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Research Statement

Mobile robots have the unrealized potential to assist or substitute for human rescuers after disasters during initial response, restoration, reconstruction, and betterment. My research is motivated by the goal of enabling robots to dramatically improve our ability to mount such after-disaster missions quickly and safely, so as to maximize our ability to save victims, restore basic facilities, reconstruct infrastructures, and improve preparedness for future disasters, while minimizing the risk to human rescuers. To accomplish this objective, future mobile robots need to be (1) highly capable of reliably moving through those challenging and most likely adversarial environments, and (2) highly intelligent so that involvement of human rescuers, both physically and intellectually, can be effectively minimized.

Disaster is among many of the potential applications of mobile robots, which also include delivery, service, healthcare, agriculture, inspection, and exploration. However, most autonomous robots being deployed in the field today either work in highly controlled workspaces (e.g., factories and warehouses), or repeatedly perform one single pre-programmed task (e.g., vacuuming and mopping). But for uncontrolled environments and for novel tasks (e.g., disaster robotics), today's robots must seek help from highly skilled humans in the field (e.g., bomb squads). Motivated by all these applications and the current limitations of how robots are being used, my research goal is to **develop highly capable and intelligent mobile robots that are robustly deployable in the real world with minimal human supervision**. In the pursuit of such real-world field robotics with capable motion planning augmented by intelligent machine learning (see Fig. 1 with all peer-reviewed publications), I build advanced robot platforms, develop complex sensing and actuation systems, design sophisticated motion planning and machine learning algorithms, and set up standardized testbeds and metrics in order to create highly capable and intelligent robots to locomote on land, in air, and at sea.

