Robots offer great promise for responding to the pressing economic, social, and environmental issues affecting our planet and its growing human population. Self-driving vehicles could save thousands of lives lost in traffic accidents, underwater robots are invaluable tools for exploring depths otherwise unreachable to humans, robotic caretakers have the potential to revolutionize quality of life of an aging population, and robotized agricultural techniques promise to be key in feeding an increasing number of people with the limited availability of farm land. As robots start transitioning from controlled lab environments into the real world, however, the crystallization of this potential is hindered by the challenging dynamic and uncertain nature of real-world environments.

With the underlying goal of benefiting the well-being of us all on Earth, in my research I build upon fundamental principles to intertwine robotic perception, planning, and control in systems capable of prolonged intelligent decision-making in the real world, where my research has demonstrably advanced the art.

I seek to ground my developments on solid theory, finding it particularly exciting when insight from other fields provides a new approach to a problem in robotics, and so I spend some of my time probing other areas of science for inspiration. And while I value theoretical guarantees and simulation, I believe it is essential to evaluate our developments on real embodied systems to assess their pitfalls and practical utility. Adhering to this approach, my work has enhanced the ability of embodied computers to make decisions in complex tasks like surveying the bottom of the ocean and driving in traffic. Some of these developments are presented next.

Uncertainty-driven Survey Planning for AUVs

Traditionally, autonomous underwater vehicle (AUV) survey missions consist in a lawn-mower pattern indicated by a human operator. During mission execution, AUVs are often able to register current sensor observations against a prior map to bound odometry drift in what is known as terrain-aided navigation (TAN). Therefore, the AUV’s path has a direct effect on its localization uncertainty, and ultimately on the quality of the resulting data product. Unfortunately, this effect is ignored by naïve (but ubiquitous) lawn-mower-like surveys.

My dissertation work bridged this gap with an algorithm that accounts for uncertainty in the survey planning process, while still meeting the desire to survey in parallel tracks to minimize turns and to obtain a predictable path from an operator’s standpoint. Results from hybrid simulations with datasets collected off the coasts of Spain, Greece, and Australia [1], as well as sea trials [2], demonstrate that the algorithm outperforms traditional survey plans in terms of position uncertainty and map self-consistency, as exemplified in Fig. 1.

![Figure 1](image_url)

Figure 1: Comparison of a standard AUV survey path (a) with a path planned with the proposed uncertainty-driven method (b). As shown by the pose uncertainty along both paths (c), the proposed method exhibits significantly lower uncertainty along the mission.

Inspection of 3D Underwater Structures

In a typical AUV survey, the vehicle covers the area of interest by navigating at a safe distance from the bottom, imaging the sea floor from an overhead view. However, this approach is not sufficient when the target area includes 3D structures like coral reefs or ship wrecks. Inspecting this sort of sites demands imaging from a richer variety of viewpoints and in closer proximity. Unfortunately, this increases the threat of collision.

In my thesis work I proposed a planning system to inspect 3D underwater structures that leverages fast online replanning to allow AUVs to navigate in close proximity, providing rich viewpoints that enable full 3D perception of the environment [3]. Data collected with this method allows to create high-quality 3D models of the inspected sites (Fig. 2) not achievable with traditional AUV surveys.
Smooth Steering Control of Self-Driving Cars

Existing approaches to autonomous vehicle navigation typically plan a trajectory and pass it on to a steering controller that commands steering wheel angle or curvature at every timestep to minimize tracking error. This approach, however, exhibits large amounts of control effort, and ignores other criteria such as smoothness or the importance of staying on plan at every time. In contrast, I have recently developed a novel integrated motion planning and control system [4] that leverages the concept of potential fields to represent a driving corridor with a desired tracking error tolerance (Fig. 3). This driving corridor continuously commands a direct steering wheel torque input to smoothly steer the vehicle with a much smaller control effort, resulting in a smoother driving experience. Further, potential fields allow to naturally incorporate obstacles in the driving corridor to circumvent them, with typically no need for expensive, explicit trajectory planning.

Multipolicy Decision-Making for Autonomous Driving

To operate reliably in real-world traffic, an autonomous car must evaluate the consequences of its potential actions by anticipating the uncertain intentions of other traffic participants. Managing these uncertainties is significant because previous methods, such as hand-tuned heuristics [5], numerical optimization [6], or partially observable Markov decision process (POMDP) solvers have difficulty scaling up to real-world scenarios. We have recently developed an integrated behavioral inference and decision-making approach that models vehicle behavior for both our vehicle and nearby vehicles as a discrete set of closed-loop policies that react to the actions of other agents [7, 8]. Each policy captures a distinct high-level behavior and intention, such as driving along a lane or turning left or right at an intersection. In this system, I have developed a Bayesian changepoint detection scheme that operates on the observed history of states of nearby cars to estimate the distribution over potential policies that each nearby car might be executing. We can then sample from these distributions to obtain high-likelihood actions for each participating vehicle and select to execute the policy that maximizes a reward function, being able to probabilistically make decisions based on coupled interactions between cars in a tractable manner (Fig. 4).

