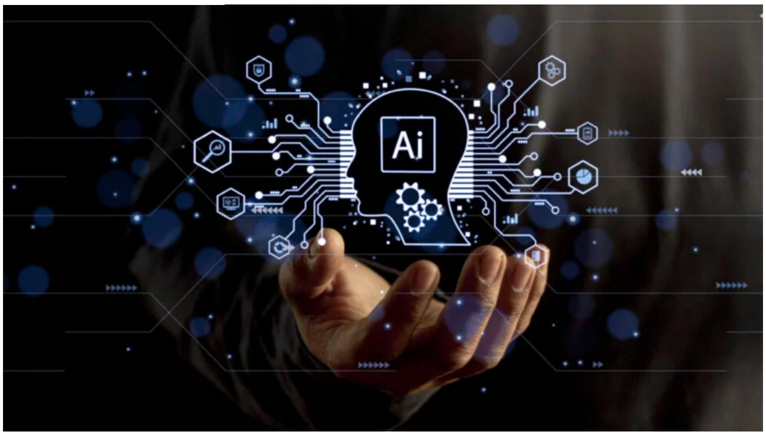

DSCD Newsletter Summer 2024 Issue

June 30, 2024

DYNAMIC SYSTEMS AND CONTROL DIVISION NEWSLETTER

Editor's Note

Dear Colleagues,

We are delighted to present the summer 2024 newsletter of ASME DSCD, hoping that all members of our community are well. This issue brings you several exciting updates and news highlights.

Our featured article, "Multi-agent Coverage Control: From Discrete Assignments to Continuous Multi-agent Distribution Matching", delves into the latest advancements and applications in multi-agent systems and provides valuable insights for our readers.

In the Honors and Awards section, we highlight several notable achievements within our community. We recognize the recipients of recent NSF CAREER Awards, sharing their inspiring journeys and significant contributions to the field. Additionally, our New Faces Spotlights and Cross-Area Angles sections showcase the accomplishments and aspirations of emerging leaders in dynamic systems and control.

We are pleased to share the latest openings and calls for papers. The Upcoming Conferences section provides a detailed list of events that promise to foster collaboration and innovation. Additionally, don't miss the announcement and Call for Papers for the new Transactions of the ASME Journal of Autonomous Vehicles and Systems.

We hope all DSCD members enjoyed a happy and productive summer 2024. Thank you for your continued support of the DSCD Newsletter. We look forward to your future submissions and continued engagement.

Best Regards,

Editor: Shu-Xia Tang, Texas Tech University
Associate Editor: Minghui Zheng, Texas A & M University

IN THIS ISSUE

Multi-agent Coverage Control: From Discrete Assignments to Continuous Multi-agent Distribution Matching

Solmaz S. Kia and Sonia Martínez

Abstract The multi-agent spatial coverage control problem encompasses a broad research domain, dealing with both dynamic and static deployment strategies, discrete-task assignments, and spatial distribution-matching deployment. Coverage control may involve the deployment of a finite number of agents or a continuum through centralized or decentralized, locally-interacting schemes. All these problems can be solved via a different taxonomy of deployment algorithms for multiple agents. Depending on the application scenario, these problems involve from purely discrete descriptions of tasks (finite loads) and agents (finite resources), to a mixture of discrete and continuous elements, to fully continuous descriptions of the same. Yet, it is possible to find common features that underline all the above formulations, which we aim to illustrate here. By doing so, we aim to point the reader to novel references related to these problems.

The short article outline is the following:

- Static coverage via concurrent area partitioning and assignment.
- Static coverage as a discrete task assignment.
- Continuum task assignment for large-scale swarms.

1 Introduction

The coverage control problem concerns the strategic placement of a limited resource, such as sensors or robots (hereafter referred to as agents), across an area of interest to optimize a specific coverage measure. One of the earliest instances of such problems can be traced back to the work of the German astronomer and mathematician Johannes Kepler in 1611. Known as the Kepler Conjecture, it proposed that the densest arrangement of equally-sized spheres in three-dimensional space is the face-centered cubic packing (or hexagonal close packing). While this primarily applies to spheres, it laid the groundwork for studying the packing of circles (disks) in two dimensions. The sphere/circle packing problem solution continues to be relevant and has been employed in various wireless sensor deployment problems (see, e.g., [14] for an overview and [24] and [30] for applications). However, the problems faced in multi-agent coverage are often much more intricate, often involving non-homogeneous agents whose footprints are not necessarily isotropic uniform disks. The number of agents can also be significantly less than what is needed for full coverage. Moreover, not all areas hold equal importance, and agent deployment is expected to be aligned with some area priority measure. Additionally, the deployment objective is not always a static configuration and may include goals such as persistent monitoring or dynamic surveillance.

In scenarios with a limited number of agents, the primary strategy involves dividing the area into subregions and assigning an agent to each. Often, geographical statistical analysis or prior information about the event of interest is used to extract a spatial probability distribution of the event of interest to guide the deployment of the agents. This distribution can be derived from various sources, such as high-altitude imaging, satellite imagery, or historical data, and can also be dynamically adjusted through online learning. To explore these complexities and strategies further, in this article we will discuss various approaches to task assignment and agent deployment in different contexts.

The general problem setting that we consider consists of a multi-agent deployment problem, where the goal is to deploy a group of N agents over a finite two-dimensional convex polytope $\mathcal{W} \subset \mathbb{R}^2$ to provide a *service*. The service can involve sensor deployment for data collection/harvesting or event detection, dispatch for service, or providing wireless hotspots. We let $\phi : \mathcal{W} \to [0,1]$ be an *a priorily* known stationary spatial probability density function that serves as the area priority function. The function ϕ can describe various scenarios, such as the distribution of crowds or animals, information sources, pollution spills, or forest fires.

Although the general problem setting is common, once we introduce specific details such as the agents' service model, coverage objective, and operational requirements, different solution approaches must be employed to solve the problem effectively. It is important to note that finding a globally optimal coverage configuration for multi-agent problems is usually very difficult, with many related facility localization problems (e.g., p-center and p-median) being NP-hard [29]. As such, various heuristic and approximation methods are often necessary to achieve practical and scalable solutions.

The remainder of this article is arranged as follows: Section 2 discusses locational optimization for optimal agent deployment using techniques like Voronoi partitions and power diagrams, and how these frameworks address heterogeneous agents and anisotropic sensory systems. Section 3 presents an alternative approach for multi-agent deployment by introducing a two-step procedure for identifying Points of Interest (PoIs) and solving the deployment problem as a discrete PoI-assignment problem. It explores methods such as Gaussian Mixture Models (GMM), K-means clustering, and the Stein Variational Gradient Descent (SVGD) method to identify and utilize PoIs effectively, followed by assignment using optimal bipartite matching and submodular maximization frameworks. Section 4 shifts focus to large-scale multi-agent systems, framing the problem at a macroscopic scale as a distribution matching problem. This section covers the use of the Wasserstein-Kantorovich metric for optimal transport problems and discusses algorithms for large-scale deployments that ensure microscopic constraints for sensing, communication, and control. Section 5 summarizes the key points discussed in the article, emphasizes the significance of multi-agent spatial coverage problems in robotics, and outlines future research directions.

2 Static coverage via concurrent area partitioning and assignment

In a static multi-agent coverage scenario for a group of N finite agents $\mathcal{A} = \{1, \cdots, N\}$, the objective is to solve a locational optimization problem, whose outcome determines the agents' final deployment locations $P = \{p_1, \cdots, p_N\} \subset \mathcal{W}$ such that some coverage objective tied to ϕ is optimized. This objective often depends on the specific type of service the agents are intended to provide.

Let us consider a facility location problem where the objective is to ensure timely dispatch or fair access to the agents' service for points in the area $\mathcal{W}$, based on the area priority function ϕ. The service quality of an agent at any point $q \in \mathcal{W}$, provided by the i-th agent deployed at location p_i, often degrades with distance. This degradation is typically modeled by a non-decreasing differentiable function $f(\|q - p_i\|) : \mathbb{R}_{\geq 0} \to \mathbb{R}_{\geq 0}$. To achieve the deployment objective, we solve the following locational optimization formulation:

$$\min H(P, \bar{\mathcal{W}}), \tag{1}$$
$$H(P, \bar{\mathcal{W}}) = \sum_{i=1}^{N} \int_{\mathcal{W}_i} f(\|q - p_i\|) \mathrm{d}(\phi(q)),$$

where $\mathcal{W}$ is partitioned into disjoint subsets $\bar{\mathcal{W}} = \{\mathcal{W}_1, \cdots, \mathcal{W}_N\}$, and $\mathcal{W} = \cup_{i=1}^{N} \mathcal{W}_i$, with each subset assigned to an agent as the agent's "dominance region". In this model, the function H should be minimized with respect to both the sensors location P, and the assignment of the dominance regions $\bar{\mathcal{W}}$. A similar deployment model to (1) has been proposed for multi-sensor deployment with the objective of event detection, particularly when a detailed spatial measurement model for the sensors is unavailable. In such scenarios, it is often customary to assume that due to noise and resolution loss, the sensing performance of a sensor at point $q \in \mathcal{W}$, measured by the i-th sensor deployed at location p_i, degrades with distance according to a non-decreasing differentiable function $f(\|q - p_i\|)$.

