL_i(p_1, \ldots, p_n) = \left(\int_{V_i(P)} \phi(q)dq\right)^{-1} \int_{V_i(P)} q\phi(q)dq.$$

Let $LL: Q^n \rightarrow Q^n$ be defined by $LL = (LL_1, \ldots, LL_n)$. Clearly, LL is continuous (indeed, C^1), and corresponds to Lloyd algorithm. Now, $\|LL_i(P) - C_{V_i}\| = 0 \leq \|p_i - C_{V_i}\|$, for all $i \in \{1, \ldots, n\}$. Moreover, if P is not centroidal, then the inequality is strict for all $p_i \neq C_{V_i}$. Therefore, LL verifies properties 1) and 2).

C. Remarks

1) Note that different sensor performance functions f in (1) correspond to different optimization problems. Provided one uses the Euclidean distance in the definition of $\mathcal{H}$ [cf. (1)], the standard Voronoi partition computed with respect to the Euclidean metric remains the optimal partition. For arbitrary f, it is not possible anymore to decompose $\mathcal{H}_{\mathcal{V}}$ into the sum of terms similar to $\mathcal{H}_{\mathcal{V},1}$ and $\mathcal{H}_{\mathcal{V},2}$. Nevertheless, it is still possible to implement the gradient flow via the expression for the partial derivative (3).

Proposition 3.5: Assume the sensors location obeys a first-order dynamical behavior, $\dot{p}_i = u_i$. Then, for the closed-loop system induced by the gradient law (3), $u_i = -\partial\mathcal{H}_{\mathcal{V}}/\partial p_i$, the sensors location $P = (p_1, \ldots, p_n)$ converges asymptotically to the set of critical points of $\mathcal{H}_{\mathcal{V}}$. Assuming this set is finite, the sensors location converges to a critical point.

2) More generally, various distance notions can be used to define locational optimization functions. Different performance function gives rise to corresponding notions of "center of a region" (any notion of geometric center, mean, or average is an interesting candidate). These can then be adopted in designing coverage algorithms. We refer to [36] for a discussion on Voronoi partitions based on non-Euclidean distance functions, and to [5] and [8] for a discussion on the corresponding locational optimization problems.

3) Next, let us discuss an interesting variation of the original problem. In [6], minimizing the expected minimum distance function $\mathcal{H}_{\mathcal{V}}$ in (2) is referred to as the *continuous p-median problem*. It is instructive to consider the worst-case minimum distance function, corresponding to the scenario where no information is available on the distribution density function. In other words, the network seeks to minimize the largest possible distance from any point in Q to any of the sensor locations, i.e., to minimize the function

$$\max_{q \in Q} \left[\min_{i \in \{1, \ldots, n\}} \|q - p_i\|\right] = \max_{i \in \{1, \ldots, n\}} \left[\max_{q \in V_i} \|q - p_i\|\right].$$

This optimization is referred to as the *p-center problem* in [6] and [7]. One can design a strategy for the p-center problem analog to the Lloyd algorithm for the p-median problem. Each vehicle moves, in continuous or discrete time, toward the center of the minimum-radius sphere enclosing the polytope. We refer to [37] for a convergence analysis of the continuous-time algorithms.

In what follows, we shall restrict our attention to the p-median problem and to centroidal Voronoi partitions.
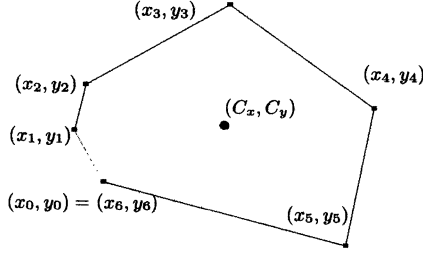
Fig. 2.   Notation conventions for a convex polygon.

D. Computations Over Polygons With Uniform Density

In this section, we investigate closed-form expression for the control laws introduced above. Assume the Voronoi region V_i is a convex polygon (i.e., a polytope in $\mathbb{R}^2$) with N_i vertexes labeled $\{(x_0, y_0), \ldots, (x_{N_i-1}, y_{N_i-1})\}$ such as in Fig. 2. It is convenient to define $(x_{N_i}, y_{N_i}) = (x_0, y_0)$. Furthermore, we assume that the density function is $\phi(q) = 1$. By evaluating the corresponding integrals, one can obtain the following closed-form expressions:

$$M_{V_i} = \frac{1}{2} \sum_{k=0}^{N_i-1} (x_k y_{k+1} - x_{k+1} y_k)$$

$$C_{V_i,x} = \frac{1}{6M_{V_i}} \sum_{k=0}^{N_i-1} (x_k + x_{k+1})(x_k y_{k+1} - x_{k+1} y_k)$$

$$C_{V_i,y} = \frac{1}{6M_{V_i}} \sum_{k=0}^{N_i-1} (y_k + y_{k+1})(x_k y_{k+1} - x_{k+1} y_k). \quad (9)$$

To present a simple formula for the polar moment of inertia, let $\bar{x}_k = x_k - C_{V_i,x}$ and $\bar{y}_k = y_k - C_{V_i,y}$, for $k \in \{0, \ldots, N_i-1\}$. Then, the polar moment of inertia of a polygon about its centroid $J_{V_i,C}$ becomes

$$J_{V_i,C_{V_i}} = \frac{1}{12} \sum_{k=0}^{N_i-1} (\bar{x}_k \bar{y}_{k+1} - \bar{x}_{k+1} \bar{y}_k)$$
$$\cdot (\bar{x}_k^2 + \bar{x}_k \bar{x}_{k+1} + \bar{x}_{k+1}^2 + \bar{y}_k^2 + \bar{y}_k \bar{y}_{k+1} + \bar{y}_{k+1}^2).$$

The proof of these formulas is based on decomposing the polygon into the union of disjoint triangles. We refer to [38] for analog expressions over $\mathbb{R}^N$.

Note also that the Voronoi polygon's vertexes can be expressed as a function of the neighboring vehicles. The vertexes of the ith Voronoi polygon that lie in the interior of Q are the circumcenters of the triangles formed by p_i and any two neighbors adjacent to p_i. The circumcenter of the triangle determined by p_i, p_j, and p_k is

$$\frac{1}{4M} \Big(\|\alpha_{kj}\|^2 (\alpha_{ji} \cdot \alpha_{ik}) p_i + \|\alpha_{ik}\|^2 (\alpha_{kj} \cdot \alpha_{ji}) p_j$$
$$+ \|\alpha_{ji}\|^2 (\alpha_{ik} \cdot \alpha_{kj}) p_k \Big) \quad (10)$$

where M is the area of the triangle, and $\alpha_{ls} = p_l - p_s$.

Equation (9) for a polygon's centroid and (10) for the Voronoi cell's vertexes lead to a closed-form algebraic expression for the control law in (6) as a function of the neighboring vehicles' location.

E. Numerical Simulations

To illustrate the performance of the continuous-time Lloyd algorithm, we include some simulation results. The algorithm is implemented in `Mathematica` as a single centralized program. For the $\mathbb{R}^2$ setting, the code computes the bounded Voronoi diagram using the `Mathematica` package `ComputationalGeometry`, and computes mass, centroid, and polar moment of inertia of polygons via the numerical integration routine `NIntegrate`. Careful attention was paid to numerical accuracy issues in the computation of the Voronoi diagram and in the integration. We illustrate the performance of the closed-loop system in Fig. 3.

IV. ASYNCHRONOUS DISTRIBUTED IMPLEMENTATIONS

In this section, we show how the Lloyd gradient algorithm can be implemented in an asynchronous distributed fashion. In Section IV-A, we describe our model for a network of robotic agents, and we introduce a precise notion of *distributed* evolution. Next, we provide two distributed algorithms for the local computation and maintenance of the Voronoi cells. Finally, in Section IV-C, we propose two distributed asynchronous implementations of Lloyd algorithm. The first one is based on the gradient optimization algorithms, as described in [32], and the second one relies on the special structure of the coverage problem.

