Design, Collaborate, and Adapt: Multi Robot Systems for Monitoring Dynamic Environments

Victoria Edwards
The GRASP Laboratory, University of Pennsylvania
Email: vmedw@seas.upenn.edu

I. Motivation

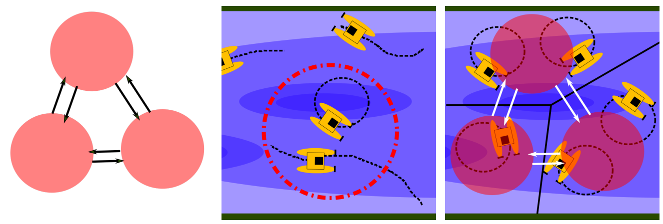
Changing climate conditions have consequences for both natural and man-made systems, *e.g.*, transportation, food production, energy consumption, and wildlife. To obtain accurate and predictive models, data samples are needed at different spatial and temporal scales [34, 37]. Unfortunately, collecting this type of data is challenging both in terms of cost and logistics. Existing solutions rely on sparse human collected data and/or temporally rich but spatially sparse static sensor network data [1]. One promising solution to overcome the data sparsity problem is to augment data collection with a robot team equipped with sensors [6].

Robot teams can cover large spaces [3], persist in challenging environments [6], and collect heterogeneous data samples [34], all while maintaining robustness against single points of failure [31]. Environmental monitoring with a robot team requires breaking down task specifications [39], assigning robots to tasks [23], communicating task essential information [17], and controlling robots in the team [3]. A persistent challenge when monitoring *dynamic* environments is ensuring robot team adaptability to changing environment conditions and/or task requirements [28, 30]. My research uses complex systems theory abstractions to design flexible, adaptive, and resilient robot team solutions for tasks in dynamic and uncertain environments, as summarized in Fig. 1.

My research lies at the intersection of Complex Systems theory, Dynamical Systems theory, and Robotics. **I aim to combine environment models with models from complex systems theory to control robot teams to monitor dynamic environments.** My interdisciplinary background makes me well suited to develop novel multi robot sensing and modeling capabilities with applications for improving climate resiliency, protecting urban infrastructure, devising evacuation strategies, and enhancing military reconnaissance. To advance robot collective capability, I plan to develop the next generation of team-wide reasoning methods to coordinate heterogeneous multi robot systems for operations in extreme environments. In addition, advanced robot team sensing capabilities enable new scientific studies about the disruptions to natural systems as a result of changing climate conditions.

II. Past and Current Research

To develop highly capable multi robot teams, I address how to effectively assign robots to informative sample locations [23]. Assignment solutions must be flexible and adaptive to reassign robots in response to changing regions of importance. My research uses model abstractions from complex systems theory that improve robot team assignment and control in changing conditions.



(a) Design (b) Collaborate (c) Adapt

Fig. 1: I use macroscopic ensemble methods to design team-wide allocation solutions (Fig. 1a). I introduce robot-robot collaboration (Fig. 1b) and environment feedback (Fig. 1c) to improve macroscopic model adaptability in dynamic settings.

1) Multi Robot Task Allocation (MRTA) in Dynamic Environments: Environmental monitoring with robot teams requires methods that effectively assign robots to informative sample locations, a variant of the MRTA problem [24, 16, 39]. Existing monitoring approaches solve the MRTA problem for each individual robot which works well if the team is small (less than 10 agents) and operating in a simple environment (an open field) [2, 36, 25, 5]. Macroscopic ensemble methods are known to easily control large heterogeneous robot teams [30, 20, 12]. Nevertheless, these methods rely on the law of large number assumption and ignore environment feedback, limiting the team allocation effectiveness in dynamic environments. To overcome these limitations, I implemented an online adaptive macroscopic ensemble allocation framework which incorporates feedback from data driven environment models [43]. I performed evaluation using four miniature Autonomous Surface Vehicles (mASVs in Figs. 2a and 2b) in mixed reality experiments [11]. The results support that effectively assigning robots improves monitoring performance in different dynamic environments when compared to adaptive coverage control baselines.