Figure 2: Planning for inspection of 3D underwater structures. (a) Execution at an underwater boulder site at **40m depth** (blue-dotted: nominal path; cyan: re-planned trajectory). Data collected with this planner enables full 3D reconstructions of the inspected sites (b).

Figure 3: An autonomous vehicle negotiating a hairpin curve using the novel torque-based integrated motion planning and control approach.

Figure 4: Fourteen passing maneuvers executed using multipolicy decision-making on a test track, overlapped on satellite imagery. In each distinctly-colored curve-circle pair, the curve shows the self-driving vehicle's trajectory, while the circle corresponds to the location of the passed vehicle halfway through the passing maneuver. Satellite imagery credit: Google.
Future Research and Expected Outcomes

Practical Robotic Systems for Surveying and Monitoring

While generic human-level robotic intelligence might seem distant, there are many practical applications where robots are ready to make a difference. Recent advances in mapping, localization, and planning have enabled robots to survey and monitor areas of interest for tasks such as structure inspection and environmental monitoring. This applies to a wide variety of systems and domains, including inspection of the underwater portion of ship hulls [9, 10], surveying of 3D structures on the ocean floor [3], ground-based search and rescue [11], and unmanned aerial vehicles [12]. At short term, I intend to partner with research labs and, in particular, with industry, to crystallize these techniques into systems that are routinely used for these applications, making them more efficient, safer, and cost-effective.

Intention-aware Decision-Making in Dynamic, Uncertain Scenarios

If we want robots to truly make an impact on our everyday lives, they must be able to interact with other dynamic agents, including people and traffic, and reason about their potential behavior. Making such systems practical is a quite compelling area. In this respect, I wish to continue and extend my work on autonomous driving to allow robots to reliably operate in complex multi-agent scenarios like city traffic, crowded environments, and construction sites.

Cost-effective Robotic Systems

Of course, for any leap in robotic capabilities to be practical it needs to be made cost-effective, and so I am determined to leverage commodity sensors and new materials, mechanisms, and fabrication processes to this aim. For example, cameras are attractive in this respect due to their ubiquity and low cost, in contrast with more expensive active sensors like sonar, lidar, or radar. Similarly, I am interested in leveraging the advent of new fabrication techniques such as 3D printing to achieve capable robotic systems at an increasingly reduced cost.

Operating in A Priori Unknown Environments

Most state-of-the-art robotic systems rely on prior knowledge of their environments to perform their tasks. This is however not an option in sites where prior knowledge is inaccurate or not available, or where the system is exposed to significant environmental disturbances: think of exploring an uncharted underwater cave, or conducting reconnaissance in a collapsed building. To tackle these situations, I am determined to study and develop robots capable of incrementally perceiving their environment, making decisions, and acting accordingly in real time to achieve their tasks. By making progress toward that goal, robotics stands to make great leaps in capabilities.

Integrating the Major Research Areas in Robotics and AI

To date, much research in robotics and artificial intelligence (AI) has been developed in relative isolation. Robotic system complexity is often factored into independent modules unaware of each other’s performance. This is exemplified by simultaneous localization and mapping (SLAM) and computer vision algorithms being most thoroughly tested on standard benchmarking datasets of these communities, or by the fact that localization and planning are often separated out, the planner assuming perfect knowledge of the robot’s position. As a result, these modules are unable to adapt their response when performance of some other component degrades, for instance.

In contrast, I wish to explore systems where perception, planning, and control cooperate in a holistic manner, perceiving their environment and making decisions in accord as they go, enabling robots to ultimately tackle challenges currently out of reach. Nonetheless, integration is often more than simply putting together a handful of components: deep integration often requires new methods at a fundamental level. For example, coupling perception, planning, and control can be formulated as a POMDP, known to be intractable, requiring suitable approximations to achieve satisfactory solutions in reasonable time. Indeed, as I have demonstrated in my work on decision-making for autonomous vehicles, it is often possible to exploit domain knowledge of the problem at hand to develop integrated approaches that scale up to full real-world systems.

Toward that goal, I am interested in fostering research projects that involve large-scale integration of often disparate fields in robotics and AI. For example, can we join forces from the mapping, computer vision, planning, and reinforcement learning communities to achieve systems capable of navigation and manipulation in challenging environments like homes, the ocean floor, or dense forests? I think we can, and developing integrated testbeds with
the joint efforts of many research teams specialized on different fields is crucial in identifying limitations and the
next steps required to make progress in robotic capabilities.

Future Plans

As a professor, I plan to tackle my research agenda by establishing a research group with some of the best students
that share my enthusiasm for robotics. With my group, I intend to gain insight into significant practical problems
and to build robotic systems that sense and act intelligently in the physical world.

I am passionate about bringing together the research agenda described above and becoming a leader in the
development of robotic systems that contribute to improve the well-being of us all and the coming generations. For
an up-to-the-minute list of publications and multimedia demonstrations of my past and current research, please visit
my research homepage at http://robots.engin.umich.edu/~egalcera/.

References

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