

UNIVERSITY OF CALIFORNIA, MERCED

Digital Twin Enabled Collective Sensing and Steering for Source Determination Problems

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*To my wife and family,
thank you for always being there and keeping me grounded with your support, love
and understanding throughout my graduate career, without it, this milestone would
not have been possible.*

*To my daughter,
through hard work, persistent effort and grit, anything is possible.*

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Abbreviations

The following abbreviations are used in this dissertation:

ADE	Advection diffusion equation
AJAX	Alpha Jet Atmospheric eXperiment
ALD	Advance Leak Detection
AMFC	Alberta Methane Field Challenge
AMOG	AutoMOBILE greenhouse Gas
ANOVA	Analysis of variance
ARPA-E	Advanced Research Projects Agency-Energy
AVIRIS-NG	Next generation Airborne visible/infrared imaging spectrometer
bLS	Backward Lagrangian Stochastic dispersion technique
bs-TDLAS	Back scatter tunable diode laser absorption spectrometer
CALMIM	California Landfill Methane Inventory Model
CARB	California Air Resources Board
CASIE	Characterization of Arctic Sea Ice Experiment
CFP	Cylindrical Flux Plane
CRDS	Cavity ring-down spectrometer
DiAL	Differential Absorption LiDAR Method
DT	Digital Twin
EC	Eddy Covariance
EDF	Environmental Defense Fund
EPA	Environmental Protection agency
EPA FLIGHT	EPA Facility Level Informationon Greenhouse gases Tool
ES	Environmental sensing
FEAST	Fugitive Emissions Abatement Simulation Toolkit
FID	Flame Ionization Detector
FLEXPART-WRF	FLEXible PARTicle-Weather Research and Forecasting
FLOM	Fractional lower order moments
FPE	Fokker–Planck equation
FTIR	Fourier Transform Infrared
GADEN	A 3D Gas Dispersion Simulator for Mobile Robot Olfaction in Realistic Environments
GDT	Gauss Divergence Theorem
GDM	Gas distribution mapping
GDMF	Gradient divergence mass flux
GHG	Greenhouse gas
GLM	General linear model
GLM-VFP	General linear model vertical flux plane
GML	Gas Mapping LiDAR™ technology
GSL	Gas source localization
QOGI	Quantitative optical gas imaging
ICOS	Integrated cavity output spectroscopy

IDW	Inverse distance weighted
IMAP-DOAS	Iterative maximum a posteriori differential optical absorption spectroscopy
LDAQ	Leak detection and quantification
LDAR	Leak detection and repair
LES	Large eddie simulation
LiDAR	Light detection and ranging
LGR	Los Gatos Research
LWIR	Long-wave infrared
MCMC	Markov Chain Monte Carlo
MEMS	Micro electrical mechanical systems
METEC	Methane Emission Testing and Evaluation Center
MGGA	Micro greenhouse gas analyzer
MOX, CMOS,MOS	Ceramic Metal oxide sensor
MMC	Standford EDF Mobile Monitoring Challenge
MMD	Micrometeorological mass difference method
MONITOR	Methane Observation Networks with Innovative Technology to Obtain Reductions
MUST	Mock Urban Test Setting
MWIR	Mid-wave infrared
NDIR	Non-dispersive Infrared
NZMB	Non-zero minimum bootstrap
NGI	Near-field Gaussian plume inversion
NIR	Near infrared
OA-ICOS	Off axis integrated cavity output spectrometer
OGI	Optical gas imaging
OPLS	Open path laser spectrometer
OTM	Other test method
OU	Ornstein-Uhlenbeck
PG	Pasquill-Gifford
PID	Photo-ionization detector
PI-VFP	Path Integrated Vertical Flux Plane
PMT	Pollution mapping tool
PSD	Power spectrum density
PSG	Point source Gaussian
PSG-CS	Conditionally sampled point source Gaussian
PSG-RB	Recursive Bayesian point source Gaussian
PSG-SBM	PSG sequential Bayesian MCMC
QOGI	Quantitative optical gas imaging
RANS	Reynolds averaged Navier Stokes
RB-LSI	Recursive Bayesian least squares inverse
RGB	Red green blue
RMLD	Remote methane leak detector
SDP	Source determination problem

