Intelligent Autonomy in Robotic Systems

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Automation is making its way into our lives in many ways, from aerospace systems to manufacturing, to the home. While many aerospace systems exhibit some autonomy, it can be argued that advancement could be much further. For example, autonomy in deep space missions, while impressive, is still well behind ground systems; scientists, rightfully so, do not trust autonomous software when many years and dollars have been spent on a project. Looking back, adoption of the autopilot had a similar resistance, as it took many years for pilots to accept a computer flying an aircraft. Factors that influence the adoption of autonomy include reliability, trust, training, and knowledge of failure modes; these factors are amplified in aerospace systems where costs and human lives are prevalent.

This paper describes two areas, which will enable more robust autonomy. The first is a deeper level of intelligence in robotic systems. Current robotic systems work very well for repeated tasks (e.g. in manufacturing). However, long term reliability for more complex tasks (e.g. driving a car) are typically lacking. Interestingly, humans can provide an intuitive benchmark because they typically perform many complex tasks well due to a level of intelligence that is difficult to emulate in software, such as learning over time, overcoming uncertain/new situations as they arise, and developing longer term strategies.

The second area is an efficient integration of autonomy with humans, which is an area of immense importance for advanced aerospace systems. For example, while a robot vacuuming the floor requires minimal interaction with the human, search and tracking using a team of UAVs with sensors and weapons requires highly efficient interaction. Tasks must be coordinated to take advantage of the strengths of each; theory must scale well with larger teams; humans must not become overloaded or bored; and external influences must be considered, such as deciding if UAVs will have the ability to make actionable decisions.

Intelligence in Robotics

Tightly integrated Perception, Anticipation and Planning

As robotic systems have matured, one of the important advancements has been the development of high throughput sensors. Consider Cornell's autonomous driving vehicle, one of six to complete the 2007 DARPA Urban Challenge (DUC) (Figure 1). The vehicle includes a perception system with a 64-scan lidar unit (100Mbits/sec), 4-scan lidar units (10MBits/sec), radars, and cameras (1200Mbits/sec).

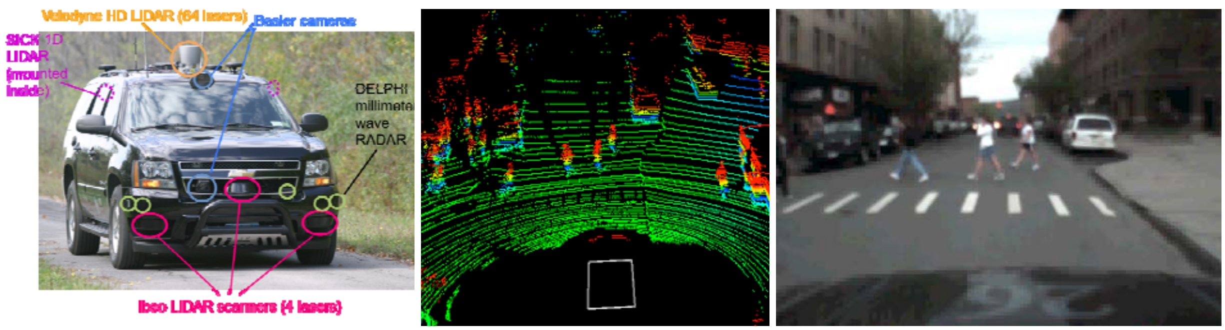

Figure 1: One challenge in automation is handling large amounts of data intelligently. Left: Robot with multi-modal sensors for perceiving the environment. Middle: Screenshot of a 64-scan lidar unit. Right: screenshot of a color camera.

While the DUC was deemed a success (Iagnemma et al 2008; Miller et al., 2008), there were many close calls, several small collisions, and a number of human assisted restarts. The fragile nature of practical robotic intelligence was shown when many simple perception mistakes cascaded into larger failures. One critical problem is the mismatch between perception, which is typically *probabilistic* framework because sensors are inherently uncertain, and planning, which is *deterministic* because plans must be implemented. To date, perception research typically provides a probabilistic `snapshot' of the environment to robotic planners, which in turn leads to `reactive' rather than `intelligent' behaviors in autonomous robots. Aerospace systems exhibit similar problems; Figure 2 shows a cooperative UAV system used to search and track objects of interest

(Campbell & Whitacre, 2007), such as tuna fish, or survivors of hurricanes and fires. Failures for this system include only searching particular areas and losing track of objects, which can occur because of object motion (e.g. moving behind a tree or under a bridge) or due to the aircraft (e.g. vibration or sensor uncertainty).