2) Collaboration in Robot Teams using Complex System Models: Some dynamic environments have predictable changes, *e.g.*, tidally impacted water systems like the ocean. Existing methods that perform assignment for each robot must undergo computationally expensive online replanning [26, 4]. In contrast, we can design top-down macroscopic ensemble models to

(a) Lab Environment (b) mASVs (c) Crazyflie

Fig. 2: I perform experimental evaluation of macroscopic allocation using custom built miniature Autonomous Surface Vehicles (mASVs) (Figs. 2a and 2b). Separately, I use the Crazyflie UAV (Fig. 2c) to evaluate collective behaviors[29].

leverage known environment changes that control robot team assignment. However, while macroscopic ensemble models are known to be scalable, the current models used in robotics can only achieve fixed steady state [12]. As a result, these methods also require replanning [30, 11]. Fortunately, existing compartment models in complex systems theory model interaction between compartments as nonlinear terms introducing the potential for periodic equilibrium [18]. To achieve time-varying populations of robots, I introduce robot-robot collaboration terms to macroscopic ensemble robot team modeling [8]. A *collaboration* is when individual robots share spatial proximity and change their task based on the desired global team state, Fig. 1b. I have shown the application of collaborative macroscopic ensemble models to environmental monitoring scenarios [9], and I have studied model predictions when the *well-mixed* assumption is violated [10]. The results demonstrate not only novel team-wide population behavior, but also suggest possibilities for using artificial systems to inform population models used in fields like epidemiology.

3) Experimental Verification of 2D Collective Motion: Biology has long inspired engineers and scientists to understand and generate artificial collective behavior; where many individuals contribute via simple rules to a global pattern [42]. A known phenomena in natural collectives is that the propagation of information through the collective is subject to delays [14]. To study this, differential delay equations are used to model artificial collective behavior [15]. It has been previously observed with mean field analysis that a spring potential model with communication delay undergoes a Hopf Bifurcation and transitions between various collective states corresponding to changes in the delay [41]. To build on this theoretical understanding, I performed mixed reality experiments with Unmanned Aerial Vehicles (UAVs). An example UAV is shown in Fig. 2c . My experiments validated the existence of the collective behaviors and demonstrated delay induced state transitions [7]. These results inspired follow-on studies led by my collaborators about previously unseen bistability [21] and more physically realistic range based delay [38].

III. Future Research

Monitoring changing environments requires highly capable, coordinated, heterogeneous robotic systems. There are three natural extensions to the work I have pursued so far: 1) incorporating environment information, *e.g.*, scalar or flow field data, into robot team control, 2) novel representations of capability, and 3) studying natural collectives to understand the interactions between multi robot systems and the environment.

1) Modeling the Environment as a Complex System: Using point sensor measurements of the environment to update robot behavior is a longstanding approach to environmental monitoring, *e.g.*, adaptive sampling [24]. The challenge when the environment changes over time is effectively allocating team resources and achieving scalable environment representations of relevant measurements [28]. One scalable approach to achieve novel team-wide allocation is to extend collaborative macroscopic ensemble methods to incorporate the environment, as is often done in chemistry [19]. Unlike other compartment modeling methods that approximate non-state model values, a robot team can provide real-time estimates of environmental concentration terms using machine learning methods. In addition, reduced order modeling (ROM) techniques like Dynamic Mode Decomposition (DMD) are scalable representations of dynamic environments [35, 37, 22], but using ROM in robotics settings requires novel methods to handle real-time data acquisition with distributed communication [34, 33].

