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Current Challenges in Autonomous Vehicle Development

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ABSTRACT

The field of autonomous vehicles is a rapidly growing one, with significant interest from both government and industry sectors. Autonomous vehicles represent the intersection of artificial intelligence (AI) and robotics, combining decision-making with real-time control. Autonomous vehicles are desired for use in search and rescue, urban reconnaissance, mine detonation, supply convoys, and more. The general adage is to use robots for anything dull, dirty, dangerous or dumb. While a great deal of research has been done on autonomous systems, there are only a handful of fielded examples incorporating machine autonomy beyond the level of teleoperation, especially in outdoor/complex environments. In an attempt to assess and understand the current state of the art in autonomous vehicle development, a few areas where unsolved problems remain became clear. This paper outlines those areas and provides suggestions for the focus of science and technology research. The first step in evaluating the current state of autonomous vehicle development was to develop a definition of autonomy. A number of autonomy level classification systems were reviewed. The resulting working definitions and classification schemes used by the authors are summarized in the opening sections of the paper. The remainder of the report discusses current approaches and challenges in decision-making and real-time control for autonomous vehicles. Suggested research focus areas for near-, mid-, and long-term development are also presented.

Keywords: autonomy, autonomous vehicles, robotics, artificial intelligence

1. INTRODUCTION

1.1 Definition of autonomy

What is autonomy? According to Webster [1], it is "the quality or state of being self-governing". However, in the field of autonomous vehicles and military applications, autonomy is usually thought of as something more synonymous with "independence" or "intelligence".

The official DoD definition of "autonomous operation", from the DoD Dictionary of Military Terms, provides an interesting perspective on the concept and separates it somewhat from just autonomous vehicles:

> "In air defense, the mode of operation assumed by a unit after it has lost all communications with higher echelons. The unit commander assumes full responsibility for control of weapons and engagement of hostile targets." [2]

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This definition also highlights the fact that autonomy does not apply only to machines, but is already a working concept within the military chain of command. Therefore, when considering autonomy, the terms "Authority" and "Agent" instead of "human" and "computer" are suggested. In this way, the discussions are not limited to the hierarchy as it is currently envisioned.

One interesting characterization of autonomy found was "[autonomy] is whatever we don't know how to do yet. Once we know how to do it, we call it an algorithm."[1] In fact, this is more widespread today than generally realized. Some functions taken for granted in cars or planes today make and execute decisions independently and thus may be considered autonomous subsystems, e.g. optimization of fuel and battery power consumption ratios in hybrid vehicles, air bags, and anti-lock brakes. However, because the whole car is not autonomous, there is a tendency to minimize the successes that have been attained thus far, and characterize them as "automatic" rather than "autonomous".

What is the difference between "automatic" and "autonomous"? One distinction may be to say that something automatic has only one "choice" between two possible states, e.g. 'on' or 'off'. Another classification would say that automatic systems take in only one input for making the decision. In either case, current air bags and anti-lock brakes would likely fall in the "automatic" instead of "autonomous" category. Autonomous systems could then be ones that process multiple inputs before acting, e.g. a braking system that considers both wheel slippage and speedometer measurements and only deploys if the car is traveling faster than 30mph. Alternately, autonomous systems may be those that have more than two possible states, and so have to make more than an "on/off" choice. The relative merits of these ways of drawing the line between "autonomous" and "automatic" are hard to measure—there are continuing debates and the presence of counterexamples in any classification system or definition proposed to date. If the line between "automatic" from "autonomous" is drawn based on number of choices or whether the system is following rules instead of "making its own decisions", then any current system would be considered "automatic", not "autonomous", because they are all deterministic in their decision making. This observation raises the question of whether any currently foreseeable system is truly autonomous; the ambiguity of the term may be why many sectors are choosing to use the term "unmanned" instead. However, in order to encourage research and development in useful near-term areas, it seems more useful to extend the "autonomy" umbrella in the other direction instead. Therefore, we propose the following working definition of an autonomous system:

> *An autonomous system is one that makes and executes a decision to achieve a goal without full, direct human control.*

Here "system" does not have to mean an entire vehicle; it could also mean a subsystem like the ABS example. By this definition, automatic is not distinct from autonomous, but is a subset instead. This inclusive definition dovetails nicely with the ongoing efforts to classify "levels of autonomy". These levels would depend on such things as mission complexity or level of required human interaction.