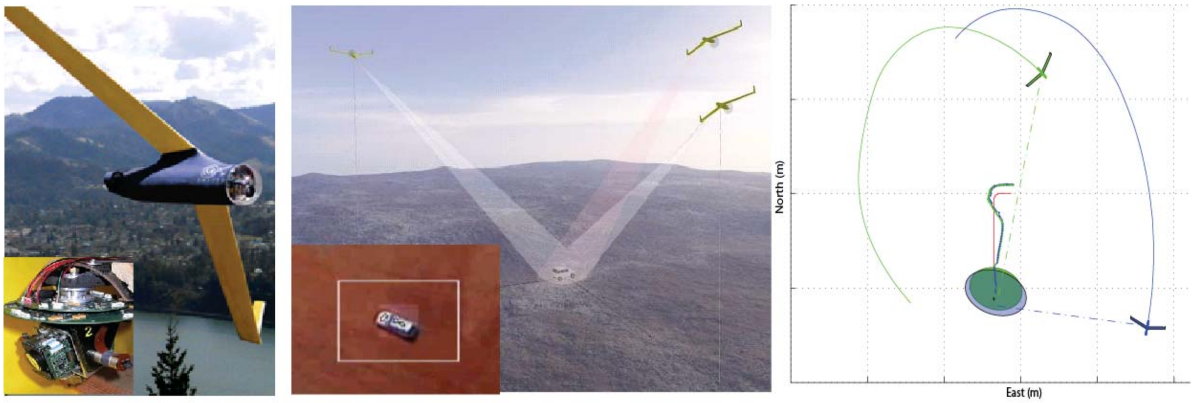

Figure 2: Multiple UAV system. Left: SeaScan UAV and its camera based turret. Center: Notional example of cooperative tracking using UAVs. Right: Flight test data of two UAVs tracking a truck over a lossy network.

Key to overcoming these problems is new theory that provides a tighter linkage between probabilistic perception and planning (Thrun et al., 2005). Many sensors, such as in Figure 1, must be fused (Diebel & Thrun, 2006; Schoenberg et al., 2010) to yield an accurate picture of the static and potentially dynamic environment, including terrain type and identity and behaviors of obstacles. Plans must then be formulated based on this probabilistic information. A new paradigm must be realized where planning occurs to a particular level of probability. In dynamic environments, planners must also anticipate changes in the environment. For autonomous driving (Figure 1), motion of other cars, cyclists and pedestrians is important for planning (Hardy & Campbell, 2010; Blackmore et al., 2010; Havlak & Campbell, 2010). For cooperative UAVs (Figure 2), motion of objects in the context of a map and other UAVs is important (Grocholsky et al., 2004; Ousingsawat & Campbell, 2007). While these methods are currently computationally demanding, humans typically overcome these issues using learned models of the object, its motion and behaviors (McClelland & Campbell, 2010).

Learning

Humans typically drive very well because they learn over time (rules, object types and motion, relative speeds, etc.). This is very challenging for robots, however. Consider Figure 3, which shows a map of the DUC course, along with an overlay of 53 instances of emergency brake slams by Cornell's robot. Interestingly, many of these brake slams occurred over multiple passes near the same areas; the most frequent (18 times) was near a single concrete barrier which jutted out from the others, making it appear (to the perception algorithms) that it was another car (Miller et al., 2008).

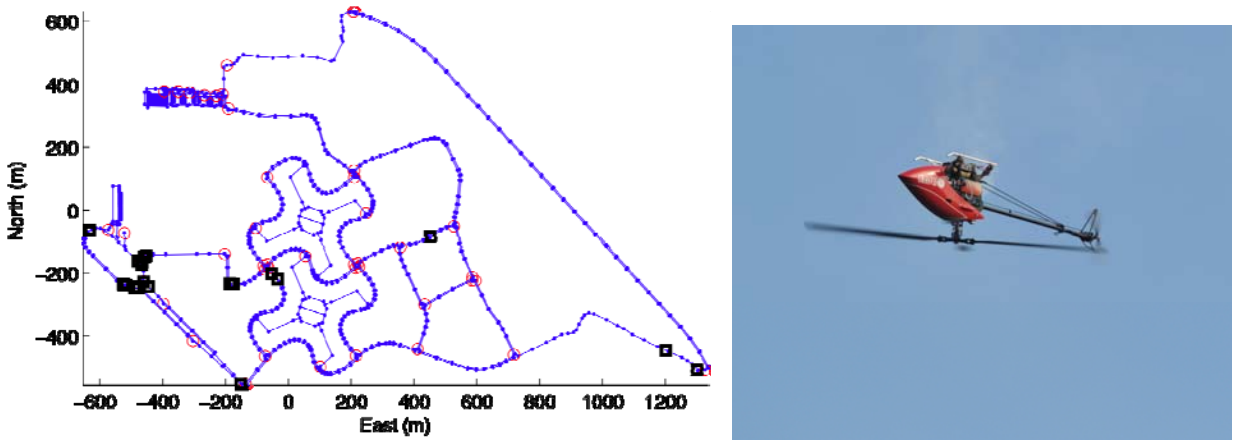

Figure 3: Left: Map of the DUC course (blue: map, red: stop signs); black squares indicate where brakes were quickly applied over the six-hour mission. Right: A helicopter in mid-maneuver (photo by E. Fratkin); these complex maneuvers can be learned from an expert or experimentation.