SEBASS	Spatially-Enhanced Broadband Array Spectrograph System
SEM	Surface emission monitoring
SESC	Stochastic extremum seeking control
SLAM	Simultaneous localization and mapping
STE	Source term estimation
sUAS	small Unmanned aircraft system
SWIR	Short-wave infrared
TDLAS	Tunable diode laser absorption spectroscopy
	Tracer dispersion method,
TDM, TCM, ATM	Tracer correlation (or dilution) method,
	Atmospheric tracer method
TIR	Thermal infrared
TSEB	Two source energy balance
UA	Ultrasonic Anemometer
UGGA	LGR Ultraportable GHG analyzer
VCSEL	Vertical cavity surface emitting laser
VFP	Vertical Flux Plane
VRPM	Vertical Radial Plume Mapping Method
WRF	Weather Research and Forecasting Model

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Publications

28. **Hollenbeck, D.**, Zheng, K., Zulevic, D., & Chen, Y. (2023). Swarm Robotic Source Seeking with Fractional Fluxotaxis. *in Proceedings of 2023 International Conference on Fractional Derivatives and Applications.* Ajman, Jordan.
27. **Hollenbeck, D.**, An, D., Krzysiak, R., & Chen, Y. (2023, June). Towards Cognitive Battery Monitoring on Hybrid VTOL Fixed-Wing sUAS with Maximized Safe Endurance. *In 2023 International Conference on Control, Mechatronics, and Automation (ICCMA).* (Planned)
26. An, D., Krzysiak, R., **Hollenbeck, D.**, & Chen, Y. (2023, June). Battery-health-aware UAV Mission Planning Using a Cognitive Battery Management System. *In 2023 International Conference on Unmanned Aircraft Systems (ICUAS).* *IEEE.* (Accepted)

25. An, D., Krzysiak, R., **Hollenbeck, D.**, & Chen, Y. (2023, June). Long Endurance Site-Specific Management of Biochar Applications Using Unmanned Aircraft Vehicle and Unmanned Ground Vehicle. *In 2023 International Federation on Automatic Control (IFAC)* (Accepted)
24. **Hollenbeck, D.**, Zulevic, D., & Chen, Y. (2022, June). Single and Multi-sUAS Based Emission Quantification Performance Assessment Using MOABS/DT: A Simulation Case Study. *In 2022 18th IEEE/ASME International Conference on Mechatronics and Embedded Systems and Applications.*
23. An, D., **Hollenbeck, D.**, Cao, K., & Chen, Y. (2022). Soil Methane Emission Suppression Control Using Unmanned Aircraft Vehicle Swarm Application of Biochar Mulch - A Simulation Study. *Journal of Information and Intelligence*
22. An, D., Liu, Z., **Hollenbeck, D.**, & Chen, Y. (2022). A Greenhouse Gas Proximity Sensing Using Chemiresistive Strip and Miniaturized Radar Array. *In 2022 10th International Conference on Control, Mechatronics and Automation.*
21. **Hollenbeck, D.**, & Chen, Y. (2022). A Digital Twin Framework For Environmental Sensing with sUAS. *Journal of Intelligent & Robotic Systems* 105 (1), 1-15.
20. An, D., **Hollenbeck, D.**, Gao, S., & Chen, Y. (2022, June). A Field Study of Soil Biochar Treatment Response Using Small Unmanned Aerial Systems (sUAS). *In 2022 International Conference on Unmanned Aircraft Systems (ICUAS). IEEE.*
19. **Hollenbeck, D.**, Zulevic, D., & Chen, Y. (2022, June). A Modified Near-Field Gaussian Plume Inversion Method Using Multi-sUAS for Emission Quantification. *In 2022 International Conference on Unmanned Aircraft Systems (ICUAS). IEEE.*
18. Viola, J., Rodriguez, C., Hollenbeck, D., and Chen, YQ. (2022). *Outliers in Control Engineering*, 237. (Book Chapter)
17. **Hollenbeck, D.**, & Chen, Y. (2021). Digital Twin Behavior Matching of Gas Plumes Using a Fixed Sensor Mesh and Dynamic Mode Decomposition. *In ASME 2021 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. American Society of Mechanical Engineers Digital Collection.*
16. **Hollenbeck, D.**, Zulevic, D., & Chen, Y. (2021). Advanced Leak Detection and Quantification of Methane Emissions Using sUAS. *Drones*, 5(4), 117.
15. **Hollenbeck, D.**, Zulevic, D., & Chen, Y. (2021, July). MOABS/DT: Methane Odor Abatement Simulator with Digital Twins. *In 2021 IEEE 1st International Conference on Digital Twins and Parallel Intelligence (DTPI) (pp. 378-381). IEEE.*