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[1] Patrick Winston, former director of MIT's Artificial Intelligence Laboratory, as quoted in "Autonomous Land Vehicles" by Dr. Hugh Durrant-Whyte.

Automatic systems (single input to single output) would occupy the lower end of any autonomy scale.

In developing this working definition of autonomy, it became clear that there are two main areas of development for an autonomous vehicle: decision-making and real-time control. Generally speaking, the decision-making side corresponds to "autonomous" (or independence) and the real-time control corresponds to "vehicle" (or execution), although the line between the two can be a bit fuzzy at times. There is clearly some local decision-making that takes place within the realm of real-time control, such as in local navigation and obstacle avoidance. Otherwise, robots would run into obstacles while trying to decide whether to go left or right to get around it. Another point regarding these two categories is that they cannot stand alone. Developers of autonomous vehicles cannot work on autonomy and computer processing separately from working on vehicle mechanics—the integration of these two areas into one physical system presents a significant challenge in and of itself. Not only does the computer equipment need to be able to physically withstand the operational environment onboard a moving vehicle, but it also needs to appropriately connect the algorithms to the incoming sensor data and decide which sensor information is needed in the first place.

Therefore, it seems prudent to define "autonomy" not as a technology that can be developed in and of itself, but rather as a capability enabled by supporting technologies. Dr. Durrant-Whyte, head of the Australian Centre for Field Robotics (ACFR), divides those technologies into five categories: mobility, localization, navigation, planning, and communication [3]. Mobility includes the real-time control and mechanics of the vehicle itself. Localization incorporates sensors and software to identify the vehicle's position, attitude, velocity, and acceleration. Navigation, also known as local obstacle avoidance, is a combination of decision-making and real-time control. Planning includes mission- and task-level decisions, waypoint generation, task allocation, etc. Communication involves all the links between the vehicle and teammates, operators, and command and control. These five categories summarize the main contributing technology areas for autonomous vehicles.

1.2 DoD's interest in autonomy

According to Congressional mandate, "by 2015, one-third of the operational ground combat vehicles [must be] unmanned." [4] This mandate highlights the attention focused on unmanned systems and autonomous vehicles in the DoD. The DARPA Grand Challenge, Littoral Combat Ship, Joint Unmanned Combat Air System, and Army Future Combat System projects are all examples of DoD programs promoting and incorporating vehicles with more autonomous capabilities.

A key desired feature of such vehicles for DoD applications would be the ability to prudently hand over control to a machine with a solid understanding of its capabilities and confidence in its performance. Achieving higher levels of performance in challenging environments and conducting increasingly sophisticated operations in the "dirty" and "dangerous" realms, instead of just the "dull" or "dumb" ones, is obviously a key interest of the DoD for autonomous vehicle development.

2. AUTONOMY LEVELS

To evaluate the current state of autonomous unmanned vehicle (AUV) technology development, it is important to refine the concept of autonomy. That is, what "counts" as autonomous? This is not a binary question, but rather, is best approached through characterizing levels of autonomy. Others have attempted to define these levels and establish a classification scheme applicable across agencies and applications. Two primary models—the Autonomous Control Levels (ACL) [5] established by Air Force Research Laboratory staff and the Autonomy Levels for Unmanned Systems (ALFUS) model [6] established by the National Institute for Standards and Technology (NIST) - use a zero-to-ten scale to delineate levels of autonomy. The ACL scale is based on the OODA loop (Observe, Orient, Decide, Act) introduced by Air Force pilot Col. John Boyd [7] to describe how pilots make decisions during combat. The ALFUS scale constitutes three axes: mission complexity, environmental difficulty, and human-robot interaction (HRI), each are subdivided into quantifiable metrics. The Sheridan model [8], developed in 1978 for the teleoperation of unmanned underwater vehicles, is another zero-to-ten scale that has long been the standard within the AI community.

From these various scales, four main categories were identified: piloted vehicle, authority-in-the-loop, authority-on-the-loop, and authority-out-of-the-loop. These categories are based on work presented by Chad Hawthorne and Dave Scheidt at the Johns Hopkins University Applied Physics Lab [9].

The ultimate goal in evaluating these classification systems was to assist the Office of the Secretary of Defense (OSD) in coordinating oversight efforts regarding autonomy research programs within the various services. One of these existing models may provide a suitable template for structuring and evaluating the department's autonomy research programs. Alternatively, some combination of the ideas utilized by each model may yield a better fit for this application. Different metrics may be more useful for oversight and others, for planning within a program. If nothing else, this review lays the groundwork for defining and understanding the problem of autonomy and has helped in identification and classification of the primary supporting technologies.