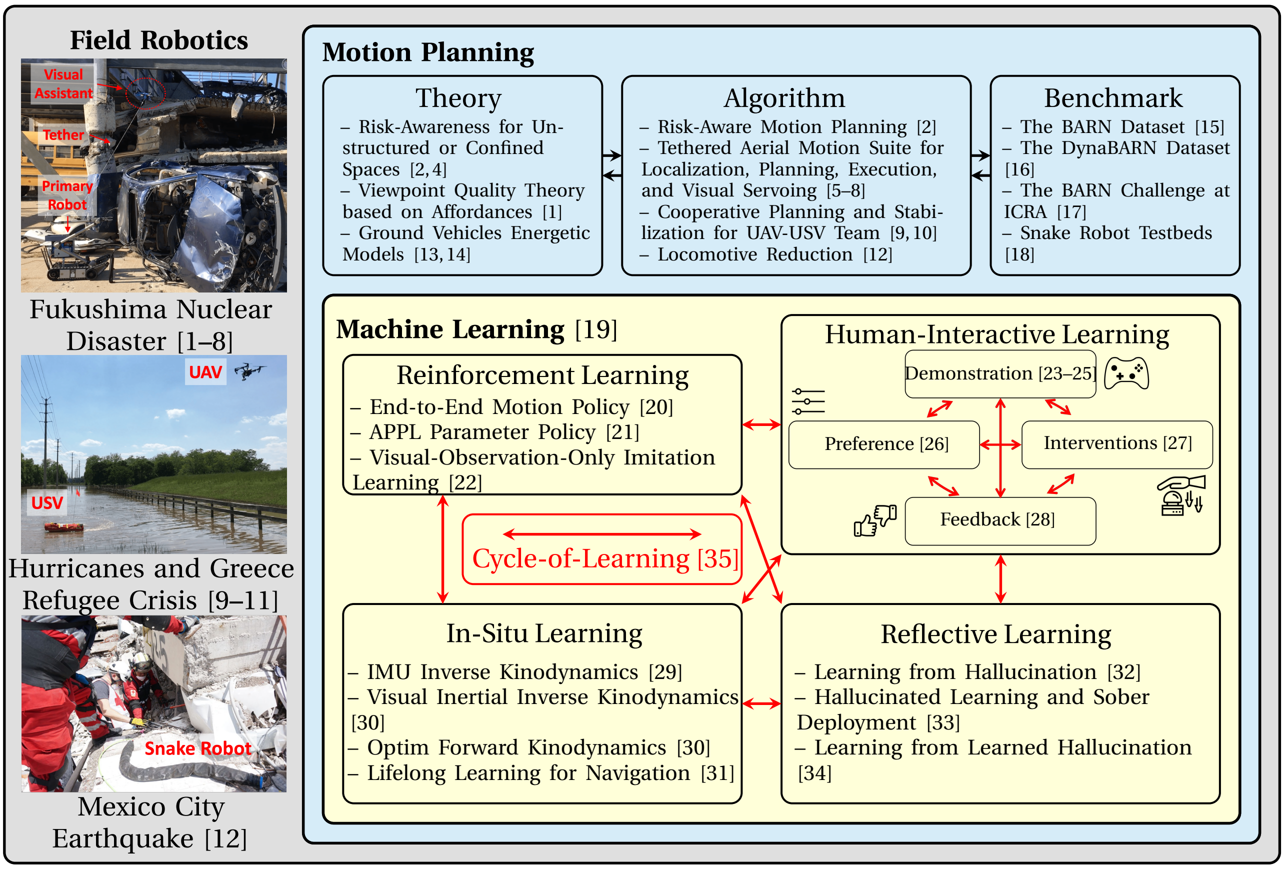

Fig. 1: Developing Field Robotics with Capable Motion Planning Augmented by Intelligent Machine Learning

Field Robotics: Collaborative Robot Teams with Human Users in Humanitarian Crises

The ultimate goal of my research aims at pushing current robots out from the labs and toward real-world robust field deployment, collaborating with or serving real-world users, e.g., fire fighters, first responders, and agency stake holders. Unlike controlled factory or lab environments, field robotics needs to consider a variety of real-world challenges and adversaries, address constraints imposed by real-world applications, and cooperate with robot teammates with different motion and sensing modalities.

Fukushima Nuclear Disaster [1–8]: The ongoing decommissioning in response to the Fukushima Daiichi nuclear disaster still completely relies on teleoperation: Multiple human rescuers have to slowly and cautiously drive a robot due to mobility and manipulation challenges. To make matters worse, this practice even requires a second teleoperated visual assistant robot to give the operators a better external viewpoint, causing problems such as difficulty in coordination between teleoperators and manually-chosen suboptimal viewpoints. These current practices are inefficient and require extensive human involvement. Aiming at automating and robustifying the aforementioned teleoperated visual assistance in the Fukushima Daiichi nuclear decommissioning, my Ph.D. thesis replaced the secondary robot and its teleoperating crew with an autonomous tethered aerial robot, which flies around the ground robot in unstructured or confined spaces and provides adaptive visual assistance [3] using a motion risk reasoning framework [2, 4], a risk-aware planner [2], a tethered aerial motion suite [5–8], and a viewpoint quality theory [1]. My autonomous, tethered, aerial visual assistant work led to media coverage by WIRED [36].

Hurricanes and Greece Refugee Crisis [9–11]: During such marine mass casualty incident responses, first responders (e.g., U.S. and Italian Coast Guards) had to manually save drowning victims. To improve response efficiency, I developed an Unmanned Aerial Vehicle and Unmanned Surface Vehicle (UAV-USV) team, in which a USV can fully autonomously navigate to drowning victims [9] with the overheard visual guidance from a UAV using motion-based viewpoint stabilization [10]. The UAV-USV team has been deployed for marine mass casualty incident responses during Hurricane Harvey and Hurricane Irma [11] and search and rescue exercises conducted by the United States Coast Guard and Galveston Fire Department during Summer Institute 2016 in Galveston, TX; Italian Coast Guard during 2016 exercise in Genoa, Italy; Brazos County Fire Department and Grimes County Emergency Management during Brazos Valley Search and Rescue Exercise 2017 in Gibbons Creek, TX; Los Angeles County Fire Department Lifeguards during 2017 exercise in Los Angeles, CA; and Department of Homeland Security during 2017 CAUSE V exercise in Bellingham, WA.