The seminal work by Cortés et al. [7] presented a solution to (1) based on the observation that, at fixed sensor locations, the optimal partition of $\mathcal{W}$ is the Voronoi partition[1] $\mathcal{V}(P) = \{\mathcal{V}_1, \cdots, \mathcal{V}_N\}$ generated by the points $P = \{p_1, \cdots, p_N\}$, where

$$\mathcal{V}_i = \{q \in \mathcal{W} \mid \|q - p_i\| \leq \|q - p_j\|, \forall j \neq i\}.$$

Thus, they proposed to write

$$H(P, \bar{\mathcal{W}}) = H_{\mathcal{V}}(P, \mathcal{V}(P)). \tag{2}$$

Next, by considering the case $f(\|q - p_i\|) = \|q - p_i\|^2$, they proposed a gradient decent flow that can be used to drive a first-order integrator dynamics for each agent $i \in \mathcal{A}$ to a local minimum of (1). This gradient flow continuously moves each agent towards its associated Voronoi centroid. The resulted closed-loop behavior is shown to be adaptive, implementable in a distributed manner by local interaction between Voronoi-neighbor[2] agents, asynchronous, and provably correct. Including the agents dynamics makes this solution in fact a coverage control problem.

Later works, such as [34, 23, 35], sought to model the heterogeneity of agents in their isotropic service capabilities using additively and multiplicatively weighted Voronoi diagrams. In the absence of a detailed model for the agents' service, the heterogeneity of the agents is often represented by power diagrams[3]. Considering an effective range $\boldsymbol{\rho} = \{\rho_1, \cdots, \rho_N\} \subset \mathbb{R}_{>0}$, referred to as the power radius of agents $i \in \mathcal{A}$, in a power diagram model, the service provided by agent i located at $p_i \in \mathcal{W}$ to a point $q \in \mathcal{W}$ is given by the power distance $\|q - p_i\|^2 - \rho_i^2$. Consequently, the area of dominance assigned to the agents is determined by the power diagram $\mathcal{P}(P, \rho) = \{\mathcal{P}_1, \cdots, \mathcal{P}_N\}$, where

$$\mathcal{P}_i = \{q \in \mathcal{W} \mid$$
$$\|q - p_i\|^2 - \rho_i^2 \leq \|q - p_j\|^2 - \rho_j^2, \forall j \neq i\}.$$

In this scenario, the locational optimization function cost becomes

$$H_{\mathcal{P}}(P, \boldsymbol{\rho}) = \sum_{i=1}^{N} \int_{\mathcal{P}_i} (\|q - p_i\|^2 - \rho_i^2) \mathrm{d}(\phi(q)).$$

A simulation scenario is shown in Fig. 1, illustrating that agents with a higher power radius ρ_i are assigned a larger area to cover. It should be noted that in the special case where $\rho_i = \rho_j$ for all $i, j \in \mathcal{A}$, the power diagram and the Voronoi diagram are identical, i.e., $\mathcal{P}_i = \mathcal{V}_i$. Similar to the homogeneous case, gradient flow solutions have been proposed to determine the final deployment locations of the agents, including approaches that aim to incorporate collision avoidance in the gradient flow dynamics [2].

In practice, however, most sensory/service systems, such as

[1] We refer to [33] for a comprehensive treatment on Voronoi diagrams.
[2] Communications structure is specified by the associated Delaunay graph [7].
[3] Power diagrams are generalized Voronoi diagrams with additive weights; see [4] for a comprehensive overview.

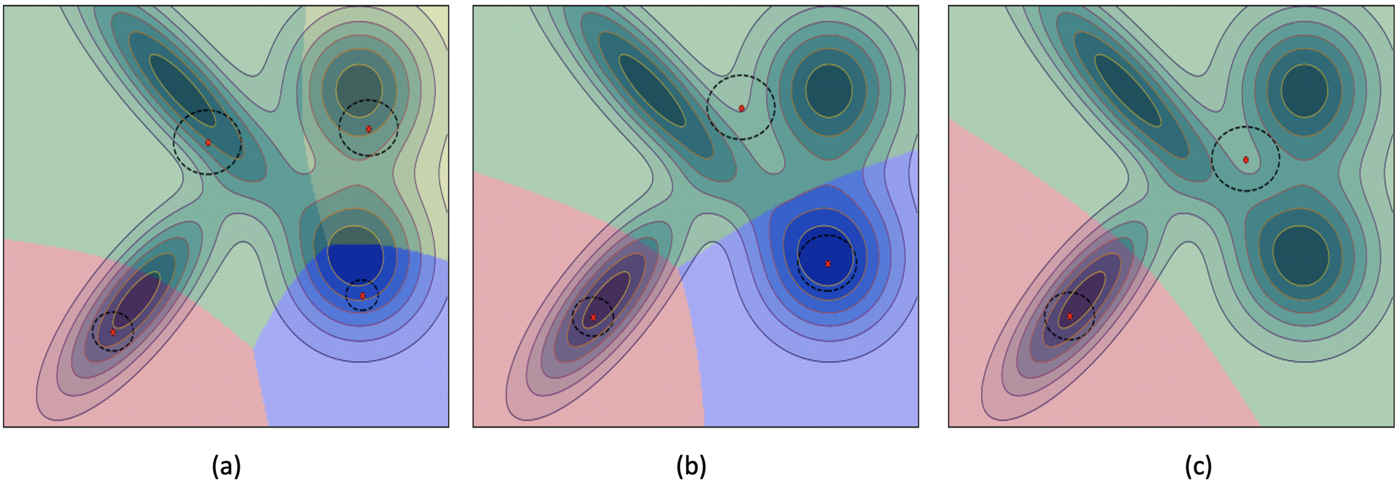

Figure 1: Weighted Voronoi-based deployment based on minimizing (2). The contour plot in the background shows the area priority density distribution function ϕ. The agents final deployment positions shown by red dots and their power disks shown with dashed circles. Plots (a), (b) and (c) show respectively, deployment results for four, three and two heterogeneous agents. Figure courtesy of Donipolo Ghimire.

cameras, directional antennas, radars, acoustic and ultrasonic sensors are anisotropic. Consequently, attempts have been made to modify Voronoi diagram-based deployment methods to account for multi-agent systems with directional services. For example, [25], [8], and [13] consider, respectively, wedge-shaped and elliptic service models and modify the Voronoi diagrams to match the features of the anisotropy of the sensors. Although these extensions incorporate the impact of sensory/service orientation, they often fall short in capturing the detailed physical operation principles of the sensors. Moreover, the sensing/service quality typically does not adhere to a simple (monotonic) functional relation with the Euclidean metric [15]. To address this gap, a line of research focused on incorporating detailed sensor models has emerged in the literature. For example, [3, 1, 6, 10, 11] considered coverage problems where the agents' quality of sensing/service is cast as a spatial probabilistic distribution. Notably, [3] proposed a specialized form of generalized Voronoi diagrams, termed conic Voronoi diagrams, that considers a visual sensing quality model consistent with the physical nature of cameras.

3 Static coverage as a discrete task assignment

In Voronoi-based deployments, the area partitioning and agent assignments occur concurrently. This simultaneous process increases the complexity and may result in a final deployment configuration that does not always place agents in high-density areas, particularly since the solution obtained is a local minimum. The challenge becomes more evident when the number of agents is less than the number of dominant modes in ϕ, as illustrated in Fig. 1 (b) and (c) for the deployment of three and two agents when ϕ has four dominant modes. As shown in these simulations, in an attempt to provide inclusive coverage, the agents sometimes deploy to points that are equidistant from two or more high-density areas rather than directly within them. While this may be acceptable for facility location applications requiring fair access or dispatch, it is suboptimal for event detection or when the objective is to provide services to points in close proximity to the deployment locations. To address these limitations, the literature has explored deployment strategies that first identify a set of Points of Interest (PoIs) in $\mathcal{W}$, informed by ϕ, as potential deployment points. These PoIs transform an infinite search space into a finite, representative model of the area. The deployment problem is then solved as a discrete assignment problem, yielding the best coverage objective for the multi-agent team. This two-step procedure also provides the flexibility to consider more sophisticated coverage utility measures. Moreover, this two-tier approach is well suited for applications such as data harvesting, multi-agent dispatch, and service vehicle deployment in urban areas, where PoIs are predetermined due to operational constraints and there is no flexibility to freely select deployment points in $\mathcal{W}$ based on ϕ.

