REQUIRED READING FOR:

- **EGR/CS434 "Green Robotics, Automation, and Machine Intelligence"** J. Wunderlich PhD
- **EGR396 "Spring Seminar"** J. Wunderlich PhD
- **PH 275 "Science and Values"** M. Silberstein PhD (J Wunderlich Ph.D. guest lecture)

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Designing robot autonomy: how tightly should we hold the leash?

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ABSTRACT: *Robot autonomy needs to be carefully designed to protect life and property; however excessive constraints can prevent discovery or even halt all progress. Applications like assisting the disabled need stringent safety constraints placed on robot autonomy; however mobile robots maneuvering on distant planets need maximum autonomy to compensate for the time required for an earth-based command to reach them; Tele-operated robots don‟t function well at great distances, so the robot must be able to learn and adapt in order to explore intelligently while protecting itself from damage. The design of this type of advanced autonomy can be enhanced by exploring forms of machine intelligence including various computer hardware and software implementations. An exploration of machine intelligence concepts can also be complimented by an understanding of biological brain function and human psychology. A study of past, present, and future NASA and ESA robotic space missions yields much insight into the autonomy and machine intelligence likely to be needed for future space missions. This paper also presents several Ph.D. and advanced undergraduate autonomous robot projects taught in the U.S. and Europe by the author.*

Introduction

Designing robot autonomy involves complex decision making including minimizing the risks to life, property, and robots. However excessive constraints can prevent discovery or even halt all progress in complex environments. This paper discusses designing robot autonomy for many types of robotic applications including tedious or high-precision tasks such as industrial assembly or medical operations; clean-up of common and hazardous waste; search and rescue operations; super-human responses such as those needed for police operations; assisting the disabled; acting as assistants or companions to humans; and for exploration of the oceans and space. An expanded discussion is included on past, present, and future space missions where robots are operating at such great distances from earth that autonomy must be maximized [1 to 13]. Additionally, a discussion of how advances in machine intelligence relates to robot autonomy is included [14,15].

Industrial Assembly

Industrial robots provide precision, repeatability, and strength. However excessive autonomy can jeopardize worker safety and damage materials. To mitigate these risks, robot designers should limit the maximum velocities, torques, and motion-ranges of any industrial robotic arm; and the work-space of the robot should be caged and have restricted access to the work-cell; this is a law in the United States per the Occupational Safety and Health Act (OSHA). Figure 1 is an example robotic arm design yielded by the research in [16] where the arm design has been optimized for many parameters including limiting maximum velocities while performing a very difficult task inside an enclosure. This research was extended to the design of industrial robotic arms for welding tasks in [17].

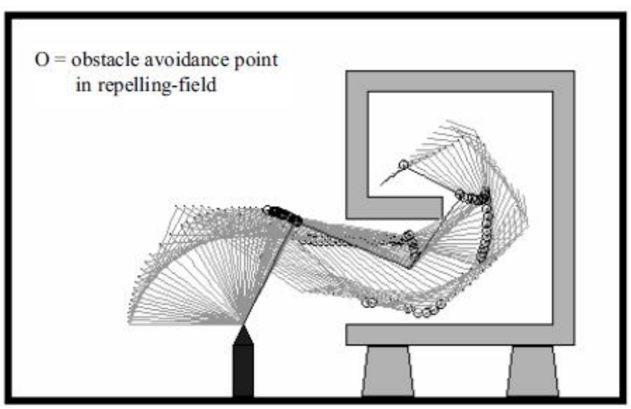

Figure 1 . Robotic arm design optimized for many parameters including limiting maximum velocities while performing a difficult task [16].

Robotic Surgery

Tele-robotic surgical robots provide improved precision and allow surgeons to perform long operations without becoming fatigued. Excessive robot autonomy could jeopardize the safety of the patient. To mitigate this, robot designers limit maximum robot velocities, torques, and motion-range. Automated surgical procedures should also be kept to a minimum. A nurse or other surgical assistant should always monitor the robot and patient at the incision point. The Da Vinci tele-robotic surgery arm has been in use for many years. In [18], a recent study of its error and failure rates shows that for 807 laparoscopic surgeries, technical errors resulting in "surgeon handicap" occurred in three cases; Four patients had their procedures aborted due to system failure at initial set-up; and four cases were either aborted or converted to a non-robotic procedure. Even though only 11 of 807 surgical procedures had robotic complications, the need for human control of the robot is still required.

Clean-Up

Robots performing general and hazardous clean-up free workers from contamination and fatigue; and robots can very efficiently pick-up and contain waste. However excessive autonomy can jeopardize the safety of people and property in close proximity to the robots. To mitigate these risks, robot designers should limit maximum robot velocity and drive-power; designers should also include both obstacle avoidance hardware & software in the robots. These robots typically have only random search strategies for finding waste and navigating around obstacles; future cleaning robots could be designed to create environmental maps of their environment to aid in optimal cleanup and therefore minimize interaction risks with humans. This involves designing not only "local" path-planners, but also "global" path-planners that understand and incrementally build maps of a robot's work environment [1,11,19,20].