Mexico City Earthquake [12]: Local responders and robotics experts had to work together to manually drive a hyper-redundant snake robot into collapsed buildings to search for victims, which requires extensive expertise about snake robot locomotion. I developed a Locomotive Reduction technique which reduces the complexity of controlling a redundant snake robot to that of navigating a differential-drive vehicle [12].

Motion Planning: Locomotors that Reason and Plan with Benchmarked Capability

To enable such robustly deployable field robotics, robots first need to reliably and efficiently move in the real world. My research in motion planning spans from theories, which allow robots to reason about the challenges and adversaries from the real world, to algorithms, including perception, planning, controls, and cooperation, and to benchmarks to quantify locomotion capability in a standardized manner.

Theory: To move reliably and efficiently, robots first need to understand and reason about the *risk*, *utility*, and *constraint* from the real world: My Ph.D. thesis developed a robot motion *risk*-awareness framework for unstructured or confined spaces with propositional logic and probability theory, which discovered that the risk a moving robot faces is not simply a function of where the robot is, but also depends on its entire motion history [2]. This discovery contradicts most existing simplified motion risk/cost assumptions and makes the risk-aware planning problem PSPACE-complete; In addition to reasoning about risk, robots also need to maximize the *utility* for themselves and for their human teammates. For the visual assistance problem in Fukushima, I developed a viewpoint theory [1] based on affordances so that the aerial visual assistant can reason about which viewpoint can best assist the human operators during task execution; Robots also need to reason about real-world *constraint*, e.g., limited onboard energy required for movement, for which I proposed an energetic model so that ground, aerial, and aquatic robots can estimate operational range and optimize the mission in both offline and online fashions [13, 14].

Algorithm: Building upon the theories to reason about the real world, I also developed algorithms to enable robots to reliably and efficiently move in the deployment environments: Based on the risk-awareness framework [4], I developed a risk-aware motion planning paradigm that can effectively trade off risk history and computation [2]. Not only suitable for the visual assistance problem in Fukushima, the risk-awareness framework and risk-aware planner are also general to most mobile robots working in unstructured or confined spaces in the real world; Considering practical real-world deployment constraints, e.g., UAVs need to be tethered to provide energy and to assure safety, I developed a full motion suite for tethered aerial robots flying in cluttered spaces [3], including tether-based localization [7], motion primitives [5], tether contact planning [6], and visual servoing [8]. This tethered motion suite opens up a new regime for resilient indoor aerial locomotion under energy and safety constraints stemming from real-world applications; For the UAV-USV team deployed in marine mass casualty incident responses, I developed a cooperative planning and stabilization method for the heterogeneous team so that stable visual feed can be provided by the UAV [10] to autonomously navigate the USV to drowning victims [9]; For the hyper-redundant snake robot deployed in the Mexico City Earthquake, I proposed a Locomotive Reduction technique based on an average body frame [37] and a set of motion primitives [38, 39] so that a snake robot with 16 Degrees of Freedom (DoFs) can be effectively and autonomously controlled as a 2-DoF differential-drive car to reach constrained spaces [12].

Benchmark: To confidently push robots out of the labs into the real world, their capability needs to be evaluated in standardized benchmarks. I launched a series of effort around Benchmark Autonomous Robot Navigation (BARN): The BARN dataset is a suite of 300 simulated navigational environments randomly generated by Cellular Automata to objectively benchmark ground navigation capabilities with quantifiable difficulty metrics [15]; DynaBARN [16] is an extension to BARN with dynamic obstacles generated in a systematic and randomized way; I organized The BARN Challenge at ICRA 2022 [17], which revealed limitations of current autonomous navigation systems and pointed out future research directions; I also reviewed existing literature on snake robot testbeds in granular and restricted maneuverability spaces and made recommendations on designing a testbed that can enable a comprehensive evaluation of a snake robot's overall capability and an objective comparison of different snakes [18].

Machine Learning: Autonomy that Learns and Improves in the Field

Although building autonomous robots with classical motion planning theories, algorithms, and benchmarks can reduce *physical* involvement of human rescuers in challenging or adversarial tasks, it still requires robotics experts' extensive *intellectual* involvement, especially when facing novel or out-of-distribution scenarios. Therefore, my research also focuses on allowing robots to actively *learn* from non-expert humans and also from their own in-situ and reflective experiences, as well as reinforcement learning, instead of only being passively *engineered*. On the other hand, my survey on motion planning and control for mobile robot navigation using machine learning revealed that mobile robots are better equipped with machine learning methods in conjunction with classical approaches to leverage the best of both worlds [19].