In many applications, ϕ is derived from the representative spatial data ("point cloud") of the event of interest (targets) over $\mathcal{W}$. A commonly used method for modeling this spatial distribution is the Gaussian Mixture Model (GMM). GMM is a probabilistic model that represents a distribution of data points as a mixture of multiple Gaussian distributions, each with its own mean and variance. The model assumes that data points are generated from several Gaussian distributions, each contributing to the overall probability distribution with some weight [28]. By modeling the distribution of the

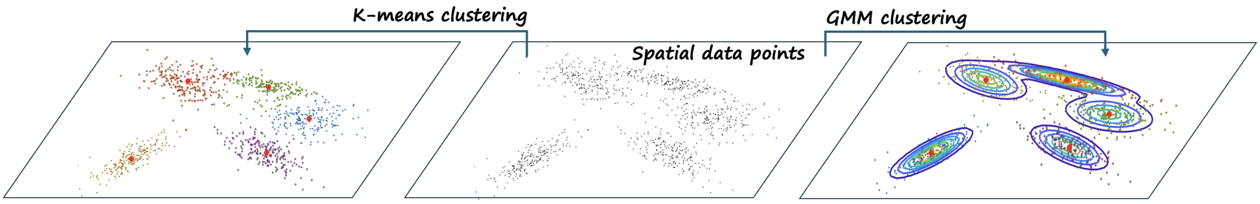

Figure 2: Extracting PoIs from K-means and GMM clustering. PoIs are shown by filled red dots.

targets, the GMM not only captures this distribution but also intrinsically clusters the targets into subgroups, each represented by a Gaussian basis. In recent work by [6], GMM clustering has been used effectively to extract PoIs for deployment. Alternatively, PoIs can also be identified through various spatial clustering methods using the spatial data themselves. Methods such as K-means clustering [16] or its variants like Fuzzy C-Means clustering [16] can be employed. K-means clustering partitions the points into $K \in \mathbb{Z}_{>1}$ clusters, ensuring that each point belongs to the cluster with the nearest mean (cluster center or centroid). An application example in multi-agent deployment can be found in [10, 18]. Figure 2 illustrates the clustering and extraction of PoIs for a set of spatial data points using GMM and K-means methods.

Clustering methods, however, require prior knowledge of the number of clusters and are sensitive to initialization. Recent work in [11] proposes an alternative approach to extracting PoIs that circumvents these challenges by using statistical sampling from ϕ. Specifically, [11] suggests utilizing the Stein Variational Gradient Descent (SVGD) method [26]. SVGD is a sampling-based deterministic statistical inference method that generates 'super samples' to accurately represent the density distribution ϕ. SVGD is known for its effectiveness even with a small number of samples, making it highly suited for extracting PoIs. However, sampling-based algorithms face the risk of generating samples too close to each other, leading to overlapping coverage by deployed agents. In light of this observation, [11] carefully designs the sample-spread mechanism of the SVGD algorithm to generate samples that are not only representative of the distribution ϕ but are also appropriately spread according to the effective service/sensing footprint of the agents.

Nevertheless, given a finite set of PoIs denoted by $\mathcal{S} = \{1, \cdots, n\}$, as depicted in Fig. 3, a natural solution for agent assignment is to use optimal bipartite matching through the optimal linear assignment problem, also known as the discrete optimal mass transport problem. This problem can be formulated as follows:

$$\boldsymbol{Z}^\star = \arg\min \sum\nolimits_{j\in\mathcal{S}} \sum\nolimits_{i\in\mathcal{A}} Z_{i,j} C^\star_{i,j}, \tag{3a}$$

$$Z_{i,j} \in \{0,1\}, \quad i \in \mathcal{A},\ j \in \mathcal{S}, \tag{3b}$$

$$\sum\nolimits_{j\in\mathcal{S}} Z_{i,j} = 1,\ \forall i \in \mathcal{A}, \tag{3c}$$

$$\sum\nolimits_{i\in\mathcal{A}} Z_{i,j} \le 1,\ \forall j \in \mathcal{S}. \tag{3d}$$

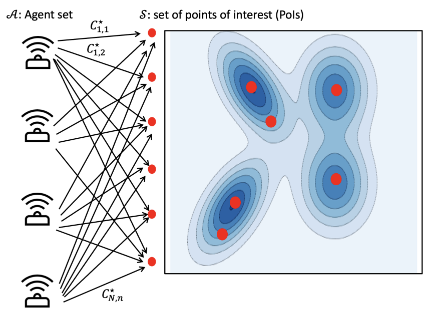

Figure 3: Schematic illustration of the multi-agent assignment as an optimal bipartite matching problem, where red dots denote PoIs.

where $Z_{i,j}$ is the assignment indicator with $Z_{i,j} = 1$ if the i-th agent is assigned to the j-th PoI and $Z_{i,j} = 0$ otherwise, and $C^\star_{i,j}$ is the minimum cost of assigning the i-th agent to the j-th PoI. With the assumption that $|\mathcal{A}| < |\mathcal{S}|$, constraint (3c) ensures that every agent gets assigned to one PoI, and constraint (3d) ensures that every PoI is assigned at most to one agent. The optimization problem (3) is a standard assignment problem and can be solved using existing algorithms such as the Hungarian algorithm [22]. It can also be solved through linear programming via a continuous relaxation approach, even in a distributed manner using, for example, the distributed simplex algorithm proposed by [5]. The solution of the assignment problem (3) gives the final deployment configuration of the agents.

Considering an effective footprint $\mathcal{C}_i(p_i, \theta_i) = \{q \in \mathcal{W} \mid F_i(q|p_i, \theta_i) \le 0\} \subset \mathcal{W}$, a compact set, for each agent $i \in \mathcal{A}$ deployed at position $p_i \in \mathcal{W}$ and orientation $\theta_i \in [0, 2\pi]$, the assignment framework provides flexibility in computing the deployment cost $C^\star_{i,j}$ via various measures such as

$$C^\star_{i,j} = \min_{\theta\in\Theta} \int_{\mathcal{C}_i(p_j,\theta)} f_i(\|q - p_j\|)\mathrm{d}\phi(q).$$

or as proposed in [11] as

$$C^\star_{i,j} = \min_{\theta\in\Theta} \{\mathcal{KL}(s_i(q|p_j,\theta)|\phi(q)) \ \text{ for } \ q \in \mathcal{C}_i(p_j,\theta)\},$$

where the Kullback–Leibler divergence (KLD)[4], denoted by $\mathcal{KL}$, is used to measure the similarity between the i-th agent's spatial ser-

[4]Given two continuous probability density distributions $\psi(\boldsymbol{x})$ and $\phi(\boldsymbol{x})$, $\boldsymbol{x} \in \mathbb{X}$, KLD is defined as $\mathcal{KL}(\psi(\boldsymbol{x})||\phi(\boldsymbol{x})) = \int_{\boldsymbol{x}\in\mathbb{X}} \psi(\boldsymbol{x}) \log \frac{\psi(\boldsymbol{x})}{\phi(\boldsymbol{x})} \mathrm{d}\boldsymbol{x}$, which is a measure of similarity (dissimilarity) between the two probability distributions; the smaller the value, the more similar the two distributions are. KLD is zero if and only if the two distributions are identical [27].

vice, cast as a probability distribution $s_i(q|p_j,\theta)$ when it is located at p_j with orientation θ, and $\phi(q)$ over the effective footprint $\mathcal{C}_i(p_j,\theta)$ of the agent. In computing $C^\star_{i,j}$ for directional agents, the models above search over a finite number of deployment orientations for each agent, that is, $\theta \in \Theta = \{\bar{\theta}_1,\cdots,\bar{\theta}_M\} \subset [0,2\pi]$.