3. DECISION-MAKING

Autonomous decision-making is an incredibly complex subject, especially given the fact that scientists do not fully understand how the human brain works and makes decisions. For autonomous vehicles, there appear to be two main categories of approaches to decision-making: reduction and learning. Shown below is a diagram from a Defense Advance Research Projects Agency/Information Processing Technology Office presentation given by Ron Brachman, the director of IPTO [10]. Figure 1 reveals just how complex autonomous decision-making processes can be. Indeed, one way to measure levels of autonomy would be to consider how many layers of the decision-making process portrayed are employed by the unmanned system.

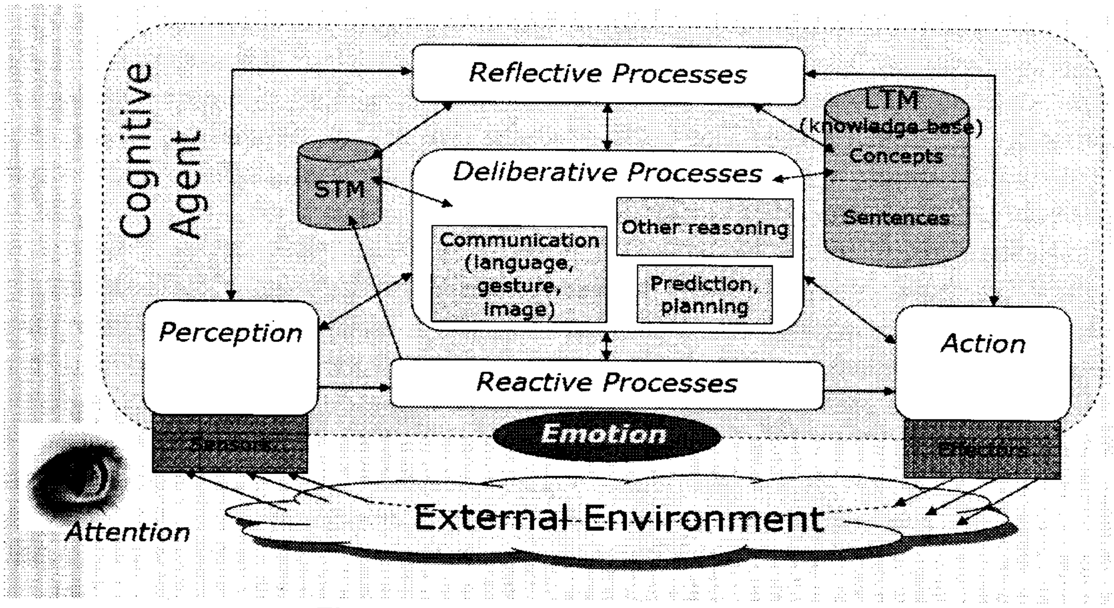

Figure 1: Diagram of a Cognitive Agent

3.1 Reduction

As can be seen in the diagram above, decision-making can involve much more than a simple binary selection. Humans incorporate a priori knowledge, context, and emotions when making decisions. In the reduction approach to autonomous decision-making, those elements are largely excluded. Instead, the problem is reduced to a simple, clearly-defined input-output mapping.

Automotive subsystems provide numerous examples of this approach. Anti-lock brake systems (ABS) have long been the standard in American cars. Anti-lock brakes use a sensor that detects changes in wheel spin rate. When that sensor readout passes a certain threshold, the automatic brake is activated. There is a direct mapping of input to output, a clear rule for which action to take and only two choices for action: activate or not. ABS incorporate both the autonomous decision-making mentioned above and real-time control, in the pumping of the brake. From the definition of an autonomous system proposed above, the "goal" declared by the human driver is to stop; the ABS then decides how to accomplish that goal - whether the pumping is required in the situation - and then executes that decision, all more quickly than a human driver could.

A similar threshold sensor with a binary output option found in automobiles is the air bag. When deceleration is faster than a certain limit, the air bag deploys. Again, the air bag is an autonomous subsystem—although in this case, even more control is ceded to the computer, because the driver cannot override the decision to deploy just by lifting his foot up the way he can with his brakes.

An extension of this method is used in the new hybrid cars to optimize the ratio between fuel and battery power consumption as a function of speed, remaining battery life, etc. In this situation there are more dimensions than for ABS or airbags: the onboard computer needs to determine the optimal split between combustion and battery power and to execute the switching back and forth.