Human-Interactive Learning: Facing novel, out-of-distribution deployment scenarios, most existing autonomous robots require robotics experts to reprogram or adjust their autonomy stack, e.g., through fine-tuning the system's hyper-parameters (e.g., maximum speed, sampling rate, inflation radius, and optimization coefficients). Such a practice requires the availability of experienced roboticists, which is not always the case. During field deployment, however, non-expert users are more easily available than expert roboticists, e.g., pedestrians walking around a delivery robot on a sidewalk and first responders that only know how to operate, but not how to program robots. To allow robots to learn from such non-expert users as well, I developed the Adaptive Planner Parameter Learning (APPL) paradigm [35], which uses sparse, light-weight, multi-model interactions with non-expert users to improve robot performance. For example, APPL can leverage teleoperated demonstration [23–25], corrective interventions [27], evaluative feedback [28], path preference [26], and self-supervised reinforcement learning [21], all from non-expert users, to improve robot navigation in a wide variety of deployment environments. In particular, APPL learns a *parameter policy* that scaffolds on classical motion planners by dynamically adjusting their hyper-parameters so that robots can enjoy both safety and explainability of classical approaches and adaptivity and flexibility of learning methods, even only through such sparse and light-weight interactions. APPL has been covered by IEEE Spectrum [40] and the US Army [41] and has been adopted by the Army Research Laboratory's autonomy stack.

In-Situ Learning: In situations where even non-expert humans are not available, e.g., during scientific exploration in remote areas, robots can also learn from the changes of the underlying environments, i.e., from their own in-situ robot-environment interaction experiences. For mobile robots, such changes can be the underlying terrain or the obstacle distributions. To enable accurate, high-speed, off-road mobility on unstructured terrain (cement, grass, mud, sand, leaves, twigs, etc.), I developed an in-situ learning approach that allows robots to learn an inverse kinodynamic model conditioned on IMU readings (IMU-IKD) [29]; Furthermore, to overcome actuation latency during high-speed maneuvers, I further extended IMU-IKD so that the learned model can not only *react* to the underlying wheel-terrain responses sensed by the IMU, but also *anticipate* future kinodynamic changes using vision, called Visual-IMU Inverse Kinodynamics (VI-IKD) [30]; Also using in-situ vehicle-terrain interactions, I further extended from high-speed, high-accuracy, off-road trajectory tracking alone to a wide array of control problems with a learned forward kinodynamic model (Optim-FKD) [42]; I also developed Lifelong Learning for Navigation (LLfN), which first self-identifies suboptimal motion plans, then gradually eliminates those plans through learning from similar self-supervised experiences, and finally allows mobile robots to achieve in-environment improvement and cross-environment adaptation without the notorious catastrophic forgetting problem for many learning systems.

Reflective Learning: Another extraordinary human capability to adapt to new environments is the ability to reflect on previous experiences, which inspired my Learning from Hallucination (LfH) paradigm for mobile robots: a motion plan optimal for a previous obstacle environment may be also optimal for future similar or even more challenging environments. To enable reflective learning, I formulated a novel "dual" problem of motion planning called *hallucination*: Instead of finding the optimal motion plan for a given obstacle configuration online, the robot can easily synthesize obstacle configurations offline, where a certain motion plan is optimal. Solving this relatively easier "dual" problem allows to generate a lot of training data for learning algorithms that give robots the ability to reflect on previous experiences to anticipate and perform well in future unseen environments. I manually designed maximal [32] and minimal [33] hallucination techniques with provable guarantees and also developed a self-supervised learning approach to generate hallucination [34], all of which are able to reflect on past experiences and achieve improved performance in future environments. Considering the conundrum that in order to produce safe motions in obstacle-occupied spaces a robot needs to first learn in those dangerous spaces without the ability of planning safe motions, such reflective learning paradigm from hallucination neither requires good-quality demonstrations (e.g., from a classical planner or a human), nor exploration based on trial-and-error (e.g., from reinforcement learning), both of which become costly in highly constrained and therefore dangerous future deployment environments.