For the special case of a Gaussian service distribution $s_i(q|p,\theta) = \mathcal{N}(q|p,\bar{\Sigma}_i(\theta))$ and PoIs extracted from a GMM clustering method, [6] defined $C^\star_{i,j}$ as the weighted KLD difference between the agent's service distribution s_i and the j-th Gaussian basis of the GMM-modeled area priority function $\phi(q) = \sum_{j=1}^n \pi_j \mathcal{N}(q|p_j,\Sigma_j)$. They showed that the optimal deployment for agent i in cluster j is to align the means of s_i and $\mathcal{N}(q|p_j,\Sigma_j)$, i.e., deploy agent i at p_j, and make the principal axis of s_i parallel to that of Σ_j. Because the distributions compared are Gaussian, [6] was able to compute $C^\star_{i,j}$ in closed form without the need to search over Θ for the best deployment orientation. Alternatively, [10] computed $C^\star_{i,j}$ by sampling from s_i and using a discrete optimal mass transport method to measure the statistical distance between the samples drawn from s_i and the target points in the j-th cluster created by the K-means method. They used a modified version of the discrete optimal mass transport where the rotation and translation of the point cloud samples drawn from s_i are part of decision variables. This method, inspired by the Iterative Closest Point (ICP) algorithm used in point-set registration in computer vision [37], allows for the computation of $C^\star_{i,j}$ at the best deployment position and orientation.

Despite the flexibility and tractability offered by the linear optimal assignment optimization in (3), this formulation does not account for the consequences of overlapping coverage. As an alternative, the PoI-assignment problem–assigning N elements from the PoIs set $\mathcal{S} = \{1,\cdots,n\}$ to N agents $\mathcal{A} = \{1,\cdots,N\}$–can be formulated as a set function maximization problem. For homogeneous agents, the set function maximization problem is expressed as:

$$\begin{aligned}\mathcal{R}^\star = \arg\max_{\mathcal{R}\subset\mathcal{S}} f(\mathcal{R}) \ \ &\text{subject to} \\ |\mathcal{R}| \leq N&,\end{aligned} \tag{4}$$

where $f(\mathcal{R}) : 2^{\mathcal{S}} \to \mathbb{R}_{\geq 0}$ represents the joint utility of deploying the agents at $\mathcal{R} \subset \mathcal{S}$. For heterogeneous agents, the set function maximization problem is given by:

$$\begin{aligned}\mathcal{R}^\star = \arg\max_{\mathcal{R}\subset\bar{\mathcal{S}}} f(\mathcal{R}) \ \ &\text{subject to} \\ |\mathcal{R}\cap\mathcal{S}_i| \leq 1,\ i \in \mathcal{A}&,\end{aligned} \tag{5}$$

where $\mathcal{S}_i = \{(i,j) \mid j \in \mathcal{S}\}$ and $\bar{\mathcal{S}} = \cup_{i\in\mathcal{A}}\mathcal{S}_i$. The constraint in (5) ensures that each agent is assigned only one PoI.

Combinatorial optimization problems of the form (4) and (5) are often NP-hard. However, for a special class of set functions known as *submodular* functions, the seminal work by Nemhauser, Wolsey, and Fisher in the 1970s [9, 32, 31] showed that the so-called *sequential greedy algorithm* can deliver a suboptimal solution with a well-defined optimality gap in polynomial time. When the utility function is submodular, the optimization problem (4) is referred to as submodular maximization subject to a uniform matroid. In this case, the sequential greedy algorithm starts with $\mathcal{R}_{\text{SG}} = \emptyset$ and iterates according to

$$\begin{aligned}&p^\star = \arg\max_{p\in\mathcal{S}\setminus\mathcal{R}_{\text{SG}}} \left(f(\mathcal{R}_{\text{SG}}\cup\{p\}) - f(\mathcal{R}_{\text{SG}})\right)\\ &\mathcal{R}_{\text{SG}} \leftarrow \mathcal{R}_{\text{SG}}\cup\{p^\star\}\end{aligned}$$

until N elements are selected. Alternatively, the optimization problem (5) is referred to as submodular maximization subject to a partition matroid. In this case, the sequential greedy algorithm starts with $\mathcal{R}_{\text{SG}} = \emptyset$ and iterates according to

$$\begin{aligned}&p^\star = \arg\max_{p\in\mathcal{S}_i} (f(\mathcal{R}_{\text{SG}}\cup\{p\}) - f(\mathcal{R}_{\text{SG}}))\\ &\mathcal{R}_{\text{SG}} \leftarrow \mathcal{R}_{\text{SG}}\cup\{p^\star\}\end{aligned}$$

until $i = N$ and each agent is assigned a PoI.

Many coverage utility functions, such as max-cover, facility location, and mutual information functions, are known to be submodular [19]. Several well-known submodular maximization frameworks can also be applied to coverage problems. For example, consider the *Exemplar-based Clustering* method introduced by [17], which aims to identify a subset of exemplars that optimally represent a large dataset by solving the K-medoid problem. This method minimizes the cumulative pairwise dissimilarities between chosen exemplars $\mathcal{S}$ and dataset elements $\mathcal{D}$:

$$L(\mathcal{R}) = \sum_{p\in\mathcal{R}} \min_{d\in\mathcal{D}} \text{dist}(p,d), \tag{6}$$

for any subset $\mathcal{R} \subset \mathcal{S}$, where $\text{dist}(p,d) \geq 0$ defines the dissimilarity, or distance, between elements. To find an optimal subset $\mathcal{R}$ that minimizes L, this problem is posed as a submodular maximization problem with the utility function:

$$f(\mathcal{R}) = L(d_0) - L(\mathcal{R}\cup d_0), \tag{7}$$

where d_0 is a hypothetical auxiliary element. This utility function quantifies the reduction in loss from the active set versus using only the auxiliary element and is submodular and monotonically increasing [12]. An instance of using exemplar-based clustering for multi-agent deployment is simulated in [36]. The problem considered is an information harvesting task that aims to collect data from sources $\mathcal{D} \subset \mathcal{W}$. The goal is to deploy N data harvesters at pre-specified points $\mathcal{S}$. In this problem, the number of agents is far less than the number of PoIs, i.e., $N < |\mathcal{S}|$. The optimal deployment minimizes the distance between each information point $d \in \mathcal{D}$ and its nearest harvester at $b \in \mathcal{S}$. [36] formulates this problem as an exemplar clustering problem using the submodular utility function (7), with $\text{dist}(b,d) = \|b - d\|$ representing the Euclidean distance. For a numerical demonstration, see [36].

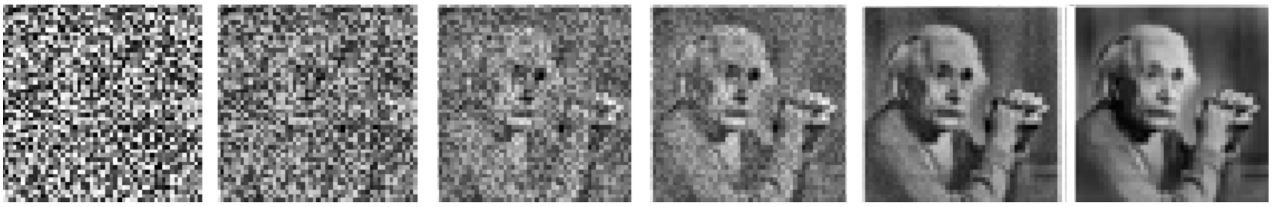

Figure 4: A swarm of agents evolve under the distributed transport algorithm of [20] to reconfigure into an image. Figure courtesy of Vishaal Krishnan.

4 Continuum task assignment for large-scale swarms

In spatial coverage control problems that involve a very large number of agents, it is more meaningful to specify both the task assignment and swarm control objectives in a macroscopic manner, as a distribution matching problem, whereby the distribution of agents is to coincide with that generating the tasks.

In fact, one may ask if such objective could be achieved by taking the limit on the number of agents to infinity in the locational optimization problem formulations of the previous section. At the same time, one may think that the problems of local optima, which result from a poor initialization of Lloyd's algorithm, may be addressed in this way. An answer to these questions can be provided via the so-called Wasserstein-Kantorovich metric, which solves the problem of optimal transport, also called the Earth Mover's problem.