14. **Hollenbeck, D.**, & Chen, Y. (2021, June). Multi-UAV Method for Continuous Source Rate Estimation of Fugitive Gas Emissions From a Point Source. *In 2021 International Conference on Unmanned Aircraft Systems (ICUAS) (pp. 1308-1313). IEEE.*
13. Schloesser, D. S., **Hollenbeck, D.**, & Kello, C. T. (2021). Individual and Collective Foraging in Autonomous Search Agents With Human Intervention. *Scientific Reports, 11(1), 1-13.*
12. Viola, J., **Hollenbeck, D.**, Rodrigez, C., & Chen, Y. (2021). Fractional-Order Stochastic Extremum Seeking Control with Dithering Noise for Plasma Impedance Matching. *In proceedings of CCTA.*
11. Fatehiboroujeni, S., **Hollenbeck, D.**, Mishra, A., & Goyal, S. (2021) Post-buckling Stability of a Cantilever Beam with Cubic Non-Linearity in Constitutive Laws. *In ASME 2021 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. American Society of Mechanical Engineers Digital Collection. (Accepted)*
10. **Hollenbeck, D.**, Manies, K., Chen, Y., Baldocchi, D., Euskirchen, E. S., & Christensen, L. (2020, December). Evaluating a UAV-based Mobile Sensing System Designed to Quantify Ecosystem-based Methane. *In AGU Fall Meeting Abstracts (Vol. 2020, pp. A115-0007).*
9. Niu, H., **Hollenbeck, D.**, Zhao, T., Wang, D., & Chen, Y. (2020). Evapotranspiration Estimation with Small UAVs in Precision Agriculture. *Sensors, 20(22), 6427.*
8. **Hollenbeck, D.**, & Chen, Y. (2020, September). Characterization of Ground-to-air Emissions with sUAS Using a Digital Twin Framework. *In 2020 International Conference on Unmanned Aircraft Systems (ICUAS) (pp. 1162-1166). IEEE.*
7. **Hollenbeck, D.**, & Chen, Y. (2020). A More Optimal Stochastic Extremum Seeking Control Using Fractional Dithering For A Class of Smooth Convex Functions. *IFAC-PapersOnLine, 53(2), 3737-3742.*
6. Schloesser, D., **Hollenbeck, D.**, & Kello, C. T. (2020). Social Foraging in Groups of Search Agents with Human Intervention. *In CogSci.*
5. Whiticar, M., **Hollenbeck, D.**, Billwiller, B., Salas, C., & Christensen, L. (2019). Application of the BC GHGMapper™ Platform for the Alberta Methane Field Challenge (AMFC). Geoscience BC Summary of Activities, 2020-02.
4. **Hollenbeck, D.**, Dahabra, M., Christensen, L. E., & Chen, Y. (2019, June). Data Quality Aware Flight Mission Design for Fugitive Methane Sniffing Using Fixed Wing sUAS. *In 2019 International Conference on Unmanned Aircraft Systems (ICUAS) (pp. 813-818). IEEE.*

3. **Hollenbeck, D.**, Oyama, M., Garcia, A., & Chen, Y. (2019, June). Pitch and Roll Effects of On-board Wind Measurements Using sUAS. *In 2019 International Conference on Unmanned Aircraft Systems (ICUAS) (pp. 1249-1254). IEEE.*
2. Chen, Y., **Hollenbeck, D.**, Wang, Y., & Chen, Y. (2018). On Optimal Tempered Lévy Flight Foraging. *Frontiers in Physics, 6, 111.*
1. **Hollenbeck, D.**, Nunez, G., Christensen, L. E., & Chen, Y. (2018, June). Wind Measurement and Estimation with Small Unmanned Aerial Systems (sUAS) Using On-board Mini Ultrasonic Anemometers. *In 2018 International Conference on Unmanned Aircraft Systems (ICUAS) (pp. 285-292). IEEE.*

Awards, Fellowships, and Grants

- CITRIS Aviation Prize (inaugural, Fall 2021)
- UC Merced ME Bobcat Fellowship (Fall 2021)
- UC Merced ME Bobcat Fellowship (Sum 2021)
- NSF NRT - Extended Intelligent Adaptive Systems Fellowship (Fall 2020 - Sum 2021)
- NSF NRT - Extended Intelligent Adaptive Systems Fellowship (Fall 2019)
- NSF NRT - Extended Intelligent Adaptive Systems Fellowship (Spring 2019 - Sum 2019)
- NSF NRT - Intelligent Adaptive Systems Fellowship (Spring 2017 - Sum 2018)
- NSF NRT - Interdisciplinary Computational Graduate Education (Spring 2017)
- UC Merced Outstanding Student Award (undergraduate, Spring 2016)