Reinforcement Learning: Reinforcement Learning (RL) utilizes self-supervised trial-and-error mostly in simulation and therefore does not require interactions with humans, in-situ learning, or reflective experiences. I applied RL to learn both end-to-end motion policies (which directly issue raw motor commands) [20] and the APPL paradigm's parameter policies (which dynamically adjust a classical motion planner's hyper-parameters) [21]. I also conducted studies to compare different RL algorithms and the two learning paradigms and pointed out findings with respect to addressing uncertainty, improving safety, learning with limited data, and generalization to unseen scenarios [43]. Furthermore, building upon a novel visual reward function, Visual-Observation-Only Imitation Learning (VOILA) allows one robot to learn from other robots' visual only observations (without access to actions) and uses real-world trial-and-error data to learn a motion policy.

Cycle-of-Learning: With all these individual machine learning techniques to improve motion planning with the ultimate goal of field deployment, I also developed a Cycle-of-Learning scheme [35] that allows robots to improve in a cyclic and continuous fashion using different learning methods with different deployment experiences (human-interactive, in-situ, reflective, and reinforcement learning) throughout their life time.

Future Research: Resilient and Task-Efficient Robots towards Full Autonomy

While my past research aims at improving robot *mobility* with motion planning augmented by machine learning to allow robots to reliably move in the field, I will further pursue future research in other two orthogonal directions: enabling *resiliency* and *task-efficiency* (see Fig. 2 with publications and preprints), both of which are also driven by my research goal to develop highly capable and intelligent mobile robots that are robustly deployable in the real world with minimal human supervision.

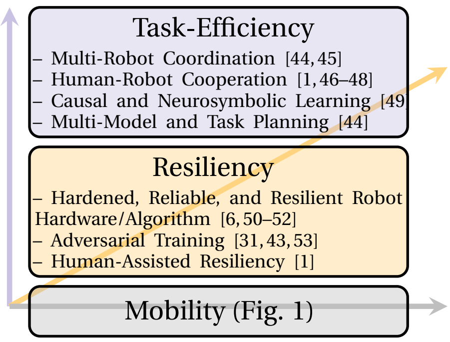

Fig. 2: Future Research

Resiliency: I aspire to create robot field resiliency through both hardware design and algorithm development. For example: a resilient tethered UAV which bootstraps the tether to recover from a collision or even a crash [6]; a redundant sensor network to cope with noise and uncertainty in the real world [52]; a sensor fusion algorithm aware of when to and not to trust the camera-IMU extrinsic calibration [50]; and a packet loss concealment technique when facing unreliable field communication [51]. Another avenue I will purse is through preemptive adversarial training [43], in which robots seek to anticipate future failure cases and be prepared to overcome them with offline computation [53] or online re-sampling [31]. Another approach to enable resiliency is through efficient feedback mechanisms [1] to convey critical information from the field to request and facilitate human assistance only when necessary through a framework to understand how to handle the difference between critical and non-critical field information. I will continue to adopt a field methodology to identify real-world problems or failures, create resilient mechatronics and algorithmic solutions, and develop corresponding intelligence adaptive to the robots, humans, and field conditions.

Task-Efficiency: Robots also need to be efficient at the task level. Building upon their superior mobility and resiliency, I anticipate four avenues towards task-efficiency: Multi-robot teams have the potential to improve efficiency, but they must first efficiently coordinate with each other to achieve the overall objective [44] while avoiding individual conflicts [45]; Humans should not only teach the robots how to execute the task alone, but also work together with them [1], and share their workspace as well [46–48]; Causal and neurosymbolic learning [49] can utilize structures of the task specification and therefore improve planning and execution efficiency; Multi-model and task planning [44] will leverage individual robots' mobility and resiliency, multi-robot teams' effective coordination, human-robot teams' smooth interaction, and learned task structure from causality and neurosymbolic reasoning, to eventually achieve overall mission success and task efficiency.

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