Currently, a number of researchers exploring learning methods; for example, Abbeel et al. (2010) have developed algorithms which learn helicopter dynamics/maneuver models over time from data by an expert pilot (Figure 3). While learning seems straightforward to we humans, it is not simple to implement algorithmically. New algorithms are required to overcome challenges such as: how to ensure safe learning over time, and how to overcome new uncertainties that have not been seen before.

Verification and Validation in the presence of Uncertainties

Current methods for validating software for autonomy in aerospace systems typically involve a series of expensive evaluation steps that heuristically develop confidence in the implementation. For example, UAV flight software typically requires validation on a software simulator, hardware in the loop simulator, and then flight tests. In addition, fault management systems operate during flights as required.

Recent research in formal logic, model checkers, and control theory have developed a set of tools that enable the ability to capture higher level specification of a set of tasks (Kress-Gazit et al., 2009; Wongpiromsarn et al., 2009). Consider the case of a car driving through an intersection, with another car in the area (Figure 4). The rules of the road can be specified by logic, and controllers for autonomous driving can be automatically generated. These tools, however, are typically only available for simple models with little to no uncertainty. New theory and methods are required which incorporate uncertainty in perception, motion and actions into a verifiable planning framework. Logic specifications must provide *probabilistic* guarantees regarding the high level behavior of the robot, such as provably safe autonomous driving to 99.9%. These methods are especially important for aerospace systems such as commercial airplanes and deep space missions, where high costs and human lives are prevalent.

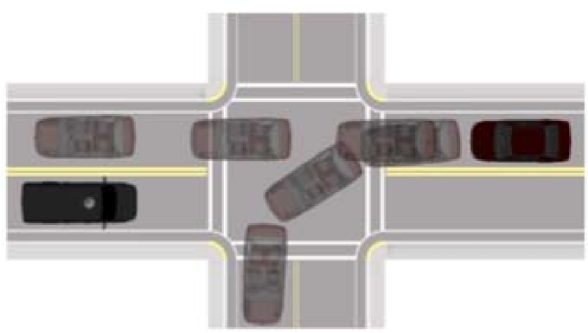

Figure 4: Example of using probabilistic anticipation for provably safe plans in autonomous driving.

Interaction of Humans and Robots

Fusion of human and robotic information

While humans typically provide high level commands to autonomous robots, it is clear that they can contribute important information themselves, such as an opinion about which area of Mars to explore, or whether a far off object is a person or a tree. Critical research is being conducted which formally models human opinions/decisions as uncertain information using machine learning methods (Ahmed & Campbell, 2008), and then fuses this with other information (Ahmed & Campbell, 2010), such as from the robot.

Consider Figure 5, which shows a search experiment with five humans, each with a satellite map overlaid with a density function that probabilistically captures the `location' of objects (Bourgault et al., 2008). The human sensor, in this case, is relatively simple: yes/no detection. A model of the human sensing process was developed by performing experiments with humans locating objects at various locations relative to their position and look vector; intuitively, the ability for a human to detect an object falls off with range and peripheral vision. During the experiment, each human moved to separate areas, while fusing their own (uncertain) sensory information; fusion with information from other humans occurred when communication only at close range. Figure 5 shows is the trajectory of one human's path and the real time fused density of the object location.