2) Capabilities as Complex Networks: Heterogeneous robotic teams allow data collection at different spatial and temporal scales, which in turn enables better dynamic environment representations and autonomous decision making [34]. However, adequately using team resources requires understanding robot and team capabilities [32, 13]. The challenge is modeling capabilities and their connections in a meaningful and computationally tractable way that does not simply require modeling the entire system. Recently, Basset-Smith and Zurn shared descriptions of how curiosity can be modeled as a complex network / graph [44]. There are similarities between robot capabilities and human curiosity which suggest a graph as a reasonable modeling tool. The benefits of using a graph are the extensive existing tools and inherent scalability. A new capability graph representation would enable novel smart planning and allocation techniques, *e.g.*, macroscopic ensemble allocation combined with ergodic planning.

3) Collective Motion Inspired by Biological Systems: Natural complex systems, *e.g.*, creatures of the ocean like Salp's, live in dynamic environments and help regulate their local ecosystems [40]. Taking inspiration from these types of natural systems, the long term goal is to enable multi robot systems to influence the environment using coordinated behavior. For example, during flooding events, a robot team could move into place and use the collective onboard propulsion to direct the flow of debris away from critical infrastructure. A promising direction is to explore 3D collective motion inspired by the novel helical trajectories of Salp Colonies studied by Sutherland et al. [40]. The first step is to design a 3D model that combines the physical state with phase coupled oscillators like in the Swarmulators [27]. The next step involves measuring the local interactions between the robots and the environment to understand how the collective impacts the world.

REFERENCES

[1] Tareq Alhmiedat et al. A survey on environmental monitoring systems using wireless sensor networks. *J. Networks*, 10(11):606–615, 2015.

[2] Alessia Benevento, María Santos, Giuseppe Notarstefano, Kamran Paynabar, Matthieu Bloch, and Magnus Egerstedt. Multi-robot coordination for estimation and coverage of unknown spatial fields. In *2020 ieee international conference on robotics and automation (icra)*, pages 7740–7746. IEEE, 2020.

[3] Jorge Cortés and Magnus Egerstedt. Coordinated control of multi-robot systems: A survey. *SICE Journal of Control, Measurement, and System Integration*, 10(6):495–503, 2017.

[4] Grace Diehl and Julie A Adams. The viability of domain constrained coalition formation for robotic collectives. *arXiv preprint arXiv:2306.05590*, 2023.

[5] Bin Du, Kun Qian, Hassan Iqbal, Christian Claudel, and Dengfeng Sun. Multi-robot dynamical source seeking in unknown environments. In *2021 IEEE International Conference on Robotics and Automation (ICRA)*, 2021.

[6] Matthew Dunbabin and Lino Marques. Robots for environmental monitoring: Significant advancements and applications. *IEEE Robotics & Automation Magazine*, 19 (1):24–39, 2012. doi: 10.1109/MRA.2011.2181683.

[7] Victoria Edwards, Philip deZonia, M Ani Hsieh, Jason Hindes, Ioana Triandaf, and Ira B Schwartz. Delay induced swarm pattern bifurcations in mixed reality experiments. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, 30(7), 2020.

[8] Victoria Edwards, Thales C Silva, and M Ani Hsieh. Stochastic nonlinear ensemble modeling and control for robot team environmental monitoring. *16th International Symposium on Distributed Autonomous Robotic Systems (DARS)*, 2022.

[9] Victoria Edwards, Thales C Silva, Bharg Mehta, Jasleen Dhanoa, and M Ani Hsieh. On collaborative robot teams for environmental monitoring: A macroscopic ensemble approach. *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2023.

[10] Victoria Edwards, Thales C. Silva, and Ani M. Hsieh. A macroscopic ensemble modeling approach to collaborative task assignment in dynamic environments. *In Distributed Autonomous Robotics Systems (DARS)*, 2024.

[11] Victoria Edwards, Thales C. Silva, and Ani M. Hsieh. Adaptive macroscopic ensemble allocation for robot teams monitoring spatiotemporal processes. *In Preparation*, 2025.

[12] Karthik Elamvazhuthi and Spring Berman. Mean-field models in swarm robotics: a survey. *Bioinspiration & Biomimetics*, 15(1):015001, nov 2019. doi: 10.1088/1748-3190/ab49a4. URL https://doi.org/10.1088/1748-3190/ab49a4.