An example of the reduction approach that has already been applied in robotics is simple obstacle avoidance. The problem can be reduced to a binary output—"can I go straight or not?" There are only two output options and potentially only one required sensor. This is a very simplified method and would probably not detect things like cliffs or chain link fences, depending on the capabilities and sensitivity of the vehicle's sensors, but it can be enough to successfully avoid obstacles in indoor or relatively uniform outdoor environments.

A variation on the reduction approach is the use of multi-robot systems. The concept is to give simple tasks/capabilities to each robot and connect them via a wireless network. By separating the overall mission into smaller subtasks, the complexity of the problem has been reduced to one that can be physically accomplished by current robots. The primary difficulty of fielding multi-robot systems lies in achieving effective and efficient communication and collaborative decision-making. Also, in some cases the capabilities of the team remain limited by the capabilities of the individual robots. For example, a mission of identifying and tracking a hostile target will not be possible if none of the robots are capable of correlating their sensor input to a correct target identification. However, target tracking in general may be more easily accomplished with multiple vehicles, because the vehicles could pass information back and forth and adjust their positions relative to each other, increasing the chances of keeping the target in sight. Similarly, there is a natural desire to pair different vehicle platforms such as UAVs and UGVs: the UAV can provide overall surveillance and highlight potential targets of interest, tasking the UGVs to inspect those targets more closely and report back to the human operator.

If the problem is more complex and a simple mapping is not obvious, researchers can conduct experiments, collect data, and write algorithms that characterize the domain within a given area (e.g. the flight envelope for an airplane autopilot). Then computing power can be employed to perform the bookkeeping and keep track of sensor data, the aerodynamic effects on the vehicle, etc.

A similar "bookkeeping" approach has been suggested for obstacle avoidance. Instead of reducing the problem down to a binary output, some developers have built up a terrain database. The robotic vehicle then maps sensor data, such as camera imagery, to the database and "recognizes" the terrain in front of it. Ideally, this method would help optimize a ground robot's route - different maximum safe speeds could be connected with each terrain type, for example. However, building up a truly comprehensive database would be quite tedious and difficult to accomplish. Not only does this approach run into the problem of how to respond to unknown terrain, but there is also the issue of processing time to search through the massive database. By the time the vehicle decided what was in front of it, it may have already moved beyond that point or exceeded the maximum safe speed and crashed.

One issue with the reduction approach is that the "rules" given to the computer are only good within the given operational envelope—it is very difficult to cope with scenarios that fall outside the bounds of predicted patterns. For example, in 2001 a P-3 was involved in a mid-air collision with a Chinese aircraft and the pilot managed to land the plane safely [11]. To accomplish this feat, the pilot had to assess the plane's changed response with enough speed and accuracy to prevent the plane from crashing. Current autopilots, such as that on the Global Hawk that recently landed safely after an engine flameout [12], may be able to recover from types of in-flight failure that have standard responses that can be programmed in ahead of time. However, other types of failure may be too far outside the operational capability of the aircraft, requiring human-level experience, intuition, and rapid learning in order to successfully recover.

3.2 Learning

The other approach is to attack complex, incompletely characterized problems with superior computing power. The example of the P-3 pilot recovering from a midair collision is exactly the type of learning that the AI world is trying to recreate in order to tackle complex, incompletely-characterized problems. There is a general belief in much of the field that missions beyond a certain level of complexity will never be possible without some leap in computer learning. For example, with the terrain database approach discussed above, because of the possibility of sudden, drastic changes in ground terrain, it seems implausible to develop a database with any significant operational envelope for an uncertain or unknown outdoor environment. Again, when the environment is structured or can be structured without disruption, it may be possible (although granted, quite difficult) to fully characterize the environment and achieve mission success within those bounds. Robots in manufacturing plants that follow lines or magnets in the floor are an example of such an application. Alternately, the DARPA Grand Challenge course, even though largely scripted, is an example of an environment with enough variation and surprise to make it highly challenging at mission-suitable speeds.

Robots need structure; that is how the variation and surprise can be restricted to levels that current processing power and algorithms can handle. Therefore, vehicle developers need to find a way to bring structure to the environment and make it navigable for the unmanned systems. However, many of the environments in which users would like to send robots are ones that cannot be structured ahead of time, especially where hostile forces are involved. Since it does not seem feasible to rely on being able to manage the environment in order to make it easier for the robots, it becomes increasingly important to develop learning capabilities so that robots can process and function in changing or unknown environments. DARPA has a number of programs focused on advancing machine learning and autonomous decision-making, such as LAGR (Learning Applied to Ground Robots) and REAL (Real World Reasoning). However, these programs are still in the early research phases and lie outside the scope of this report.