A. Modeling an Asynchronous Distributed Network of Mobile Robotic Agents

We start by modeling a robotic agent that performs sensing, communication, computation, and control actions. We are interested in the behavior of the asynchronous network resulting from the interaction of finitely many robotic agents. A framework to formalize the following concepts is the theory of distributed algorithms; see [30].

Let us here introduce the notion of *robotic agent with computation, communication, and control capabilities* as the ith element of a network. The ith agent has a processor with the ability of allocating continuous and discrete states and performing operations on them. Each vehicle has access to its unique identifier i. The ith agent occupies a location $p_i \in Q \subset \mathbb{R}^N$ and it is capable of moving in space, at any time $t \in \mathbb{R}_+$ for any period of time $\delta t \in \mathbb{R}_+$, according to a first-order dynamics of the form

$$\dot{p}_i(s) = u_i, \quad \|u_i\| \le 1, \quad \forall s \in [t, t+\delta t]. \quad (11)$$

The processor has access to the agent's location p_i and determines the *control pair* $(\delta t, u_i)$. The processor of the ith agent has access to a local clock $t_i \in \mathbb{R}_+$, and a *scheduling sequence*, i.e., an increasing sequence of times $\{T_{i,k} \in \mathbb{R}_+ \mid k \in \mathbb{N}_0\}$ such that $T_{i,0} = 0$ and $0 < t_{i,\min} < T_{i,k+1} - T_{i,k} < t_{i,\max}$. The processor of the ith agent is capable of transmitting information to any other agent within a closed disk of radius $R_i \in \mathbb{R}_+$. We assume the communication radius R_i to be a quantity controllable by the ith processor and the corresponding communication bandwidth to be limited. We represent the information flow between the agents by means of "send" (within specified radius R_i) and "receive" commands with a finite number of arguments.
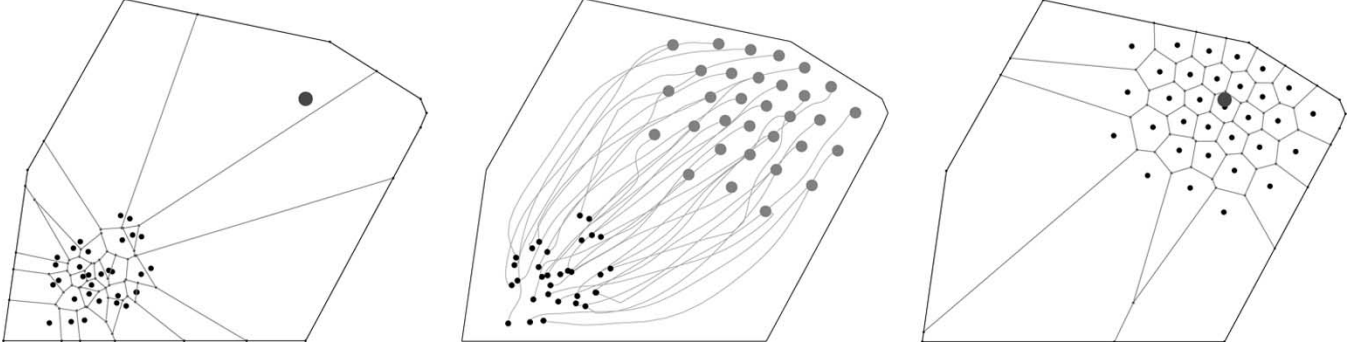
Fig. 3.   Lloyd continuous-time algorithm for 32 agents on a convex polygonal environment, with the Gaussian density function of Fig. 1. The control gain in (6) is $k_{\text{prop}} = 1$ for all the vehicles. The left (respectively, right) figure illustrates the initial (respectively, final) locations and Voronoi partition. The central figure illustrates the gradient descent flow.

We shall alternatively consider networks of *robotic agents with computation, sensing, and control capabilities*. In this case, the processor of the ith agent has the same computation and control capabilities as before. Furthermore, we assume the processor can detect any other agent within a closed disk of radius $R_i \in \mathbb{R}_+$. We assume the sensing radius R_i to be a quantity controllable by the processor.

Remark 4.1: We assume all communication between agents and all sensing of agents' locations to be always accurate and instantaneous.

Consider the closed-loop system formed by the evolution of the n agents of a network, according to (11). The network evolution is said to be *Voronoi-distributed* if each $u_i(p_1, \ldots, p_n)$ can be written as a function of the form $u_i(p_i, p_{i_1}, \ldots, p_{i_m})$, with $i_k \in \mathcal{N}(i)$, $k \in \{1, \ldots, m\}$. It is well known that there are, at most, $3n - 6$ neighborhood relationships in a planar Voronoi diagram [9, Sec. 2.3]. As a consequence, the number of Voronoi neighbors of each site is, on average, less than or equal to six, i.e., $m \leq 6$. (Recall that sites are Voronoi neighbors if they share an edge, not just a vertex.) Accordingly, we argue that Voronoi-distributed algorithms lead to scalable networks. Finally, note that the set of indexes $\{i_1, \ldots, i_m\}$ for a specific generator p_i of a Voronoi-distributed dynamical system is not the same for all possible configurations of the network. In other words, the identity of the Voronoi neighbors changes along the evolution, i.e., the topology of the closed-loop system is dynamic.

B. Voronoi Cell Computation and Maintenance

A key requirement of the Lloyd algorithms presented in Section III is that each agent must be able to compute its own Voronoi cell. To do so, each agent needs to know the relative location (distance and bearing) of each Voronoi neighbor. The ability of locating neighbors plays a central role in numerous algorithms for localization, media access, routing, and power control in ad-hoc wireless communication networks; e.g., see [39]–[41] and references therein. Therefore, any motion-control scheme might be able to obtain this information from the underlying communication layer. In what follows, we set out to provide a distributed asynchronous algorithm for the local computation and maintenance of Voronoi cells. The algorithm is related to the synchronous scheme in [41], and is based on basic properties of Voronoi diagrams.

TABLE I
ADJUST-SENSING-RADIUS ALGORITHM

Name:	ADJUST SENSING RADIUS ALGORITHM
Goal:	distributed Voronoi cell
Requires:	sensor with controllable radius R_i

At time t_i, local agent i performs:
1: initialize R_i, detect all p_j within radius R_i
2: update $P^i(t_i)$, compute $W(p_i(t_i), R_i)$
3: **while** $R_i < 2 \max_{q \in W(p_i(t_i), R_i)} \|p_i(t_i) - q\|$ **do**
4:     set $R_i := 2R_i$
5:     detect all p_j within radius R_i
6:     update $P^i(t_i)$, compute $W(p_i(t_i), R_i)$
7: **end while**
8: set $R_i := 2 \max_{q \in W(p_i(t_i), R_i)} \|p_i(t_i) - q\|$
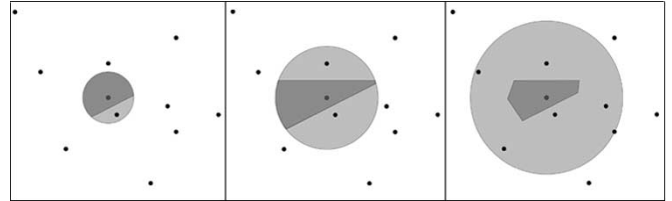9: set $V_i := W_i(p_i(t_i), R_i)$

Fig. 4.   An execution (from left to right) of the adjust-communication-radius algorithm. The sensing disk $\overline{B}(p_i, R_i)$ is in light gray, and the Voronoi cell estimate $W(p_i, R_i)$ is the darker gray region.