Formally, given two measures μ, ν over a space $\mathcal{W}$ with bounded p moments, the p-Wasserstein-Kantorovich metric W_p is defined as

$$W_p^p(\mu,\nu) = \min_{\pi\in\Pi(\mu,\nu)} \int_{\mathcal{W}\times\mathcal{W}} c(x,y)^p \mathrm{d}\pi(x,y),$$

where c is the cost of transport from x to $y \in \mathcal{W}$ and $\Pi(\mu,\nu)$ is the set of measures over $\mathcal{W}\times\mathcal{W}$ with marginals μ and ν, respectively. The Wasserstein metric finds many applications, and directly generalizes the solution of a discrete optimal task assignment problem

It turns out that the most basic Expected Value metric (locational optimization cost) for coverage control is equal to the best optimal transport from an agent-based discrete distribution to the target distribution of tasks, $\mathrm{d}\phi$ [21]. Specifically, such discrete distribution is naturally defined via the Voronoi partition $\mathcal{V} = \{\mathcal{V}_1, \dots, \mathcal{V}_N\}$ generated by the agent locations $p_1, \dots, p_N$, and $\nu = \mathrm{d}\phi(q)$. To define it, let w_i be the mass of $\mathrm{d}\phi(q)$ over the Voronoi region $\mathcal{V}_i$, and δ_{p_i} be the delta distribution over p_i, for $i \in \{1,\dots,N\}$. Then, the associated discrete measure is $\mu_{\mathcal{V}} = \sum_{i=1}^N w_i\delta_{p_i}(q)$, assigning all the mass w_i to the location of agent i, p_i. It is not hard to show that that $W_2(\mu_{\mathcal{V}}, \mathrm{d}\phi) = \mathcal{H}_{\mathcal{V}}(P)$. This property sheds light on the both questions above: first, at very large scales, when the number of agents goes to infinity, the cost $\mathcal{H}_{\mathcal{V}}(P)$ approaches zero. Thus, in the limit, the original $\mathcal{H}$ can be brought down to 0 just by adding (uniformly at random) more and more agents, regardless of their positions inside their Voronoi regions. Thus, the most basic locational optimization cost does not lead to the large-scale goal of distribution matching. As discussed in [21], the utilization of *generalized Voronoi partitions* as in [23] that are also *equitable*; that is, for which region masses are identical; $w_i = w_j$ for all $i,j \in \{1,\dots,N\}$, solves this problem. Under this constraint, we do have consistency of problems and objectives.

The Wasserstein metric has additional convexity properties that can help us answer the question of optimality as well: while the finite-agent locational optimization problems are non-convex, W_2 enjoys generalized convexity (in sense of the so-called displacement interpolations, and convexity with respect to a target measure), which allows us to roughly state that, by taking the limit in the number of agents to infinity, we are "making the problem convex".

However, while this is satisfactory theoretically, the question of how to devise new and tractable algorithms that can be still applicable for a large, but finite number of agents still remains. As actuation rests at the microscopic scale and the individual agents, it is still necessary to ensure that the obtained algorithms satisfy the microscopic constraints that make them implementable, such as that of limited sensing, communication, computation, asynchronous interactions, and distributed control.

One can look for an answer to this question by considering modern, discrete-time optimization techniques that, at the macro-scale, solve the desired optimization problem, and that, at the micro-scale, behave adequately for discrete multi-agent systems. In [21, 20] we propose an algorithmic approach that exploits proximal gradient optimization together with variational problem discretization via sampling. In particular, the proposed algorithms retain the distributed implementation properties required by scalable multi-agent coordination algorithms.

Figure 4 illustrates an implementation of one of such algorithms for the optimal transport to a target distribution. The target distribution is a pixelated image of Einstein (higher intensity represents higher number of agents at that location). The algorithm allows agents to compute the global optimal optimal transport to the target density in a distributed manner, in the sense of the graph induced by the Voronoi partition. The cost of transport $c(x, y)$ is given by the Euclidean distance.

5 Concluding Remarks

The multi-agent spatial coverage problem is a fundamental challenge in robotics, with wide-ranging applications that demand innovative and adaptive solutions. Throughout this note, we have provided a quick exposition to various methodologies that address its various aspects, providing insights into different strategies and their applicability to specific scenarios.

While this note is by no means a comprehensive overview of the vast literature on multi-agent spatial coverage, it aims to showcase some solution approaches and illustrate how different problem settings and operational assumptions can significantly influence the solution strategies we develop. By covering a wide range of methodologies, from classic Voronoi-based deployments to modern statistical sampling techniques, and exploring both deployment problems with a limited number of agents and a continuum of agents, we hope to provide a useful perspective on this complex and evolving field.

The multi-agent spatial coverage problem continues to be a vibrant area of research with numerous practical applications, ranging from environmental monitoring and data harvesting to service vehicle deployment and large-scale swarm behavior. The diverse approaches discussed in this paper highlight the flexibility and adaptability required to tackle various challenges inherent in different operational contexts.

Future research in this area is likely to benefit from advances in machine learning, optimization algorithms, and decentralized control methods. Embracing these theories can lead to more efficient, scalable, and robust solutions. Moreover, addressing open challenges, such as dealing with overlapping coverage, optimizing deployment in heterogeneous environments, and developing methods that can adapt to dynamic changes in real time, will further enhance the effectiveness of multi-agent systems.

Ultimately, we hope this note will serve as an introduction and a reference point for researchers and practitioners, encouraging them to explore the rich and diverse methodologies available for solving multi-agent spatial coverage problems. By understanding the impact of different problem settings and operational assumptions, we can develop more tailored and effective solutions, advancing the state-of-the-art in this fascinating field.

6 Bios

Solmaz Kia is an Associate Professor of Mechanical and Aerospace Engineering at the University of California, Irvine (UCI), CA, USA. She also holds a joint appointment as an Associate Professor in the Computer Science Department at UCI. Kia obtained her Ph.D. in Mechanical and Aerospace Engineering from UCI in 2009, and her M.Sc. and B.Sc. in Aerospace Engineering from Sharif University of Technology, Iran, in 2004 and 2001, respectively. From June 2009 to September 2010, she was a Senior Research Engineer at SySense Inc., El Segundo, CA. She held postdoctoral positions in the Department of Mechanical and Aerospace Engineering at the University of California, San Diego, and UCI. Kia was a recipient of the UC President's Postdoctoral Fellowship in 2012–2014, an NSF CAREER Award in 2017, and the Best Control System Magazine Paper Award in 2021. She is a Senior Member of IEEE. Kia serves as an Associate Editor for Automatica, IEEE Transactions on Control of Network Systems, and IEEE Open Journal of Control Systems. Her main research interests include distributed optimization, coordination, estimation, nonlinear control theory, and probabilistic robotics navigation and motion planning.

Sonia Martinez Sonia Martinez is a Professor of Mechanical and Aerospace Engineering at the University of California, San Diego, CA, USA. She received her Ph.D. degree in Engineering Mathematics from the Universidad Carlos III de Madrid, Spain, in May 2002. She was a Visiting Assistant Professor of Applied Mathematics at the Technical University of Catalonia, Spain (2002- 2003), a Postdoctoral Fulbright Fellow at the Coordinated Science Laboratory of the University of Illinois, Urbana-Champaign (2003-2004) and the Center for Control, Dynamical systems and Computation of the University of California, Santa Barbara (2004-2005). Her research interests include the control of networked systems, multi-agent systems, nonlinear control theory, and planning algorithms in robotics. She became a Fellow of IEEE in 2018. She is a co-author (together with F. Bullo and

J. Cortés) of "Distributed Control of Robotic Networks" (Princeton University Press, 2009). She is a co-author (together with M. Zhu) of "Distributed Optimization-based Control of Multi-agent Networks in Complex Environments" (Springer, 2015). She is the Editor in Chief of the recently launched CSS IEEE Open Journal of Control Systems, and Senior Editor for Surveys of Automatica.

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Editorial Board

Honors and Awards

Robotics Leader Dawn Tilbury Elected to National Academy of Engineering

Dawn Tilbury, the Ronald D. and Regina C. McNeil Department Chair of Robotics at the Univeristy of Michigan, has been recognized with one of engineering's greatest honors — election to the National Academy of Engineering.

Tilbury will be formally inducted, as part of her class of 114 new U.S. members, during the NAE's annual meeting Sept. 29, 2024. The organization underscored her work in manufacturing network control and human-robot interaction. Tilbury's smart-manufacturing work includes digital twins, managing the health of manufacturing systems and reconfiguring such systems. The announcement also named human-robot teaming.

Dawn Tilbury Tilbury has also been a leader in many arenas in engineering. Most recently at U-M, she led faculty from many engineering departments as well as from across campus to coalesce into a robotics graduate program, a Robotics Institute, a new building for robotics, and an undergraduate program and department. Tilbury also served as the assistant director for engineering at the National Science Foundation from 2017-21.

Earlier in her career, Tilbury was a thrust area leader and testbed director in the Engineering Research Center for Reconfigurable Manufacturing Systems. She directed the Ground Robotics Research Center, which studied the reliability of autonomous ground vehicles, and was the deputy director of the Automotive Research Center from 2011-13. Beyond disciplinary research, Tilbury also has been a leader for women faculty members, co-organizing two Big 10 Women's Workshops in 2010 and 2013. These workshops connected junior women faculty with both senior and peer mentors and cultivated collaboration.