3.3 Summary

Consider the fact that a soldier has had a minimum of 18 years of "learning" prior to enlisting, as well as additional specialized training for the environment and tasks he is to perform. The idea of bypassing that training or even just accelerating it in an autonomous vehicle seems highly unrealistic. Some AI programs anticipate placing unmanned systems in unknown or uncertain environments and having them perform at the level of a human without having to hard code all the possible options and outcomes. That is not attempted even for humans –soldiers are trained, use flight simulators, and also rely on those 18 years of life learning. Most robot learning at this point in time involves error correction feedback loops and "learning from mistakes". In order to do this, the robot must be allowed to make mistakes, something may not be acceptable for meaningful missions and that may end up being quite costly, both in time and in resources spent repairing and retraining the vehicle.

It is clear that mission complexity for fully autonomous systems will be severely limited until significant AI developments are achieved. However, there are still a number of useful steps that could be taken, and it is in these areas that research and development would be most useful in the near-term. High payoff pursuits for near-term development include:

- Further characterizing the environment, i.e. quantifying and expanding the understood operational envelope for ground vehicles
- Increasing reliability of communication links in order to progress from tethered teleoperation to wireless
- Making sensible choices about the role and application of autonomous vehicles and focusing development on those applications,
- Building machines robust enough to withstand less fine-toothed decision-making

4. REAL-TIME CONTROL

Real-time control concerns, in part, the physical aspects of an autonomous vehicle, as well as the translation from decision to action. Decision-making is still largely regarded as "science" and the real-time control is primarily considered "engineering". However, this does not mean that all the unsolved problems are on the decision-making side and that successful real-time control is just a matter of working out some engineering details.

One continually difficult problem is local navigation and obstacle avoidance. Vehicles need to fuse and process sensor data at fast enough speeds and with enough accuracy to prevent running into things or getting stuck before higher-level decisions can be made. In a way, obstacle avoidance captures both real-time control and decision-making, albeit on the small-scale, local level. Current appropriate sensor packages are few and far between. While the problem may be "solved" in a performance sense, if the sensor that has been developed does not meet space, weight, power, and cost constraints, then that sensor is not a solution at all. Because the work done in this field is so application-specific, there appear to be numerous individual claims of solutions or successful demonstrations. Yet those successes do not readily translate to other programs or platforms. Therefore, it would be premature to consider such issues "solved" problems.

Much of the difficulty in developing autonomous vehicles capable of complex missions is that researchers don't understand how humans make decisions or perform those same tasks. The same is true for some aspects of real-time control. The human hand is an incredibly complex array of sensors and interconnected effectors. The sensitivity of force sensors in our fingers is unparalleled. There is also a certain amount of local processing that takes place—for example, if a person touches a hot stove, his hand jerks away before the brain has even had time to register that the surface was hot. Similarly, if someone walks into a door frame, they don't break a shoulder; they automatically start reducing the pressure applied at the point of contact. A robot, on the other hand, can snap an appendage off if it runs into a doorframe or tries to find a light switch and flip it on in a dark room.

So there is a tradeoff between sensitivity and precision. The current sensor packages available for autonomous vehicles provide much less information to the decision-making algorithm than humans use on a regular basis. While building a humanoid robot may not be a primary interest for the military, this example highlights one of the significant limiting factors in the application of robots. Therefore, the best focus for development efforts is on tasks at which robots exceed human performance, rather than ones that just try to mimic humans.

A final challenge facing autonomous vehicle development from the real-time control side is systems integration. It is essential that all the components be mounted on board a mission-appropriate vehicle and that they survive the mission. Current sensor packages are generally too expensive or too bulky for practical applications—especially on ground vehicles. The vehicle also needs to be robust enough to protect all of the sensor and computing equipment when navigating in rough terrain. Similarly, a highly advanced sensor may be developed that would allow for significantly increased autonomy, but if that sensor requires a massive power supply, the vehicle would not be able to move very far from the base station. The systems integration challenge highlights a key issue in future autonomous vehicle development—specialization vs. generalization. While general programs and packages applicable across platforms appear to be the ideal, truly successful robots to date have been developed for specific missions. The specialized approach limits the systems integration issues, because the pieces are designed to go together more readily. While a common architecture or sensor platform may be on the research horizon, for the near-term, the field might be better served to focus development on more capable, task-specific vehicles.