We present the algorithm for a robotic agent with sensing capabilities (as well as computation and control). The processor of the ith agent allocates the information it has on the position of the other agents in the state variable P^i. The objective is to determine the smallest distance R_i for agent i which provides enough information to compute the Voronoi cell V_i. Define the following convex set:

$$W(p_i, R_i) = \overline{B}(p_i, R_i) \cap \left(\cap_{j:\|p_i - p_j\| \leq R_i} S_{ij} \right) \qquad (12)$$

where $\overline{B}(p_i, R_i) = \{q \in Q| \ \|q - p_i\| \leq R_i\}$ and the half planes S_{ij} are

$$\{q \in \mathbb{R}^N| \quad \|q - p_i\| \leq \|q - p_j\|\}.$$

Provided R_i is twice as large as the maximum distance between p_i and the vertexes of $W(p_i, R_i)$, one can show that all Voronoi neighbors of p_i are within distance R_i from p_i and the equality $V_i = W(p_i, R_i)$ holds. The minimum adequate sensing radius is, therefore, $R_{i,\min} = 2 \max_{q \in W(p_i, R_{i,\min})} \|p_i - q\|$. This argument guarantees the correctness of the adjust-communica-

TABLE II
MONITORING ALGORITHM

Name:	MONITORING ALGORITHM
Goal:	Cell maintenance & event detection
Requires:	(i) sensor with controllable radius R_i
	(ii) positive reals t_0, δt
	(iii) ADJUST SENSING RADIUS ALGORITHM

Local agent i performs for $t_i \in [t_0, t_0 + \delta t]$:
1: initialize $P^i(t_0)$ and $V_i(t_0)$, set $w :=$ weight$(P^i(t_0))$
2: **while** $t_i \leq t_0 + \delta t$ **do**
3:    run ADJUST SENSING RADIUS ALGORITHM
4:    **if** for any j, $|\text{weight}_j(P^i(t_i)) - w_j| \geq 2$ **then**
5:      **if** weight$_j(P^i(t_i)) - w_j \geq 2$ **then**
6:        set *event* := true
7:      **end if**
8:      set $w :=$ weight$(P^i(t_i))$
9:    **end if**
10: **end while**

TABLE III
COVERAGE BEHAVIOR ALGORITHM I

Name:	COVERAGE BEHAVIOR ALGORITHM I
Goal:	distributed optimal agent location
Requires:	(i) Voronoi cell computation
	(ii) centroid and mass computation
	(iii) positive real δ_0
	(iv) ADJUST COMMUNICATION RADIUS ALGORITHM

For $i \in \{1, \ldots, n\}$, ith agent performs at $t_i = T_{i,0} = 0$:
0: set $P^i(T_{i,0}) := (p_1^i(T_{i,0}), \ldots, p_n^i(T_{i,0}))$
0: compute Voronoi region $V_i(T_{i,0})$
0: set $V_i := V_i(T_{i,0})$ and $R_i := 2 \max_{q \in V_i} \|p_i - q\|$

For $i \in \{1, \ldots, n\}$, the ith agent performs at time $t_i = T_{i,k}$ either one of the following threads or both. For some $B_i \in \mathbb{N}$, we require that each thread is executed at least once every B_i steps of the scheduling sequence.

[Information thread]
1: run ADJUST COMMUNICATION RADIUS ALGORITHM

[Control thread]
1: compute centroid C_{V_i} and mass M_{V_i} of V_i
2: apply control pair $\left(\delta_0, \ M_{V_i}(C_{V_i} - p_i(T_{i,k})) \right)$

tion-radius algorithm in Table I. The execution of this algorithm is illustrated in Fig. 4.

A similar adjust-communication-radius algorithm can be designed for a robotic agent with communication capabilities. The specifications go as in the previous algorithm, except for the fact that steps 2 and 6 are substituted by

send (request to reply, $p_i(t_i)$) within radius R_i

receive (response, p_j) from all agents within radius R_i.

Further, we have to require each agent to perform the following event-driven task: if the ith agent receives at any time t_i a "request to reply" message from the jth agent located at position p_j, it executes

send (response, $p_i(t_i)$) within radius $\|p_i(t) - p_j\|$.

Next, we present the monitoring algorithm (cf. Table II), whose objective is to maintain the information about the Voronoi cell of the ith agent, and detect certain events. We consider robotic agents with sensing capabilities. We call an agent *active* if it is moving, and we assume the ith agent can determine whether any agent within radius R_i is active or not. It turns out that (only) the following two events are of interest: 1) a Voronoi neighbor of the ith agent becomes active; and 2) an active agent becomes a Voronoi neighbor of the ith agent. In both cases, we record the event by setting a Boolean variable *event* to true (as we shall later show, this will trigger an appropriate control action). The map weight $P^i \in \mathbb{R}^{N \times n} \mapsto (w_1, \ldots, w_n) \in \mathbb{N}_0^n$ in Table II is defined by

$$w_j = \begin{cases} 3, & \text{if } j \in \mathcal{N}(i) \text{ and } j \text{ is active} \\ 1, & \text{if } j \in \mathcal{N}(i) \text{ and } j \text{ is not active} \\ 0, & \text{if } j \notin \mathcal{N}(i). \end{cases}$$

We denote by weight$_j$ the jth component of weight. The algorithm is designed to run for times $t_i \in [t_0, t_0 + \delta t]$.

The correctness of the monitoring algorithm is guaranteed by the following argument: if an event of type 1) occurs at time $t_i \in [t_0, t_0 + \delta t]$, i.e., an agent (say, the jth) that is a Voronoi neighbor of the ith agent becomes active, then weight$_j(P^i(t_i)) - w_j = 2$,

and therefore, *event* is set to true. Similarly, if an event of type 2) occurs at time $t_i \in [t_0, t_0 + \delta t]$, i.e., a new active agent (say, the jth) becomes a Voronoi neighbor of the ith agent, then weight$_j(P^i(t_i)) - w_j = 3$, and *event* is set to true.

C. Asynchronous Distributed Implementations of Coverage Control

Let us now present two versions of Lloyd algorithm for the solution of the optimization problem 1) that can be implemented by an asynchronous distributed network of robotic agents. For simplicity, we assume that at time 0, all clocks are synchronized (although they later can run at different speeds), and that each agent knows at 0 the exact location of every other agent. The coverage behavior algorithm I (cf. Table III) is designed for robotic agents with communication capabilities, and requires the adjust-communication-radius algorithm (while it does not require the monitoring algorithm).

As a consequence of the results in [32, Th. 3.1 and Cor. 3.1] (see Appendix II, *Theorem 2.2* below for a brief exposition), we have the following result.

Proposition 4.2: Let $P_0 \in Q^n$ denote the initial sensors location. Let $\{T_k\}$ be the sequence in increasing order of all the scheduling sequences of the agents of the network. Assume $\inf_k \{T_k - T_{k-1}\} > 0$. Then, there exists a sufficiently small $\delta_* > 0$ such that if $0 < \delta_0 \leq \delta_*$, the coverage behavior algorithm I converges to the set of critical points of $\mathcal{H}_\mathcal{V}$, that is, the set of centroidal Voronoi configurations.

Next, we focus on distributed asynchronous implementations of Lloyd algorithm that take advantage of the special structure of the coverage problem. The coverage behavior algorithm II (cf. Table IV) is designed for robotic agents with sensing capabilities; it requires the monitoring and the adjust-sensing-radius algorithms. Two advantages of this algorithm over the previous one are that there is no need for each agent to exactly go toward the centroid of its Voronoi cell nor to take a small step at each stage.