[13] Yousef Emam, Siddharth Mayya, Gennaro Notomista, Addison Bohannon, and Magnus Egerstedt. Adaptive task allocation for heterogeneous multi-robot teams with evolving and unknown robot capabilities. In *2020 IEEE International Conference on Robotics and Automation (ICRA)*, pages 7719–7725. IEEE, 2020.

[14] Jerome Fehrenbach, Jacek Narski, Jiale Hua, Samuel Lemercier, Asja Jelic, Cécile Appert-Rolland, Stéphane Donikian, Julien Pettré, and Pierre Degond. Time-delayed follow-the-leader model for pedestrians walking in line. 2014. doi: 10.3934/nhm.2015.10.579.

[15] Eric Forgoston and Ira B Schwartz. Delay-induced instabilities in self-propelling swarms. *Physical Review E—Statistical, Nonlinear, and Soft Matter Physics*, 77(3): 035203, 2008.

[16] Brian P Gerkey and Maja J Matarić. A formal analysis and taxonomy of task allocation in multi-robot systems. *The International Journal of Robotics Research*, 23(9): 939–954, 2004.

[17] Jennifer Gielis, Ajay Shankar, and Amanda Prorok. A critical review of communications in multi-robot systems. *Current Robotics Reports*, 3(4):213–225, 2022.

[18] Daniel T Gillespie. Exact stochastic simulation of coupled chemical reactions. *The journal of physical chemistry*, 81 (25), 1977.

[19] Daniel T Gillespie. Stochastic simulation of chemical kinetics. *Annu. Rev. Phys. Chem.*, 58(1):35–55, 2007.

[20] John Harwell, Angel Sylvester, and Maria Gini. Characterizing the limits of linear modeling of non-linear swarm behaviors. *arXiv preprint arXiv:2110.12307*, 2021.

[21] Jason Hindes, Victoria Edwards, Sayomi Kamimoto, Ioana Triandaf, and Ira B Schwartz. Unstable modes and bistability in delay-coupled swarms. *Physical Review E*, 101(4):042202, 2020.

[22] Tom Z Jiahao, M Ani Hsieh, and Eric Forgoston. Knowledge-based learning of nonlinear dynamics and chaos. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, 31(11), 2021.

[23] Alaa Khamis, Ahmed Hussein, and Ahmed Elmogy. Multi-robot task allocation: A review of the state-of-the-art. *Cooperative Robots and Sensor Networks 2015*, pages 31–51, 2015.

[24] Kian Hsiang Low, Geoffrey J Gordon, John M Dolan, and Pradeep Khosla. Adaptive sampling for multi-robot wide-area exploration. In *Proceedings 2007 IEEE International Conference on Robotics and Automation*, 2007.

[25] Kensuke Nakamura, María Santos, and Naomi Ehrich Leonard. Decentralized learning with limited communications for multi-robot coverage of unknown spatial fields. *arXiv preprint arXiv:2208.01800*, 2022.

[26] Changjoo Nam and Dylan A Shell. When to do your own thing: Analysis of cost uncertainties in multi-robot task allocation at run-time. In *2015 IEEE International Conference on Robotics and Automation (ICRA)*, pages 1249–1254, 2015. doi: 10.1109/ICRA.2015.7139351.

[27] Kevin P O'Keeffe, Hyunsuk Hong, and Steven H Strogatz. Oscillators that sync and swarm. *Nature communications*, 8(1):1504, 2017.

[28] Derek A Paley and Artur Wolek. Mobile sensor networks and control: Adaptive sampling of spatiotemporal processes. *Annual Review of Control, Robotics, and Autonomous Systems*, 3:91–114, 2020.

[29] James A Preiss, Wolfgang Honig, Gaurav S Sukhatme, and Nora Ayanian. Crazyswarm: A large nano-quadcopter swarm. In *2017 IEEE International Conference on Robotics and Automation (ICRA)*, pages 3299–3304. IEEE, 2017.