5. CONCLUSIONS

Research efforts in AI and cognitive computing have been largely theoretical or simulation-based. There is a disconnect between the field of robotics and the field of cognitive computing, especially when it comes to real-world implementation. Current artificial intelligence research is, by and large, not being designed for implementation on board a moving vehicle; yet robots will only be able to achieve a certain minimal level of complexity without integrating AI concepts and developments. If any significant advances beyond teleoperation are to be made in autonomous vehicle development, these two research fields need to come together and use advances from each area in the development of new vehicles.

Up to this point, autonomous vehicle development has been either highly application specific or too theoretical to apply on board an actual vehicle. There is a commonly-held hope that a single architecture or navigation method could be developed that would apply across platforms or applications, but that does not appear to be an option in the near term. Basic research should continue to provide new capabilities. However, it seems that there are many factors specific to each mission and/or environment that require specific development efforts for both the decision-making approach and the real-time control for each application. Thus far, the more useful a vehicle has been, the more specialized its development was. This paradigm has led to natural difficulties transferring successful technologies and approaches between platforms or applications. Although many are pursuing the ideal of a common system or architecture that would work on all robotic platforms, that is too far in the future to be useful at this time.

The benefits of commonality across the field may not outweigh the burdens on each particular platform. In order to field a robot best suited to the given mission, task, or environment, at least for now that robot needs to have been developed for those conditions. Programs that focus on real-world implementation will have more success and, while their progress along the autonomy scale may be in baby steps, they are already out in the desert saving soldiers' lives. At the same time, DoD acquires general-purpose equipment precisely because it is more difficult to anticipate operational needs than commercial ones. Therefore, the primary goal for the Department of Defense seems to be to increase the mission complexity and environmental variability in which unmanned vehicles are capable of performing. In this way human soldiers can be removed from dangerous, dull, dirty, and dumb situations. By increasing the inherent mobility and survivability of vehicles, they will be able to withstand harsh conditions and hostile environments. They will be able to accomplish more significant missions but without gaining significant autonomy. Similarly, working to decrease the cost of the sensors, computing equipment, and power supplies will allow for more rapid development as the test and rebuild cycle shortens and becomes less expensive. More readily available, lightweight, small, robust, and inexpensive sensors and other packages would also help open doors for more multi-vehicle systems and new approaches to missions. Table 1 illustrates possible focus areas for DoD to pursue in various time frames.

Table 1: Summary of research focus areas for each timeframe (near-, mid-, and far-term)

Near-term	Mid-term	Far-term
Increase robustness and inherent mobility of UGVs	Multi-robot systems: tackle more complex missions with multiple single-function robots	AI: Incorporate context and intuition
Impose structure on the operating environment	AI: real-time outdoor obstacle avoidance	AI: transfer learning
Decrease cost and size of sensors, computing equipment, and power supplies.	Integrate AI systems on board robotic vehicle platforms	Multi-robot systems: common architecture and communication across all platforms on a battlefield

Basic AI research is still required, especially in the area of transfer learning—generalizing from a previous example to a novel situation. Until this trait of humans is more fully understood and accomplished in computers - or its effects mimicked - there will continue to be long training times and high costs. In the slightly closer-term, there are a few areas where focused AI research would yield enormous payoffs once the barrier was broken. These include work on integrating AI systems on board robotic platforms—it is time to move out of the theoretical, simulation world and focus on what happens in real world environments. Researchers also need to find a way to model and incorporate context and intuition into machine systems—or at least understand their role in human decision-making processes well enough to assess the impact of their absence in autonomous vehicles.

Outdoor obstacle avoidance remains a key issue for ground vehicles and is probably the area that already incorporates significant AI but also runs into the most problems due to the incredible variability of the terrain. Obstacle avoidance is much more straightforward for a UAV: not only are there far fewer obstacles above tree level, there is also less variation in the environment. On the ground, significant variability in terrain makes it difficult to effectively characterize the entire environment. There is also a much higher degree of potential uncertainty. Indoor environments and highly structured outdoor environments such as those in agricultural applications are clear exceptions to this problem, specifically because structure has been imposed on the environment. Final issues involve communication methods and the fact that line of sight is much more easily obstructed on the ground than in the air. It is even more difficult underwater without a significant power source. Thus ground vehicles are an important area on which to focus development in the near future.

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