TABLE IV
COVERAGE BEHAVIOR ALGORITHM II

Name:	COVERAGE BEHAVIOR ALGORITHM II
Goal:	distributed optimal agent location
Requires:	(i) Voronoi cell computation
	(ii) centroid computation
	(iii) MONITORING ALGORITHM

For $i \in \{1, \ldots, n\}$, *i*th agent performs at $t_i = T_{i,0} = 0$:

0: set $P^i(T_{i,0}) := (p_1^i(T_{i,0}), \ldots, p_n^i(T_{i,0}))$
0: compute Voronoi region $V_i(T_{i,0})$
0: set $V_i := V_i(T_{i,0})$ and $R_i := 2 \max_{q \in V_i} \|p_i - q\|$

For $i \in \{1, \ldots, n\}$, *i*th agent performs at $t_i = T_{i,k}$:

1: choose $0 < \delta t_i < t_{i,min}$
2: set $s := T_{i,k}$, compute centroid $C_{V_i}(s)$
3: choose u_i, with $u_i \cdot (C_{V_i} - p_i(s)) \geq 0$, with strict inequality if $p_i(s) \neq C_{V_i}$, set *event* := false
4: **while** $t_i \leq T_{i,k} + \delta t_i$ **do**
5:    run MONITORING ALGORITHM for $(T_{i,k}, \delta t_i)$
6:    **while** *event* = false **do**
7:       $\dot{p}_i = u_i$
8:    **end while**
9:    set $s := t_i$, compute centroid $C_{V_i}(s)$
10:   choose u_i, with $u_i \cdot (C_{V_i} - p_i(s)) \geq 0$, with strict inequality if $p_i(s) \neq C_{V_i}$, set *event* := false
11: **end while**

Remark 4.3: The control law in step 7 of the coverage behavior algorithm II can be defined via a saturation function. For instance, SR: $\mathbb{R}^N \to \mathbb{R}^N$

$$\mathrm{SR}(x) = \begin{cases} x, & \text{if } \|x\| \leq 1 \\ \frac{x}{\|x\|} & \text{if } \|x\| \geq 1. \end{cases}$$

Then set $u_i = \mathrm{SR}(C_{V_i} - p_i)$.

With respect to the correctness of the coverage behavior algorithm II, one can consider the time instants when the computation of the centroid of the Voronoi region of any agent is made, together with the time instants when any agent decides to stop, and regard the execution of this algorithm as a discrete-time mapping. Resorting to the discussion in Section III-B on the convergence of the discrete Lloyd algorithms, one can prove that the coverage behavior algorithm II verifies properties 1) and 2). As a consequence of *Proposition 3.3*, we then have the following result.

Proposition 4.4: Let $P_0 \in Q^n$ denote the initial sensors location. The coverage behavior algorithm II converges to the set of critical points of $\mathcal{H}_\mathcal{V}$, that is, the set of centroidal Voronoi configurations.

V. EXTENSIONS AND APPLICATIONS

In this section, we investigate various extensions and applications of the algorithms proposed in Sections II–IV. We extend the treatment to vehicles with passive dynamics and we also consider discrete-time implementations of the algorithms for vehicles endowed with a local motion planner. Finally, we describe interesting ways of designing density functions to solve problems apparently unrelated to coverage.

A. Variations on Vehicle Dynamics

Here, we consider vehicle systems described by more general linear and nonlinear dynamical models.

Coordination of vehicles with passive dynamics. We start by considering the extension of the control design to nonlinear
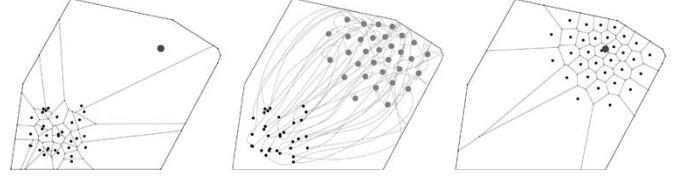

Fig. 5.   Coverage control for 32 vehicles with second-order dynamics. The environment and Gaussian density function are as in Fig. 3. The control gains are $k_{\mathrm{prop}} = 6$ and $k_{\mathrm{deriv}} = 1$.

control systems whose dynamics are passive [42]. Relevant examples include networks of vehicles and robots with general Lagrangian dynamics, as well as spatially invariant passive linear systems. Specifically, assume that for each $i \in \{1, \ldots, n\}$, the *i*th vehicle state includes the spatial variable p_i, and that the vehicle's dynamics are passive with input u_i, output $\dot{p}_i$, and storage function $S_i: Q \to \mathbb{R}_+$. Furthermore, assume that the input preserving the zero-dynamics manifold $\{\dot{p}_i = 0\}$ is $u_i = 0$.

For such systems, we devise a proportional derivative (PD) control via

$$u_i = -k_{\mathrm{prop}} M_{V_i}(p_i - C_{V_i}) - k_{\mathrm{deriv}} \dot{p}_i \qquad (13)$$

where k_{prop} and k_{deriv} are scalar positive gains. The closed-loop system induced by this control law can be analyzed with the Lyapunov function

$$\mathcal{E} = \frac{1}{2} k_{\mathrm{prop}} \mathcal{H}_\mathcal{V} + \sum_{i=1}^{n} S_i$$

yielding the following result.

Proposition 5.1: For passive systems, the control law (13) achieves asymptotic convergence of the sensors location to the set of centroidal Voronoi configurations. If this set is finite, then the sensors location converges to a centroidal Voronoi configuration.

Proof: Consider the evolution of the function $\mathcal{E}$

$$\begin{aligned} \frac{d}{dt}\mathcal{E} &= \frac{1}{2} k_{\mathrm{prop}} \frac{d}{dt} \mathcal{H}_\mathcal{V} + \sum_{i=1}^{n} \dot{S}_i \\ &\leq k_{\mathrm{prop}} M_{V_i}(p_i - C_{V_i}) + \dot{p}_i u_i \\ &= -k_{\mathrm{deriv}} \sum_{i=1}^{n} \dot{p}_i^2 \leq 0. \end{aligned}$$

By LaSalle's principle, the sensors location converges to the largest invariant set contained in $\{\dot{p}_i = 0\}$. Given the assumption on the zero dynamics, we conclude that $p_i = C_{V_i}$ for $i \in \{1, \ldots, n\}$, i.e., the largest invariant set corresponds to the set of centroidal Voronoi configurations. If this set is finite, LaSalle's principle also guarantees convergence to a specific centroidal Voronoi configuration.   ∎

In Fig. 5, we illustrate the performance of the control law (13) for vehicles with second-order dynamics $\ddot{p}_i = u_i$ and storage function $S_i = 1/2\dot{p}_i^2$.

Coordination of vehicles with local controllers. Next, consider the setting where each vehicle has arbitrary dynamics and is endowed with a local feedback and feedforward controller. The controller is capable of strictly decreasing the distance to any specified position in Q in a specified period of time δ.
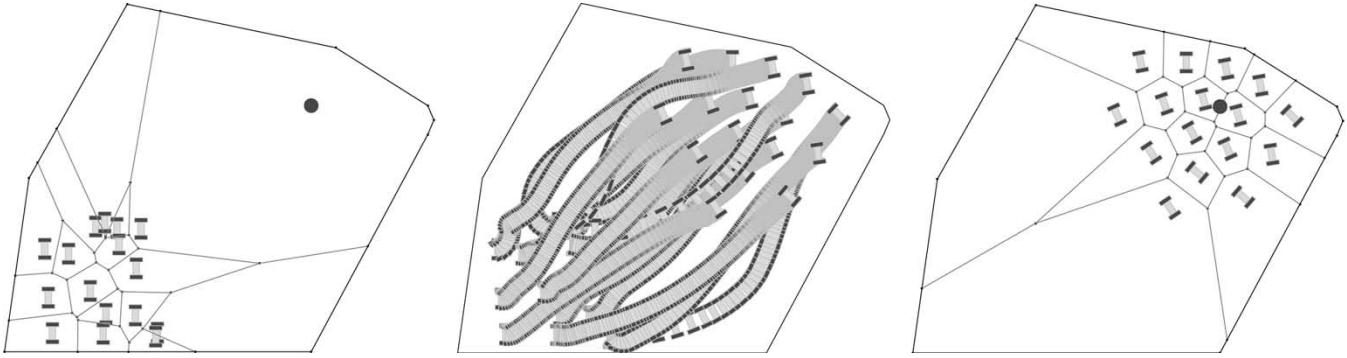
Fig. 6.   Coverage control for 16 vehicles with mobile wheeled dynamics. The environment and Gaussian density function are as in Fig. 3, and $k_{\text{prop}} = 3$.