Presentations

- ICUAS 2022 Sum 2022 (title: A Modified Near-Field Gaussian Plume Inversion Method Using Multi-sUAS for Emission Quantification)
- CITRIS Research Exchange Spring 2022 (title: Long Endurance Edge-AI Platform For Research Opportunities and Data Gathering)
- PhD Dissertation Qualifying Exam Spring 2022 (title: Digital Twin Enabled Collective Sensing and Steering for Source Determination Problems)

- MESA Lab Research Group Meeting Fall 2021 (title: The empirical gramian and why it is important)
- MSNDC 2021 Sum 2021 (title: Post-buckling Stability of a Cantilever Beam with Cubic Non-linearity in Constitutive Laws)
- ICUAS 2021 Sum 2021 (title: Multi-UAV Method for Continuous Source Rate Estimation of Fugitive Gas Emissions from a Point Source)
- DTPI 2021 Sum 2021 (title: MOABS/DT: Methane Odor Abatement Simulator with Digital Twins)
- MESA Lab Research Group Meeting Spring 2021 (title: Swarm Robotic Source Seeking with Fractional Fluxotaxis and Seasonal Meandering)
- MESA Lab Research Group Meeting Fall 2020 (title: Physicomemetics, Chemical Plume Tracing, and Fluxotaxis (I))
- MESA Lab Research Group Meeting Fall 2020 (title: MOAB/DT: Towards Smart Swarming for Methane Emission Sensing and Understanding/Quantification)
- ICUAS 2020 Workshop Tutorial Sum 2020 (title: A digital twin framework on using drones as edge devices for environmental monitoring)
- ICUAS 2020 Workshop Tutorial Sum 2020 (title: Methane sensing drones with machine learning)
- UC Agriculture and Natural Resources (UCANR) DroneCamp Spring 2020 (title: Methane emission drone swarm sensing to better understand permafrost thawing dynamics.)
- MESA Lab Research Group Meeting Fall 2019 (title: Fractional Order Modeling of Atmospheric Dispersion)
- MESA Lab Research Group Meeting Spring 2019 (title: UAV Gas Sensing, a Digital Twin, and PET (POSIM Experimental Testbed))
- Invited Talk – Applied Math Optimization Research Group Spring 2019 (title: tbd) NSF NRT Retreat Meeting Spring 2019 (title: Collective Foraging Among Loosely Coupled Agents)
- Invited Talk – NSF NRT Fall Kickoff Meeting Fall 2018 (title: On Collective Behavior of Foraging Vultures and Individual Impact)
- NSF NRT Retreat Meeting Spring 2018 (title: Collective Foraging Among Loosely Coupled Agents)

- Invited Talk – Applied Math Optimization Research Group Fall 2017 (title: Fractional Calculus Enhanced Source Seeking of Fugitive Methane)
- Guest Lecture ME190 – Sum 2017 (topics: Communication Basics, Long Distance Drones, UTM)
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Abstract

Digital Twin Enabled Collective Sensing and Steering for Source Determination Problems

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Motivated by climate change and the global warming potential of methane (86 times more potent than CO_2), this dissertation focuses on the source determination problem using collective sensing and Digital Twins. Recently, Digital Twins have been developed to provide better performance assessment, fault prognosis and predict future behavior of complex systems. The term ‘collective’, refers to the group of mobile sensors that, as a whole, provide more information than a single mobile sensor can. The mitigation of methane emissions into the atmosphere is important to focus on in reducing the effects of global warming in the near term. In order to mitigate emissions, the leaks have to first be detected and assessed before they can be repaired. Many of these emissions can be modeled as a point source governed by partial differential equations (PDE), which, solutions are typically time-stepped into the future (i.e. the forward problem). In many cases, the emission plume is subject to turbulence which requires the use of turbulence models, such as large eddy simulations (LES), to compute. In both cases, the computational requirements and run-time can prevent real-time or near real-time analysis. Considering hybrid modeling approaches (e.g. deterministic and stochastic), the forward behavior matched Digital Twin model can be computed in near-real time and used for improving emission quantification methodologies as well as perform optimization (e.g. sensor placement and mobile or fixed-location sensing / actuation policy). The dissertation is broken into four main parts: the first part is on source seeking based optimization using random search, collective foraging, Fluxotaxis, and Extremum Seeking Control; the second part is on the application of leak detection and quantification with sUAS (including: sensors, platforms, and methods) as well as controlled release and real world field campaigns; the third part is on Digital Twins (POSIM and MOABS/DT) and how to use them for environmental sensing, method development, and performance evaluation case studies; the last part is on the sensor placement problem and how the observability Gramian combined with Digital Twins, can be used for smarter collective sensing and steering.