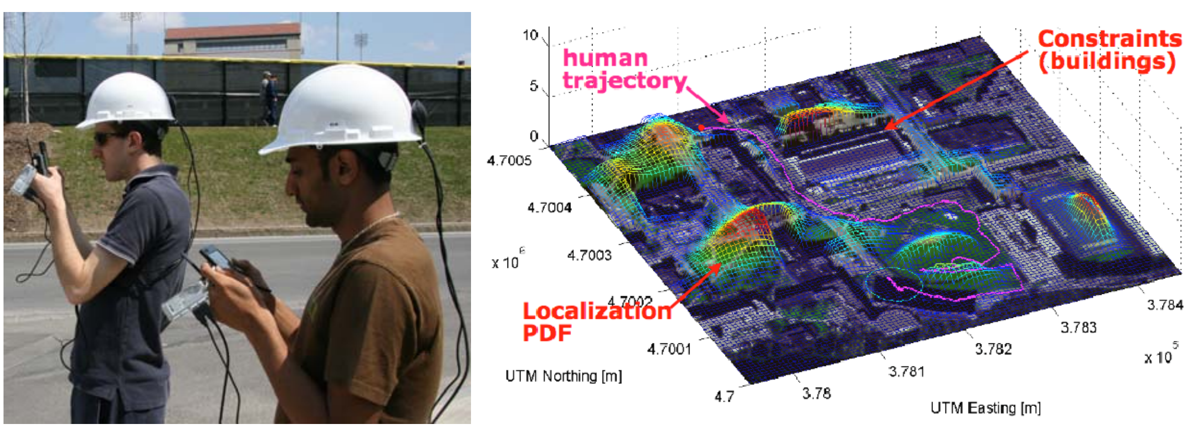

Figure 5: Search experiment with a network of five humans. Left: Humans with handheld PC's, local network, GPS, compass. Right: Overlay of satellite imagery with a density of "probable" locations.

While this example demonstrated initial decision modeling and fusion results, the human decision was decidedly simple. Research is required in modeling more complex outputs such as strategic decisions over time, or decisions where little data is known. New fusion methods are required for the very different information sources.

Natural, Robust and High Performing Interaction Approaches

When considering a `team' of humans and robots, it is important to understand the strengths and weaknesses of both. Humans can provide critical strategic analyses, yet can have problems with boredom, stress, fatigue, and biases (Parasuraman et al., 2000; Shah et al., 2009). Robots, on the other hand, can provide many repetitions of the same task without bias or feeling. These constraints lead to challenges while attempting to form a team of humans and robots which can work well together.

Current research is focused on multi-modal interactions, taking advantage of recent commercial developments in the computer industry to allow the human to interact at the strategic level. Finomore et al. (2007), for example, have explores voice and chat inputs. Shah and Campbell (2010) explore drawing commands on a tablet PC (Figure 6), where pixels are used infer the `most probable' commands. The human can then over-ride a command if it is not correct, and the next most probable command is suggested. Results have shown a high statistical accuracy in command recognition.

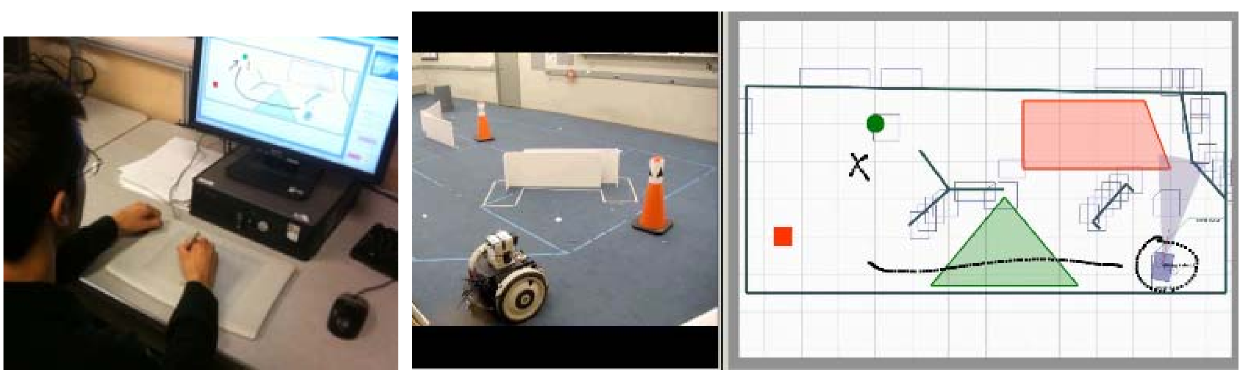

Figure 6: Human drawn gesture commands for robots. Left: human operator at a tablet based computer. Center: a robot exploring an environment. Right: a screen shot of how the human has selected a robot, drawn a potential path, and selected an area to explore.

More advanced systems are also being developed. Kress-Gazit et al. (2008) presents a natural language parser which takes spoken language, selects the appropriate command, and develops a provably correct controller for a robot. Boussemart and Cummings (2008), Hoffman and Breazeal (2010) present methods which models the human as a simplified, event based decision maker; the robot then `anticipates' what the human may want to do, and makes decisions appropriately. While currently applied to simplified systems, the approach has the potential to increase team performance.

Scalable Theory that enables Easy Adoption as well as Formal Analysis

Finally, a key constraint on the development of theory and implementations of teams of humans and robots is the ability to scale to larger numbers (McLoughlin & Campbell, 2007; Sukkarieh et al., 2003). This is particularly true in defense applications, where hundreds or more humans/vehicles must share information and plan together. Typically, hierarchical structures are envisioned, but fully decentralized structures could also be used (Ponda et al., 2010). Recent research has focused almost exclusively on large teams of cooperative vehicles; however, given some level of human modeling, many of these methods could be envisioned for human-robot teams as well. Testing and adoption will continue to be challenges, as they are inherently tied to cost and reliability.

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