Assume the dynamics of the ith vehicle are described by $\dot{x}_i = f_i(t, x_i, u)$, where $x_i \in \mathbb{R}^m$ denotes its state, and $\pi_i\colon \mathbb{R}^{m_i} \to Q$ is such that $\pi_i(x_i) = p_i$. Assume also that for any $p_{\text{target}} \in Q$ and any $x_0 \in \mathbb{R}^m \setminus \pi_i^{-1}(p_{\text{target}})$, there exists $\overline{u}(t, x(t), p_{\text{target}})$ such that the solution $\overline{x}_i(t)$ of

$$\dot{\overline{x}}_i = f_i(t, \overline{x}_i(t), \overline{u}(t, \overline{x}_i(t), p_{\text{target}})), \quad \overline{x}_i(0) = x_0$$

verifies $\|\pi_i(\overline{x}_i(t_0 + \delta)) - p_{\text{target}}\| < \|\pi_i(\overline{x}_i(t_0)) - p_{\text{target}}\|$.

Proposition 5.2: Consider the following coordination algorithm. At time $t_k = k\delta$, $k \in \mathbb{N}$, each vehicle computes $V_i(t_k)$ and $C_{V_i}(t_k)$; then, for time $t \in [t_k, t_{k+1}]$, the vehicle executes $\overline{u}(t, x(t), C_{V_i}(t_k))$. For this closed-loop system, the sensors location converges to the set of centroidal Voronoi configurations. If this set is finite, then the sensors location converges to a centroidal Voronoi configuration.

The proof of this result readily follows from *Proposition 3.3*, since the algorithm verifies properties 1) and 2) of Section III-B.

As an example, we consider a classic model of mobile wheeled dynamics, the *unicycle model*. Assume the ith vehicle has configuration $(\theta_i, x_i, y_i) \in \text{SE}(2)$ evolving according to

$$\dot{\theta}_i = \omega_i, \quad \dot{x}_i = v_i \cos \theta_i, \quad \dot{y}_i = v_i \sin \theta_i$$

where (ω_i, v_i) are the control inputs for vehicle i. Note that the definition of (θ_i, v_i) is unique up to the discrete action $(\theta_i, v_i) \mapsto (\theta_i + \pi, -v_i)$. Given a target point p_{target}, we use this symmetry to require the equality $(\cos \theta_i, \sin \theta_i) \cdot (p_i - p_{\text{target}}) \leq 0$ for all time t. Should the equality be violated at some time $t = t_0$, we shall redefine $\theta_i(t_0^+) = \theta_i(t_0^-) + \pi$ and v_i as $-v_i$ from time $t = t_0$ onward.

Following the approach in [43], consider the control law

$$\omega_i = 2k_{\text{prop}} \arctan \frac{(-\sin \theta_i, \, \cos \theta_i) \cdot (p_i - p_{\text{target}})}{(\cos \theta_i, \, \sin \theta_i) \cdot (p_i - p_{\text{target}})}$$

$$v_i = -k_{\text{prop}}(\cos \theta_i, \, \sin \theta_i) \cdot (p_i - p_{\text{target}})$$

where k_{prop} is a positive gain. This feedback law differs from the original stabilizing strategy in [43] only in the fact that no final angular position is preferred. One can prove that $p_i = (x_i, y_i)$ is guaranteed to monotonically approach the target position p_{target} when run over an infinite time horizon. We illustrate the performance of the proposed algorithm in Fig. 6.

B. Geometric Patterns and Formation Control

Here, we suggest the use of decentralized coverage algorithms as formation control algorithms, and we present various density functions that lead the multivehicle network to prede-
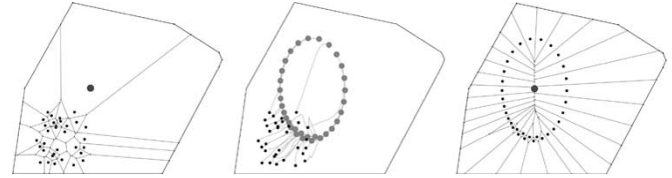

Fig. 7.   Coverage control for 32 vehicles with ϕ_{ellipse}. The parameter values are $k = 500$, $a = 1.4$, $b = 0.6$, $x_c = y_c = 0$, $r^2 = 0.3$, and $k_{\text{prop}} = 1$.
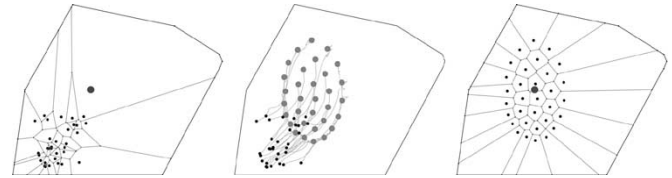

Fig. 8.   Coverage control for 32 vehicles to an ellipsoidal disk. The density function parameters are the same as in Fig. 7, and $\ell = 10$, $k_{\text{prop}} = 1$.

termined geometric patterns. In particular, we present simple density functions that lead to segments, ellipses, polygons, or uniform distributions inside convex environments.

Consider a planar environment, let k be a large positive gain, and denote $q = (x, y) \in Q \subset \mathbb{R}^2$. Let a, b, c be real numbers, consider the line $ax + by + c = 0$, and define the density function

$$\phi_{\text{line}}(q) = \exp(-k(ax + by + c)^2).$$

Similarly, let (x_c, y_c) be a reference point in $\mathbb{R}^2$, let a, b, r be positive scalars, consider the ellipse $a(x - x_c)^2 + b(y - y_c)^2 = r^2$, and define the density function

$$\phi_{\text{ellipse}}(q) = \exp\left(-k\left(a(x - x_c)^2 + b(y - y_c)^2 - r^2\right)^2\right).$$

Fig. 7 illustrates the performance of the closed-loop network corresponding to this density function. During the simulations, we observed that the convergence to the desired pattern was rather slow.

Finally, define the smooth ramp function $\text{SR}_\ell(x) = x(\arctan(\ell x)/\pi + (1/2))$, and the density function

$$\phi_{\text{disk}}(q) = \exp(-k\text{SR}_\ell(a(x - x_c)^2 + b(y - y_c)^2 - r^2)).$$

This density function leads the multivehicle network to obtain a uniform distribution inside the ellipsoidal disk $a(x - x_c)^2 + b(y - y_c)^2 \leq r^2$. We illustrate this density function in Fig. 8.

It appears straightforward to generalize these types of density functions to the setting of arbitrary curves or shapes. The proposed algorithms are to be contrasted with the classic approach

to formation control, based on rigidly encoding the desired geometric pattern. One disadvantage of the proposed approach is the requirement for a careful numerical computation of Voronoi diagrams and centroids. We refer to [14] and [15] for previous work on algorithms for geometric patterns, and to [17] and [18] for formation control algorithms.