Professor Azim Eskandarian Elevated to IEEE Fellow

Alice T. and William H. Goodwin Jr. Dean for the College of Engineering, Azim Eskandarian, DSc, has been elevated to IEEE fellow for his contributions to the communication and control of intelligent autonomous vehicles. "For any professional society, becoming a fellow is one of the biggest technical honors you can receive," Eskandarian said. "I am incredibly grateful for this recognition and that my colleagues and peers senior to me recognize my contributions to this field."

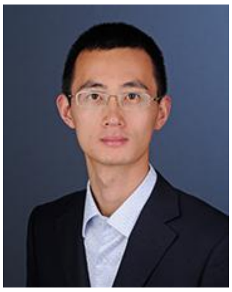
Within IEEE, Eskandarian was nominated through the Intelligent Transportation Systems Society, which focuses on advancing innovative technologies in the field of intelligent transportation systems.

Eskandarian's career includes experience in academic leadership, research, scholarship and teaching, as well as industry. Serving as department head at Virginia Tech since 2015, he has worked collaboratively in the department and college to enhance innovation and degree programs, improve services, enhance diversity, increase enrollment & external funding, advance faculty & student success.

2023 TTE Prize Paper Award

Dr. Huazhen Fang, along with Drs. Amir Farakhor, Di Wu, and Yebin Wang, received a 2023 IEEE Transactions on Transportation Electrification (TTE) Prize Paper Award, Second Place, for "A novel modular, reconfigurable battery energy storage system: Design, control, and experimentation," in IEEE Transactions on Transportation Electrification, vol. 9, no. 2, pp. 2878-2890, 2023 (first author: Amir Farakhor). According to TTE, this award recognizes the best papers among those published in the journal.

Professor Huazhan Fang Received Scholarly Achievement Award



Dr. Huazhen Fang received the University Scholarly Achievement Award at the University of Kansas (KU) in 2024. This is a marquee award for mid-career faculty members at KU to recognize a significant scholarly or research contribution, creative work or a series of closely related contributions. `https://chancellor.ku.edu/four-researchers-named-recipients-university-scholarly-achievement-award`

Interview with Recent NSF CAREER Awardees

Qiugang (Jay) Lu

Bio: Dr. Qiugang (Jay) Lu is an assistant professor at the Department of Chemical Engineering at the Texas Tech University (TTU). He received his B.Eng. and M.Sc. in Control Science and Engineering from Harbin Institute of Technology, China, in 2011 and 2013, respectively, and Ph.D. in Chemical and Biological Engineering from the University of British Columbia in 2018. Prior to TTU, he was a Postdoctoral Research Associate at the University of Wisconsin-Madison. His research interests include advanced process control, data analytics, system identification, and process monitoring, with applications to battery management, HVAC systems, and pulp & paper. Dr. Lu is a Vanier Scholar of Canada (2015), and received the Best Presenter Award at PACWEST Conference (2015), and Certificate of Service Award from the Journal of the Franklin Institute (2019). He is also the holder of 4 US patents, and also the recipient of the 2024 NSF CAREER Award.

Q: Congratulations on your recently awarded CAREER project! Can you please introduce it to our readers?

A: Thank you very much. The focus of my CAREER project is on *Intelligent Battery Management with Safe, Efficient, Fast-Adaption Reinforcement Learning and Physics-Inspired Machine Learning: From Cells to Packs*. Lithium-ion batteries have been widely applied to many applications such as electric vehicles. However, a number of bottlenecks still exist in the advanced management of battery cells and packs, e.g., the excessively slow charging speed, safety concerns caused by battery degradation, and cell-to-cell variations in battery modules and packs. This project aims to tackle these challenges by developing novel reinforcement learning and physics-informed deep learning methods to enable the next-generation battery intelligent management for both battery cells and packs. The outcomes of this project are anticipated to address existing bottlenecks such as mileage anxiety and battery safety hazards that limit the wider adoption of electric vehicles, to further promote transportation electrification.

Q: What are your suggestions how to prepare a successful CAREER proposal?

A: First, I think starting and planning early are critical. Allocating enough time for the proposal allows you to think carefully all the aspects and technique details of the proposal and prepare sufficient preliminary data for the specific objectives. Second, we can ask senior faculty and colleagues with previous experience for feedback and suggestions for both the research and education content of the project. Third, discover the resources of the university and local community to develop innovative outreach and education activities for the project.

Q: What are the most exciting research challenges and opportunities in your research fields?

A: I think the intersection between energy systems, modeling, and control, with the emerging machine learning techniques offers unprecedent opportunities to trigger the next-generation energy storage techniques for promoting clean energy utilization and reducing carbon footprint. Specific to batteries, a few exciting opportunities exist to further advance this field. For instance, it remains to be further explored on how to develop hybrid models that leverage the existing battery physics models, often highly complex to solve, with machine learning techniques to achieve high accurate while computationally affordable modeling (e.g., hybrid reduced-order modeling) of various electrochemical behaviors of batteries. For large-scale battery packs, as often employed by modern electric vehicles, how to extend existing battery modeling and control technique to handle such a large number of battery cells, as well as their interactions, with only very sparse sensors available, still remains a challenge for practical applications. Extensive research on large-scale battery packs is expected to offer many exciting opportunities in this field.

Q: Can you please describe your career up to date?

A: I received my PhD degree from University of British Columbia in 2018. After that, I worked at General Motors of Canada for 1.5 years as a Control and Prognostics Engineer. Then I moved to University of Wisconsin-Madison as a postdoctoral research associate. I joined Texas Tech University in the Department of Chemical Engineering in the Fall of 2020. I am grateful to the supportive environment of the department for me to fully delve into exciting areas in system dynamics, control, and energy systems optimization and monitoring.

Q: It could be challenging to start as a new faculty member. What are your suggestions about how to grow an academic career for new faculty colleagues of our community?

A: As a junior faculty, I'm also learning how to grow the academic career better. I feel that it is critical for us to establish our research independence earlier in the community. Identifying the specific areas that we are primarily interested into and would like to work on in a relatively long term is beneficial to generate important results in those fields. Also, we would need to delve deep into those areas to produce impactful research outcomes and at the same time try to expand our areas for the growth of the research team. Creating collaborations with colleagues and peers is also of importance to broaden our vision for identifying new research opportunities.

Q. Thank you for your sharing!

A: Thank you for the opportunity and for the great work with the Newsletter.

Philip E. Paré

Bio: Dr. Philip E. Paré is the Rita Lane and Norma Fries Assistant Professor in the Elmore Family School of Electrical and Computer Engineering at Purdue University. He was a 2023 recipient of the NSF CAREER Award, a 2023-2024 Teaching for Tomorrow Fellow at Purdue, and an inaugural Societal Impact Fellow in 2021 at Purdue as well.

Q: Congratulations on your recently awarded CAREER project! Can you please introduce it to our readers?

A: Thank you! The goal of my project is to develop a class of multi-resolution models that enable nonlinear control design that spans and adapts along the model-based vs. data-driven spectrum and is focused on the application of networked epidemic processes.

Q: What are your suggestions how to prepare a successful CAREER proposal?

A: I think it's useful to serve on an NSF panel to learn about the process, write a proposal with a more senior PI, and/or ask a few friends/colleagues to see a copy of their successful CAREER proposal. Further, if you're not funded on your first try (which is fairly standard), talk to the program manager about your proposal before you revise and resubmit it.

Q: What are the most exciting research challenges and opportunities in your research fields?

A: One of the biggest upcoming questions is how we can ensure resilience and robustness of our (networked) control systems as the world becomes more excited about/dependent on AI systems such as LLMs.

Q: Can you please describe your career up to date?

A: After completing my PhD from the University of Illinois at Urbana-Champaign in 2018, I went to KTH Royal Institute of Technology in Stockholm, Sweden to be a Postdoctoral Scholar for a year and a half. I started at Purdue in 2020, which was difficult given the pandemic but ended up working out well given my main application area. My second PhD student successfully defended his dissertation last week, so things are going really well.

Q: It could be challenging to start as a new faculty member. What are your suggestions about how to grow an academic career for new faculty colleagues of our community?

A: For me, building community was very important. One way I have done this is by serving in the IEEE Control Systems Society (CSS) and its conferences (CDC and ACC). I am currently running to serve on the CSS Board of Governors. Those of you who are in both ASME and IEEE, please consider voting for me :)

Q. Thank you for your sharing!

A: Thank you so much!