[30] Amanda Prorok, M Ani Hsieh, and Vijay Kumar. The impact of diversity on optimal control policies for heterogeneous robot swarms. *IEEE Transactions on Robotics*, 33(2):346–358, 2017.

[31] Amanda Prorok, Matthew Malencia, Luca Carlone, Gaurav S Sukhatme, Brian M Sadler, and Vijay Kumar. Beyond robustness: A taxonomy of approaches towards resilient multi-robot systems. *arXiv preprint arXiv:2109.12343*, 2021.

[32] Harish Ravichandar, Kenneth Shaw, and Sonia Chernova. Strata: unified framework for task assignments in large teams of heterogeneous agents. *Autonomous Agents and Multi Agent Systems*, 34(2):38, 2020.

[33] Tahiya Salam and M Ani Hsieh. Adaptive sampling and reduced-order modeling of dynamic processes by robot teams. *IEEE Robotics and Automation Letters*, 4 (2):477–484, 2019.

[34] Tahiya Salam and M Ani Hsieh. Heterogeneous robot teams for modeling and prediction of multiscale environmental processes. *Autonomous Robots*, pages 1–24, 2023.

[35] Tahiya Salam, Alice Kate Li, and M Ani Hsieh. Online estimation of the koopman operator using fourier features. *arXiv preprint arXiv:2212.01503*, 2022.

[36] Maria Santos, Udari Madhushani, Alessia Benevento, and Naomi Ehrich Leonard. Multi-robot learning and coverage of unknown spatial fields. In *2021 International Symposium on Multi-Robot and Multi-Agent Systems (MRS)*, pages 137–145. IEEE, 2021.

[37] Diya Sashidhar and J Nathan Kutz. Bagging, optimized dynamic mode decomposition for robust, stable forecasting with spatial and temporal uncertainty quantification. *Philosophical Transactions of the Royal Society A*, 380 (2229):20210199, 2022.

[38] Ira B Schwartz, Victoria Edwards, Sayomi Kamimoto, Klimka Kasraie, M Ani Hsieh, Ioana Triandaf, and Jason Hindes. Torus bifurcations of large-scale swarms having range dependent communication delay. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, 30(5), 2020.

[39] Yoonchang Sung, Zhiang Chen, Jnaneshwar Das, Pratap Tokekar, et al. A survey of decision-theoretic approaches for robotic environmental monitoring. *Foundations and Trends® in Robotics*, 11(4):225–315, 2023.

[40] Kelly R. Sutherland, Alejandro Damian-Serrano, Kevin T. Du Clos, Brad J. Gemmell, Sean P. Colin, and John H. Costello. Spinning and corkscrewing of oceanic macroplankton revealed through in situ imaging. *Science Advances*, 10(20):eadm9511, 2024. doi: 10.1126/sciadv.adm9511. URL https://www.science.org/doi/abs/10.1126/sciadv.adm9511.

[41] Klementyna Szwaykowska, Ira B Schwartz, Luis Mier-y Teran Romero, Christoffer R Heckman, Dan Mox, and M Ani Hsieh. Collective motion patterns of swarms with delay coupling: Theory and experiment. *Physical Review E*, 93(3):032307, 2016.

[42] Kolbjørn Tunstrøm, Yael Katz, Christos C. Ioannou, Cristián Huepe, Matthew J. Lutz, and Iain D. Couzin. Collective states, multistability and transitional behavior in schooling fish. *PLOS Computational Biology*, 9(2): 1–11, 02 2013. doi: 10.1371/journal.pcbi.1002915. URL https://doi.org/10.1371/journal.pcbi.1002915.

[43] Christopher KI Williams and Carl Edward Rasmussen. *Gaussian processes for machine learning*, volume 2. MIT press Cambridge, MA, 2006.

[44] Perry Zurn and Dani S Bassett. *Curious minds: The power of connection*. MIT Press, 2022.