VI. CONCLUSIONS

We have presented a novel approach to coordination algorithms for multivehicle networks. The scheme can be thought of as an interaction law between agents, and as such it is implementable in a distributed scalable asynchronous fashion.

This paper leaves numerous important extensions open for further research. First, we envision considering the setting of structured environments (ranging all the way from simple nonconvex polygon to more realistic ground, air, and underwater environments); it might be useful, for example, to design distributed algorithms for the art gallery problem. Second, it is clearly important to consider nonisotropic sensors, such as cameras and directional microphones, as well as limited footprint sensors, as studied, for example, in the literature on coverage path planning. Third, we plan to extend the algorithms to provide collision avoidance guarantees and to vehicle dynamics which are not locally controllable. Finally, to investigate the effect of measurement errors on our proposed algorithms and to quantify their closed-loop robustness, we are implementing these algorithms on a network of all-terrain vehicles. All these problems provide nontrivial challenges that go beyond our current treatment.

APPENDIX I
INVARIANCE AND CONVERGENCE PRINCIPLES

In this section, we collect some relevant facts on descent flows both in the continuous and in the discrete-time settings. We do this following [44] and [45], respectively. We include *Proposition 1.4*, as we are unable to locate it in the linear and nonlinear programming literature.

A. Continuous-Time Descent Flows

Consider the differential equation $\dot{x} = X(x)$, where $X: D \subset \mathbb{R}^N \to \mathbb{R}^N$ is locally Lipschitz and D is an open connected set. A set M is said to be (positively) invariant with respect to X if $x(0) \in M$ implies $x(t) \in M$, for all $t \in \mathbb{R}$ (resp. $t \geq 0$). A descent function for X on Ω, $V: D \to \mathbb{R}$, is a continuously differentiable function such that $\mathcal{L}_X V \leq 0$ on Ω. We denote by E the set of points in Ω where $\mathcal{L}_X V(x) = 0$ and by M be the largest invariant set contained in E. Finally, the distance from a point x to a set M is defined as $\operatorname{dist}(x, M) = \inf_{p \in M} \|x - p\|$.

Lemma 1.1 (LaSalle's Principle): Let $\Omega \subset D$ be a compact set that it is positively invariant with respect to X. Let $x(0) \in \Omega$ and x_* be an accumulation point of $x(t)$. Then $x_* \in M$ and $\operatorname{dist}(x(t), M) \to 0$ as $t \to \infty$.

The following corollary is [44, Exercise 3.22].

Corollary 1.2: If the set M is a finite collection of points, then the limit of $x(t)$ exists and equals one of them.

B. Discrete-Time Descent Flows

Let X be a subset of $\mathbb{R}^N$. An algorithm T is a continuous mapping from X to X. A set C is said to be positively invariant with respect to T if $x_0 \in C$ implies $T(x_0) \in C$. A point x_* is said to be a fixed point of T if $T(x_*) = x_*$. We denote the set of fixed points of T by Γ. A descent function for T on C, $Z: X \to \mathbb{R}_+$, is any nonnegative real-valued continuous function satisfying $Z(T(x)) \leq Z(x)$ for $x \in C$, where the inequality is strict if $x \notin \Gamma$. Typically, Z is the objective function to be minimized, and T reflects this goal by yielding a point that reduces (or at least does not increase) Z.

Lemma 1.3 (Global Convergence Theorem): Let $T: X \to X$ be an algorithm with a compact, positively invariant set $C \subset X$ and a descent function Z. Let $x_0 \in C$ and denote $x_m = T(x_{m-1})$, $m \geq 1$. Let x_* be an accumulation point of the sequence $\{x_m \in C | \ m \in \mathbb{N}\}$. Then $x_* \in \Gamma$, $\operatorname{dist}(x_m, \Gamma) \to 0$ and $Z(x_m) \to Z(x_*)$ as $m \to \infty$.

Proposition 1.4: If the set Γ is a finite collection of points, then $\{x_m \in C | \ m \in \mathbb{N}\}$ converges and equals one of them.

Proof: Let x_* be an accumulation point of $\{x_m\}$ and assume the whole sequence does not converge to it. Then, there exists an $\epsilon > 0$ such that for all m_0, there is a $m' > m_0$, such that $\|x_{m'} - x_*\| > \epsilon$. Let d be the minimum of all the distances between the points in Γ. Fix $\epsilon' = \min\{d/2, \epsilon\}$. Since T is continuous and Γ is finite, there exists $\delta > 0$ such that $\|x - z\| < \delta$, with $z \in \Gamma$, implies $\|T(x) - z\| < \epsilon'$ (that is, for each $z \in \Gamma$, there exists such $\delta(z)$, and we take the minimum over Γ).

Now, since $\operatorname{dist}(x_m, \Gamma) \to 0$, there exists m_1 such that for all $m \geq m_1$, $\operatorname{dist}(x_m, \Gamma) < \delta$. Also, we know that there is a subsequence of $\{x_m | \ m \in \mathbb{N}\}$ which converges to x_*, let us denote it by $\{x_{m_k} | \ k \in \mathbb{N}\}$. For δ, there exists m_{k_1} such that for all $k \geq k_1$, we have $\|x_{m_k} - x_*\| < \delta$.

Let $m_0 = \max\{m_1, m_{k_1}\}$. Take k such that $m_k \geq m_0$ Then

$$\|x_{m_k+1} - x_*\| = \|T(x_{m_k}) - x_*\| < \epsilon'. \tag{14}$$

Now we are going to prove that $\|x_{m_k+1} - x_*\| < \delta$. If $d/2 \leq \delta$, then this claim is straightforward, since $\epsilon' \leq d/2$. If $d/2 > \delta$, suppose that $\|x_{m_k+1} - x_*\| > \delta$. Since $m_k + 1 > m_0 \geq m_1$, then $\operatorname{dist}(x_{m_k+1}, \Gamma) < \delta$. Therefore, there exists $y \in \Gamma$ such that $\|x_{m_k+1} - y\| < \delta$. Necessarily, $y \neq x_*$. Now, by the triangle inequality, $\|x - y\| \leq \|x - x_{m_k+1}\| + \|x_{m_k+1} - y\|$. Then

$$\|x_{m_k+1} - x_*\| \geq \|x - y\| - \|x_{m_k+1} - y\|$$
$$\geq d - \delta > \frac{d}{2}$$

which contradicts (14). Therefore, $\|x_{m_k+1} - x_*\| < \delta$. This argument can be iterated to prove that for all $m \geq m_0$, we have $\|x_m - x_*\| < \delta$. Let us take now $m' > m_0$ such that $\|x_{m'} - x_*\| > \epsilon$. Since $m' - 1 \geq m_0$, we have $\|x_{m'-1} - x_*\| < \delta$, and therefore

$$\|x_{m'} - x_*\| = \|T(x_{m'-1}) - x_*\| < \epsilon' \leq \epsilon$$

which is a contradiction. Therefore, $\{x_m | \ m \in \mathbb{N}\}$ converges to x_*. ∎

APPENDIX II
ASYNCHRONOUS GRADIENT ALGORITHMS

In this section, we present a brief account of the results in [32] concerning asynchronous gradient optimization algorithms. We do not review them in their full generality, but rather formulate them in a form readily applicable to our setting.

Let $H_1, \ldots, H_L$ be finite-dimensional real vector spaces, and let $H = H_1 \times H_2 \times \cdots \times H_L$. If $x = (x_1, \ldots, x_L), x_l \in H_l$, we refer to x_l as the lth component of x. Let $\{1, \ldots, M\}$ be a set of processors that participate in the computation. The algorithms considered here evolve in discrete time. This restriction does not involve any loss of generality, since the events of interest (an update by a processor, a transmission of a message, etc.) may be indexed by a discrete variable. The value stored by the ith processor at time n (global) is denoted by $x^i(n)$. This global clock is only need for analysis purposes. The processors may be working without having access to it; instead, they may have access to a local clock or to no clock at all.