New Faces Spotlights

Manashita Borah

Dr Manashita Borah is an Assistant Professor in the Department of Electrical Engineering, Tezpur University, India. She joined the DSCD community in 2023. She is a recipient of the prestigious Fulbright fellowship at University of California, Berkeley, USA (2022-2023). The Fulbright fellowship is esteemed globally, with numerous recipients going on to win prestigious awards such as the **Nobel Prize** (62 Fulbrighters) including the Nobel Prize in Physics in 2022 and the Pulitzer Prize (89 Fulbrighters). As a Fulbright fellow, she worked with Prof Scott Moura and his group at the Energy, Controls and Applications Laboratory (eCAL), University of California, Berkeley on the project *"Smart storage for green energy infrastructure: A physics-informed machine learning integrated fractional order dynamical framework."*

Dr Borah's research interest is in control systems, energy storage, fractional order systems, nonlinear dynamics and machine learning. Dr Borah's work delves into novel frameworks of modelling Lithium-ion batteries in electric vehicles. She uses a fresh approach of a fractional-order dynamical framework to unravel and understand the inherent dynamics of the battery; which integer order models fail to capture. She is working on the concept of developing fractional-order machine learning algorithms by incorporating physical information, so that the tedious training networks involving big data can be reduced using the information provided by the physical laws. These nonlinear, fractional-order physics informed machine learning models have yielded improved results in addressing the open problem of state of charge estimation of LiFePO4 batteries. This endeavour also involved her collaboration with multinational battery industry leader TotalEnergies from France. One of her recent papers on "'Weaknesses and Improvements of the Extended Kalman Filter for Battery State-of-Charge and State-of-Health Estimation", has been selected as a Finalist in the Best Student Paper Award at the 2024 American Control Conference, Toronto. She has been invited to deliver talks on her research findings in several universities such as University of Texas, Austin (30th March, 2023), University of California, Irvine (16th Feb, 2023), University of Colorado, Denver (31st Jan, 2023), University of Colorado, Colorado Springs (30th Jan, 2023), University of California Merced (October, 2023). It is noteworthy that, describing her research contributions as quot;exemplaryquot;, the Department of Science and Technology, Govt. of Assam, India awarded her with the Young Scientist Award. She is the **first** woman to win this award.

Among her hobbies, she likes to read, travel and dance. She has a Bisharad degree in Indian classical dance forms of Bharat Natyam and Shattriya where she trained for 12 years.

Cross-Area Angles: Bridging Academia and Industry

Ziran Wang

Bio: Ziran Wang is an Assistant Professor in the Autonomous and Connected Systems Initiative and the Lyles School of Civil Engineering at Purdue University. Prior to joining Purdue, Dr. Wang worked for Toyota R&D in Silicon Valley as a Principal Researcher. He also serves as Founding Chair of the IEEE Technical Committee on Internet of Things in Intelligent Transportation Systems, and Associate Editor of four academic journals. His achievements were demonstrated at the Consumer Electronics Show (CES) in Las Vegas, and acknowledged by five best paper awards, the First Prize in IEEE Shape the Future of ITS Competition, and the U.S. Department of Transportation Dissertation Award.

Q: Congratulations on successfully transitioning between industry and academia. Could you please share your experience with our readers?

A: Thank you. I started to work for Toyota R&D as a research intern during my Ph.D. career in 2018 and continued to work on their projects throughout the final year of my Ph.D. In 2019, I joined Toyota as a full-time research scientist upon my graduation and was promoted to principal researcher in 2022. I was leading multiple research projects both internally at the company and externally with several U.S. universities, supervising research interns from top Ph.D. programs, and attending conferences to present papers. My industry role was not that different from that of a university faculty, so my career transition decision was made naturally.

Q: What are the biggest challenges you faced during this transition?

A: The mindset. In industry, no matter what type of company or department you are working for, the end goal is profitability – your project cannot be sustained if it does not bring value to the company. This will sometimes make you only focus on short-term goals, while in academia your long-term research visions might be more crucial to lead to a successful career.

Q: What are the most exciting opportunities in transitioning between industry and academia?

A: The ability to understand the needs of both industry and academia, and identify unique research opportunities that leverage resources from both sides. My industry experience has been helping me shape my research roadmap, allowing me to conduct research that not only stays in papers but also benefits our daily lives.

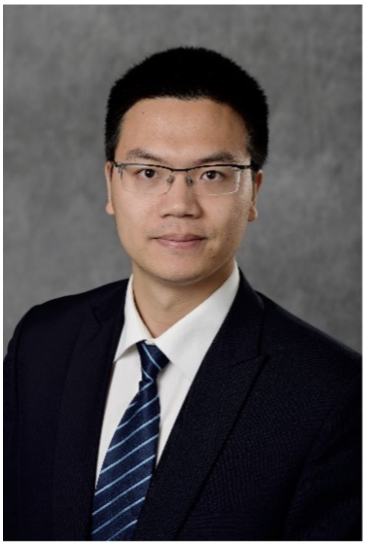
Q: What suggestions would you offer to others navigating a similar transition?

A: If you are still a Ph.D. student and looking for an industry opportunity that can make you a faculty in the future, then focus on those research positions instead of engineering positions. If you are already in the industry then try to remain active in academia by attending conferences, publishing papers, and collaborating with universities.

Q. Thank you for your sharing!

A: Thank you for the opportunity.

Zhaojian Li



Bio: Dr. Zhaojian Li is a Red Cedar Distinguished Associate Professor in the Department of Mechanical Engineering at Michigan State University. He obtained M.S. (2013) and Ph.D. (2015) in Aerospace Engineering (flight dynamics and control) at the University of Michigan, Ann Arbor. Dr. Li worked as an algorithm engineer at General Motors from January 2016 to July 2017. His research interests include Learning-based Control, Nonlinear and Complex Systems, and Robotics and Automated Vehicles. He is the author of more than 65 top journal articles and several patents. He is currently the Associate Editor for IEEE Transactions on Intelligent Vehicles and IEEE Transactions on Control System Technology. He is a senior member of IEEE and a recipient of the 2021 NSF CAREER award.

Q: Congratulations on successfully transitioning between industry and academia. Could you please share your experience with our readers?

A: Hello Readers, my name is Zhaojian Li, and I am currently an Associate Professor in the Department of Mechanical Engineering at Michigan State University (MSU). I worked at the NextGen Controls group at General Motors from January 2016 to July 2017. Afterwards, I joined MSU in August 2017 and have been directing the Robotics and Intelligent Vehicle Automation Lab (RIVAL).

Q: What are the biggest challenges you faced during this transition?

A: The biggest challenge for me during this transition was proposal writing. I had no prior experience in proposal writing before joining MSU, and it took some time to learn how to write high-quality proposals.

Q: What are the most exciting opportunities in transitioning between industry and academia?

A: I was able to maintain connections with my colleagues at General Motors and Ford Motor Company (where I completed several summer internships), leading to several collaborative projects. My industry experience has been invaluable in developing research programs with strong industry relevance.

Q: What suggestions would you offer to others navigating a similar transition?

A:Keep communicating ideas with your former colleagues and leverage your industrial experience to build your research program.

Q. Thank you for your sharing!

A: Thank you for the opportunity.

Openings and Calls

Postdoc Opening at University of Maryland

The Laboratory for Control and Information Systems at University of Maryland is looking for a postdoc researcher in the fields of control, ML, and inference. The Laboratory for Control and Information Systems conducts research on closed-loop control and automation challenges in a broad range of healthcare and medical systems. Current active projects include: closed-loop control of various medical treatments, estimation and prediction for physiological monitoring, worst-case analysis of complex closed-loop controlled medical treatments, ML-enabled cardiovascular health and disease monitoring, etc. Interested candidates should send up-to-date CV and the names of up to 3 references to jhahn12@umd.edu.

Responsibilities

The postdoc researcher will work independently on an assigned research project as well as collaborate and co-advise PhD students in other projects in the group. The postdoc researcher is responsible for conducting research as well as documenting and disseminating research outcomes to peer-reviewed journals and conferences.

Qualifications

- PhD in mechanical engineering or related field
- Knowledge in control theory and applications
- Knowledge in ML and statistical inference
- Knowledge in mechatronics (desired but not required)
- Excellent verbal/written communication skills

Three Research Scientist Open Positions

In support of the research and development (R&D) contract from the U.S. Army Ground Vehicle Systems Center (GVSC), the Autonomous Vehicle Mobility Institute (AVMI) `https://www.wpi.edu/research/centers/avmi` at Worcester Polytechnic Institute (WPI) `https://www.wpi.edu/` in Massachusetts offers three Research Scientist positions. Interested candidates should email a single PDF that includes:

1. **A cover letter** with a statement of purpose for a particular position (include the Position Reference Index),
2. **CV** with their qualifications, research achievements and clear indication of previous accomplishments, and motivation in a position of their interest. The names and contact information of three references should be included in the CV (the references will be contacted once an interview is scheduled)

to **Prof. Vladimir Vantsevich** vvantsevich@wpi.edu and **Prof. Lee Moradi** lmoradi@wpi.edu.