Consider the *specialization setting* [32], where each processor updates a particular component of the vector x specifically assigned to it and relies on the information provided by the other processors for the remaining components. Formally:

1) $M = L$;
2) processor i may update only its own component x_i^i;
3) processor j only sends messages containing elements of H_j. If processor i receives such a message, it uses it to reset the x_j^i equal to the value received.

Let T_i^i be the set of all times when processor i performs a computation involving the ith component of x. If a message from processor j, containing an element of H_j, is received by processor i at time n, let $t_j^{ij}(n)$ denote the time that this message was sent. The content of the message is, therefore, $x_j^j(t_j^{ij}(n))$. Naturally, it is assumed $t_j^{ij}(n) \leq n$, and we set $t_i^{ii}(n) = n$. Finally, T_j^{ij} denotes the set of all times when processor i receives a message from processor j.

Let $\mathcal{J}: H \to \mathbb{R}_+$ be a C^1-function whose derivative is a Lipschitz function. Consider the *deterministic gradient algorithm* given by

$$x_i^i(n+1) = \begin{cases} x_i^i(n), & n \notin T_i^i \\ -\gamma_0 \frac{\partial \mathcal{J}}{\partial x_i}(x^i(n)), & n \in T_i^i \end{cases} \quad (15a)$$

$$x_j^i(n+1) = \begin{cases} x_j^i(n), & n \notin T_j^{ij} \\ x_j^j(t_j^{ij}(n)), & n \in T_j^{ij} \end{cases} \quad (15b)$$

where $\gamma_0 > 0$, $n \in \mathbb{N}$ and $i, j \in \{1, \ldots, M\}$. The specific conclusions of [32, Th. 3.1 and Cor. 3.1] that we need for the specialization setting are presented in the following result.

Theorem 2.1: Assume each processor i communicates its components x_i^i to every other processor at least once every B_1 time units, for some constant B_1. Then, there exists a constant $\gamma^* > 0$ such that if $0 < \gamma_0 \leq \gamma^*$, the deterministic gradient algorithm (15) verifies

$$\lim_{n \to \infty} \|x^i(n) - x^j(n)\| = 0$$

$$\lim_{n \to \infty} \frac{\partial \mathcal{J}}{\partial x_i}(x^i(n)) = 0$$

for all $i, j \in \{1, \ldots, M\}$.

In the particular case when, for each $i \in \{1, \ldots, M\}$, the partial derivative $\partial J / \partial x_i(x)$ only depends on x_l, with $l \in \mathcal{M}(x, i) \cup \{i\}$ for certain set $\mathcal{M}(x, i)$, the previous result can be restated in the following form.

Theorem 2.2: Assume each processor i communicates its components x_i^i to every other processor in $\mathcal{M}(x, i)$ at least once every B_1 time units, for some constant B_1. Then, there exists a constant $\gamma^* > 0$ such that if $0 < \gamma_0 \leq \gamma^*$, the deterministic gradient algorithm (15) verifies

$$\lim_{n \to \infty} \|x_l^i(n) - x_l^j(n)\| = 0$$

$$\lim_{n \to \infty} \frac{\partial \mathcal{J}}{\partial x_i}(x^i(n)) = 0$$

for all $i, j \in \{1, \ldots, M\}$ and all $l \in (\mathcal{M}(x, i) \cup \{i\}) \cap (\mathcal{M}(x, j) \cup \{j\})$.

REFERENCES

[1] C. R. Weisbin, J. Blitch, D. Lavery, E. Krotkov, C. Shoemaker, L. Matthies, and G. Rodriguez, "Miniature robots for space and military missions," *IEEE Robot. Automat. Mag.*, vol. 6, pp. 9–18, Mar. 1999.

[2] E. Krotkov and J. Blitch, "The defense advanced research projects agency (DARPA) tactical mobile robotics program," *Int. J. Robot. Res.*, vol. 18, no. 7, pp. 769–76, 1999.

[3] P. E. Rybski, N. P. Papanikolopoulos, S. A. Stoeter, D. G. Krantz, K. B. Yesin, M. Gini, R. Voyles, D. F. Hougen, B. Nelson, and M. D. Erickson, "Enlisting rangers and scouts for reconnaissance and surveillance," *IEEE Robot. Automat. Mag.*, vol. 7, pp. 14–24, Apr. 2000.

[4] T. B. Curtin, J. G. Bellingham, J. Catipovic, and D. Webb, "Autonomous oceanographic sampling networks," *Oceanography*, vol. 6, no. 3, pp. 86–94, 1993.

[5] A. Okabe, B. Boots, and K. Sugihara, "Nearest neighborhood operations with generalized Voronoi diagrams: A review," *Int. J. Geograph. Inform. Syst.*, vol. 8, no. 1, pp. 43–71, 1994.

[6] Z. Drezner, Ed., *Facility Location: A Survey of Applications and Methods.* ser. Series in Operations Research. New York: Springer Verlag, 1995.

[7] A. Suzuki and Z. Drezner, "The p-center location problem in an area," *Location Sci.*, vol. 4, no. 1/2, pp. 69–82, 1996.

[8] A. Okabe and A. Suzuki, "Locational optimization problems solved through Voronoi diagrams," *Eur. J. Oper. Res.*, vol. 98, no. 3, pp. 445–56, 1997.

[9] A. Okabe, B. Boots, K. Sugihara, and S. N. Chiu, *Spatial Tessellations: Concepts and Applications of Voronoi Diagrams*, 2nd ed, ser. Wiley Series in Probability and Statistics. New York: Wiley, 2000.

[10] Q. Du, V. Faber, and M. Gunzburger, "Centroidal Voronoi tessellations: Applications and algorithms," *SIAM Rev.*, vol. 41, no. 4, pp. 637–676, 1999.

[11] S. P. Lloyd, "Least-squares quantization in PCM," *IEEE Trans. Inform. Theory*, vol. IT-28, pp. 129–137, Jan. 1982.

[12] R. M. Gray and D. L. Neuhoff, "Quantization," *IEEE Trans. Inform. Theory*, vol. 44, pp. 2325–2383, Oct. 1998.

[13] H. Yamaguchi and T. Arai, "Distributed and autonomous control method for generating shape of multiple mobile robot group," in *Proc. IEEE/RSJ Int. Conf. Intelligent Robots and Systems*, Munich, Germany, Sept. 1994, pp. 800–807.

[14] K. Sugihara and I. Suzuki, "Distributed algorithms for formation of geometric patterns with many mobile robots," *J. Robot. Syst.*, vol. 13, no. 3, pp. 127–39, 1996.

[15] I. Suzuki and M. Yamashita, "Distributed anonymous mobile robots: Formation of geometric patterns," *SIAM J. Comput.*, vol. 28, no. 4, pp. 1347–1363, 1999.

[16] H. Ando, Y. Oasa, I. Suzuki, and M. Yamashita, "Distributed memoryless point convergence algorithm for mobile robots with limited visibility," *IEEE Trans. Robot. Automat.*, vol. 15, pp. 818–828, Oct. 1999.

[17] T. Balch and R. Arkin, "Behavior-based formation control for multi-robot systems," *IEEE Trans. Robot. Automat.*, vol. 14, pp. 926–939, Dec. 1998.

[18] J. P. Desai, J. P. Ostrowski, and V. Kumar, "Modeling and control of formations of nonholonomic mobile robots," *IEEE Trans. Robot. Automat.*, vol. 17, pp. 905–908, Dec. 2001.

[19] R. Bachmayer and N. E. Leonard, "Vehicle networks for gradient descent in a sampled environment," in *Proc. IEEE Conf. Decision and Control*, Las Vegas, NV, Dec. 2002, pp. 112–117.

[20] C. Tomlin, G. J. Pappas, and S. S. Sastry, "Conflict resolution for air traffic management: A study in multiagent hybrid systems," *IEEE Trans. Automat. Contr.*, vol. 43, pp. 509–521, May 1998.

[21] A. Jadbabaie, J. Lin, and A. S. Morse, "Coordination of groups of mobile autonomous agents using nearest neighbor rules," *IEEE Trans. Automat. Contr.*, vol. 48, pp. 988–1001, June 2003.

[22] E. Klavins, "Communication complexity of multirobot systems," in *Algorithmic Foundations of Robotics V*. ser. STAR, Springer Tracts in Advanced Robotics, J.-D. Boissonnat, J. W. Burdick, K. Goldberg, and S. Hutchinson, Eds. Berlin, Germany: Springer Verlag, 2003, vol. 7.

[23] R. Olfati-Saber and R. M. Murray, "Consensus problems in networks of agents with switching topology and time-delays," *IEEE Trans. Automat. Contr.*, submitted for publication.

[24] R. A. Brooks, "A robust layered control-system for a mobile robot," *IEEE J. Robot. Automat.*, vol. RA-2, pp. 14–23, Feb. 1986.

[25] R. C. Arkin, *Behavior-Based Robotics*. Cambridge, U.K.: Cambridge Univ. Press, 1998.

[26] M. S. Fontan and M. J. Mataric, "Territorial multirobot task division," *IEEE Trans. Robot. Automat.*, vol. 14, pp. 815–822, Oct. 1998.

[27] A. C. Schultz and L. E. Parker, Eds., *Multi-Robot Systems: From Swarms to Intelligent Automata*. Dordrecht, The Netherlands: Kluwer, 2002.

[28] T. Balch and L. E. Parker, Eds., *Robot Teams: From Diversity to Polymorphism*. Natick, MA: A. K. Peters, 2002.

[29] A. Howard, M. J. Mataric, and G. S. Sukhatme, "Mobile sensor network deployment using potential fields: A distributed scalable solution to the area coverage problem," in *Proc. Int. Conf. Distributed Autonomous Robotic Systems*, Fukuoka, Japan, June 2002, pp. 299–308.

[30] N. A. Lynch, *Distributed Algorithms*. San Mateo, CA: Morgan Kaufmann, 1997.

[31] G. Tel, *Introduction to Distributed Algorithms*, 2nd ed. Cambridge, U.K.: Cambridge Univ. Press, 2001.

[32] J. N. Tsitsiklis, D. P. Bertsekas, and M. Athans, "Distributed asynchronous deterministic and stochastic gradient optimization algorithms," *IEEE Trans. Automat. Contr.*, vol. AC-31, pp. 803–812, Sept. 1986.

[33] D. P. Bertsekas and J. N. Tsitsiklis, *Parallel and Distributed Computation: Numerical Methods*. Belmont, MA: Athena Scientific, 1997.

[34] H. Choset, "Coverage for robotics—A survey of recent results," *Ann. Math. Artif. Intell.*, vol. 31, pp. 113–126, Jan. 2001.

[35] E. U. Acar and H. Choset, "Sensor-based coverage of unknown environments: Incremental construction of Morse decompositions," *Int. J. Robot. Res.*, vol. 21, no. 4, pp. 345–366, 2002.

[36] R. Klein, *Concrete and Abstract Voronoi Diagrams*, ser. Lecture Notes in Computer Science. New York, NY: Springer-Verlag, 1989, vol. 400.

[37] J. Cortés and F. Bullo, "Coordination and geometric optimization via distributed dynamical systems," *SIAM J. Contr. Optimizat.*, submitted for publication.

[38] C. Cattani and A. Paoluzzi, "Boundary integration over linear polyhedra," *Comput.-Aided Des.*, vol. 22, no. 2, pp. 130–135, 1990.

[39] J. Gao, L. J. Guibas, J. Hershberger, L. Zhang, and A. Zhu, "Geometric spanner for routing in mobile networks," in *Proc. ACM Int. Symp. Mobile Ad-hoc Networking, Computing*, Long Beach, CA, Oct. 2001, pp. 45–55.

[40] X. -Y. Li and P.-J. Wan, "Constructing minimum energy mobile wireless networks," *ACM J. Mobile Comput. Commun. Survey*, vol. 5, no. 4, pp. 283–286, 2001.

[41] M. Cao and C. Hadjicostis, "Distributed algorithms for Voronoi diagrams and application in ad-hoc networks," unpublished.

[42] A. J. van der Schaft, *L2-Gain and Passivity Techniques in Nonlinear Control*, 2nd ed. New York: Springer-Verlag, 1999.

[43] A. Astolfi, "Exponential stabilization of a wheeled mobile robot via discontinuous control," *ASME J. Dynam. Syst., Meas., Contr.*, vol. 121, no. 1, pp. 121–127, 1999.

[44] H. K. Khalil, *Nonlinear Systems*, 2nd ed. Englewood Cliffs, NJ: Prentice-Hall, 1995.

[45] D. G. Luenberger, *Linear and Nonlinear Programming*, 2nd ed. Reading, MA: Addison-Wesley, 1984.

Jorge Cortés (M'03) received the Licenciatura degree in mathematics from the Universidad de Zaragoza, Zaragoza, Spain, in 1997, and the Ph.D. degree in engineering mathematics from the Universidad Carlos III de Madrid, Madrid, Spain, in 2001.

From January to June 2002, he held a Postdoctoral position at the Systems, Signals and Control Department, University of Twente, Enschede, The Netherlands. He is currently a Postdoctoral Research Associate at the Coordinated Science Laboratory, University of Illinois at Urbana-Champaign. His current research interests focus on mathematical control theory and geometric integration, with a special emphasis on Lagrangian and Hamiltonian systems and the role of symmetry principles, and motion coordination algorithms for groups of autonomous vehicles.

Sonia Martínez (M'02) received the Licenciatura degree in mathematics from the Universidad de Zaragoza, Zaragoza, Spain, in 1997, and the Ph.D. degree in engineering mathematics from the Universidad Carlos III de Madrid, Madrid, Spain, in 2002.

From September 2002 to September 2003, she held a Postdoctoral position at the Department of Applied Mathematics IV, Universidad Politécnica de Cataluña, Cataluña, Spain. Since October 2003, she has been a Postdoctoral Fulbright Fellow at the Coordinated Science Laboratory, University of Illinois at Urbana-Champaign. Her current research interests include optimal control policies for robotic locomotion, controllability analysis and motion planning for underactuated systems, and low-complexity representations of mechanical systems.

Timur Karataş received the B.S. degree in mechanical engineering from the Middle East Technical University, Istanbul, Turkey, in 1999, and the M.S. degree in general engineering in 2001 from the University of Illinois at Urbana-Champaign, where he is currently working toward the Ph.D. degree.

His research interests include trajectory generation and path planning for autonomous vehicles, cooperative control and distributed algorithms.

Francesco Bullo (S'95–M'98–SM'03) received the Laurea degree *magna cum laude* in electrical engineering from the University of Padova, Padova, Italy, in 1994, and the Ph.D. degree in control and dynamical systems from the California Institute of Technology, Pasadena, in 1999.

He is an Assistant Professor with the Department of General Engineering and with the Coordinated Science Laboratory, University of Illinois at Urbana-Champaign, Urbana. His research interests include motion planning and coordination for autonomous vehicles, geometric control of mechanical systems, and distributed and adaptive algorithms.