Review of applications will continue until the positions are filled. Successful candidates may be appointed as early as September 1, 2024.

Position Index: AVMI-NAI-2024
This Research Scientist position is offered for basic and applied research in Natural and Responsible Artificial Intelligence. R&D work is in frontier areas of neural, non-neural, and distributed intelligence, and might include, but not limited to thinking and task learning, intelligent behavior when fulfilling a task and multi-task operations in dynamic environments, non-neural controls, and cognition and reasoning issues. Applications include Human-Machine Integrated Formations of humans and autonomous vehicles, vehicle autonomous systems, and systems of autonomous vehicles at various levels of autonomy and intelligence.
The person hired for this position is expected to develop new research direction(s) in one or several above-listed areas and build a technical laboratory to lead his/her R&D at AVMI and contribute to the DE ecosystem. US citizenship or Permanent Residency is required.

Position Index: AVMI-CSE-2024
This Research Scientist position is offered in computer science and software engineering and relates to algorithm design and software application design and development, testing, deploying and maintenance. R&D work is expected to be in frontier areas of digital engineering to enable real-time and faster-than-real-time physics-based simulation and virtualization in the ecosystem of Human-Machine Integrated Formations by advancing the ecosystem's software framework and its modularity, improving and optimizing robustness of the operational system, middleware, and application software.
The person hired for this position is expected to serve as a technical lead for the AVMI Autonomous Systems Laboratory by developing basic research and applied R&D in the above- listed areas. US citizenship or Permanent Residency is required.

Position Index: AVMI-PVS-2024
This Research Scientist position is in research areas of physics-based modeling, simulation, and design of

1. **Exteroceptive sensors** for the use in autonomous vehicles for navigation, perception, localization, look-ahead landscape/terrain identification, weather assessment, and terrain traffi-

cability assessment in-real time, and

2. Proprioceptive sensors embedded in vehicle powertrain and chassis systems for the use in autonomous control of autonomous vehicle systems. The research work will also include physical sensor design, physical and virtual sensor validation in varieties of environmental conditions and terrain texture, soil density and mechanical properties, etc.

The person admitted for this position is expected to develop a new research direction(s) in one or several above-listed areas that include, although are not limited to sensors for facilitating vehicle autonomy, non-destructive soil identification methods, managing data of exteroceptive and proprioceptive sensors, machine learning algorithms for terrain recognition, etc.

The successful candidate will build a technical laboratory to lead his/her sensor-related R&D at AVMI and contribute to the DE ecosystem. US citizenship or Permanent Residency is required.

Upcoming Conferences

2024 American Control Conference

Toronto, Canada, July 8-12, 2024

https://acc2024.a2c2.org/

2024 IEEE/ASME International Conference on Advanced Intelligent Mechatronics

Boston, MA, USA, July 15-18, 2024

https://aim2024.org/

6th Annual Learning for Dynamics Control Conference

Oxford, UK, July 15-17, 2024

https://l4dc.web.ox.ac.uk

2024 International Symposium on Mathematical Theory of Networks and Systems

Cambridge, UK, Aug. 19-23, 2024

https://mtns2024.eng.cam.ac.uk

8th IEEE Conference on Control Technology & Applications

Newcastle upon Tyne, UK, August 21-23, 2024

https://ccta2024.ieeecss.org/

4th Modeling, Estimation and Control Conference

Chicago, Illinios, USA, October 27-30, 2024

https://mecc2024.a2c2.org

2024 Conference on Decision and Control

Milan, Italy, December 16-19, 2024

https://cdc2024.ieeecss.org/

TRANSACTIONS OF THE ASME

JOURNAL OF AUTONOMOUS VEHICLES AND SYSTEMS

(Continued on back)

ABOUT

The purpose of Journal of Autonomous Vehicles and Systems is to provide an international platform for the communication and discussion of technical knowledge and solutions in the transformative areas of the research and engineering design of autonomous vehicles and systems that operate in all media and inter-medium environments: ground, air, space, and water.

The focus of this journal is on an autonomous vehicle system-of-systems approach to modeling, simulation, design, and physical and virtual testing. The vehicle applications include, but are not limited to personal and cargo transportation, construction and forestry, farming, scientific research, investigation of the underground, air and water, exploration of other planets, infrastructure monitoring, surveillance, and military, etc

SCOPE

- Artificial intelligence and machine learning with application to autonomous vehicles
- Artificial intelligence mimicking human intelligence for self-operation, shared mental and cooperative multi-physics environment models
- Intelligent perception and cognitive architectures for autonomous operation, planning, global positioning, navigation and localization, decision making, controls and observation
- Modeling, simulation and designing autonomous vehicle systems for their autonomy of different levels
- Vehicle-to-X interaction with X being Human, Vehicle, Infrastructure, etc.
- Operator-vehicle interaction includes but not limited to communication, operator trust in autonomous vehicle and autonomy transparency, teaming and task allocation
- Shared control and mixed initiatives of autonomous vehicles, haptic feedback based autonomous operation, and driver-assistance systems
- Active payload models
- Proprioceptive sensors in autonomous vehicle systems and exteroceptive sensors for autonomous vehicle and environment interactions
- Outdoor and cyber-physical indoor proving grounds and research facilities
- Inputs/outputs and environmental models in autonomous vehicle simulation and design
- Gaming environments

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asmedigitalcollection.asme.org/autonomousvehicles

TRANSACTIONS OF THE ASME
JOURNAL OF AUTONOMOUS VEHICLES AND SYSTEMS

ASSOCIATE EDITORS

DECEMBER 2023

The American Society of Mechanical Engineers®
ASME®

ASME
SETTING THE STANDARD

AIM2024 Half-day Workshop
(https://www.aim2024.org/)
Poster Submission: see website

Future of Work in the Age of Robotics and AI

Speakers and Tentative Schedule

Time: 09:00 – 12:30 EST, Monday, July 15th, 2024
Website: https://zh.engr.tamu.edu/workshops/
Location: THE FENS, 5th floor, Sheraton Boston Hotel, 39 Dalton Street, Boston

9:00 -- 9:10 Opening and Remarks

9:10 -- 9:25

Ben Armstrong, Executive Director
MIT's Industrial Performance Center
Why Automation Fails: Barriers to Robot Adoption in Manufacturing

9:25 -- 9:40

Jingang Yi, Professor
Rutgers University
Wearable Safety Sensing and Knee Assistive Exoskeletons for Construction Workers

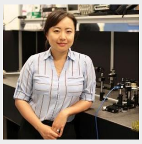
9:40 -- 9:55

Taskin Padir, Professor
Northeastern University
Experiential Robotics for Accelerating the Future of Work

9:55 -- 10:10

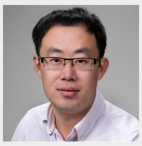
Jonathon E. Slightam, Postdoctoral appointee
Sandia National Laboratories
Data-driven and Physics-Informed AI Approaches for Manipulation

10:10 --10:20



Ellen Mazumdar, Assistant Professor
Georgia Institute of Technology
Additive Manufacturing for Electromagnetic Actuators and Mechatronic Systems

10:20 -- 10:30



Hao Su, Associate Professor
North Carolina State University
AI-Powered Soft Wearable Robots for Augmenting and Restoring Human Performance

10:30 -- 11:00 Coffee Break

11:00 -- 11:40 Poster and Voting

11:40 -- 11:55

Yufeng (Kevin) Chen, Associate Professor
MIT
Muscle-like Soft Actuators for Human-robot Interaction

11:55 -- 12:10

Kamal Youcef-Toumi, Professor
MIT
AI or Human Brain: Who will lead the future of Intelligence?

12:10 -- 12:25

Jordan M. Berg, Program Officer
National Science Foundation
Robots in the Workplace: The NSF After Sunset

12:25 -- 12:30 Closing and Poster Awards Announcement

Introduction:

While robotics and AI are rapidly changing the landscape of jobs and work, there are numerous obstacles to overcome to establish new industries and job roles, all while striving to improve productivity and the overall quality of work life. This workshop is designed to bring together individuals involved in robotics across various sectors. Its goal is to facilitate discussions on cutting-edge robotics research, including topics like human-robot collaboration, motion planning and control, and artificial intelligence. By examining these advancements, we seek to understand how robotics and AI will impact future work across industries such as manufacturing, construction, transportation, warehousing, and more. Through collaborative exploration and discussion, the workshop aims to shed light on the potential implications of these technologies for the workforce of tomorrow.

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