Search and Rescue

Search and rescue robots are typically tele-operated and assist first-responders to save human lives during man-made and natural disasters. These robots prevent responders from injury and can endure extremes in temperature, pressure, oxygen-levels, and radiation. Excessive robot autonomy could however jeopardize the safety of people being rescued and could result in the robot getting damaged or lost. To mitigate these risks robot designers should minimize robot manipulation of those being rescued and always have a human in control and fully aware of a robot's actions via tele-robotic control. The robot's velocity and manipulability-power should be limited when interacting with humans. Additionally, as shown in [21], search and rescue robots can be networked to help each other in searches, and can relay information back to a central station where a large comprehensive environmental map can be incrementally built for the disaster area. Search information can then be sent back to the robots to improve their search and to send specialized robots to specific areas of need for digging; fire-suppression; delivery of first-aid, food, water, and oxygen;

to aid in removal of people from hazardous environment; and to contain chemical or radioactive materials.

Military and Police

Both robotic arms and mobile robots can protect soldiers and police in hostile environments. However excessive robot autonomy can result in brutality, death, and even Geneva Convention violations. To mitigate this, robot designers must minimize weaponization on autonomous robots, and always ensure that a human is:

- In control of the robot
- Is fully aware of the context of the *situation*
- Has been screened to be highly ethical and have an understanding of *"rules of engagement."*

A detailed discussion of these issues can be found in [22].

Assisting the Disabled

Robots to assist the disabled can greatly improve the lives of those disabled by injury, birth, or old-age. Excessive robot autonomy could easily jeopardize the safety of the these people and therefore extreme caution must be taken to ensure safety. This can include limiting maximum robot velocities, torques, and motion-range, plus adding obstacle avoidance hardware and software on robotic arms and mobile robots. These robots can be as simple as an intelligent wheel chair, or as complex as a tele-operated system to map the reduced dexterity of a quadriplegic person to useful movements of a robotic arm [23].

Assistants/Companions

Some robots that are almost fully autonomous can assist and provide companionship to humans. They need to have enough autonomy to function almost completely on their own and are often given humanoid form to better interact with humans and to more easily operate equipment designed for humans. For safety, these robots are often designed with very limited velocities and power. They are even sometimes designed to have non-threatening appearance and actions, and to invoke a feeling of servitude companionship. Treating them as sentient could become problematic. A good review of many Japanese robots designed for such tasks can be found in [24].

Exploration

Robots allow exploration of dangerous or distant places and allow humans to safely observe collected data from a safe distance. Long distances between planets also mandates the need for maximizing robot autonomy since the time needed for commands to be received from a distant human operator can be so large that the robot cannot be productive. For example, it can take over 20 minutes for a signal to reach Mars from Earth, and the distances to new exploration sites (like the moons of Jupiter) are much further. Space exploration robots are always hardened for extreme temperatures, pressures, and radiation [3,4,7,9,10]. This could be considered a type of autonomy since it would be very difficult (and expensive) for a human to be equipped to survive these conditions. Robots can also be left in space which eliminates the considerable risk an financial costs of retuning an astronaut to Earth. The robotic autonomy needed for exploration can be related historically to the simplest navigation techniques of early explorers. When Christopher Columbus discovered America in the 1492 he used only the crudest navigation techniques to estimate his position and orientation in space (i.e., his "Pose"). Simple celestial navigation tools, a compass, a crude clock, and the crude map shown in Figure 1 where all he needed to navigate . The speed of the ship was calculated by measuring the time it took for debris in the water to float between two fixed points on the side of the ship. In Figure 2 Europe and Africa are shown on the right, the Atlantic and Pacific oceans combined as one ocean in the middle, and an earth-centric depiction of our solar system on the left (with all planets orbiting the earth).

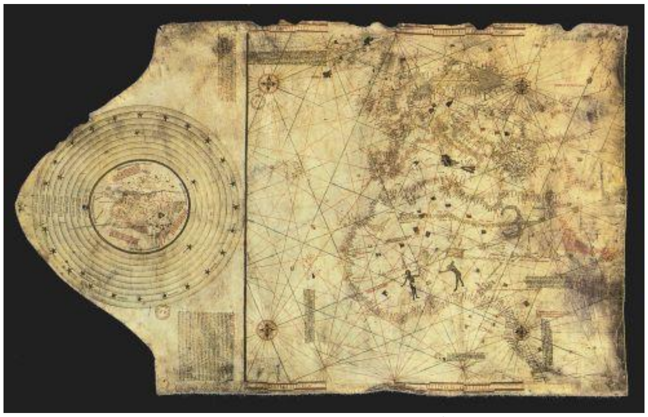

Figure 2. Christopher Columbus map of the world.

Pose estimation later became an extremely important part of robot autonomy and has been incorporated into NASA space exploration missions since the first Lunar rovers in the 1970's [3,4,9,10]. Although these rovers were manned, they had the ability to measure their location, orientation, and tilt – plus they could calculate a shortest path back to the lander. Recent NASA Mar's rovers have increasingly more sophisticated autonomy in addition to pose estimation [11,12,13]. In 1996, Mars *Pathfinder "Sojourner,"* a semi-autonomous tele-operated mobile robot had stereo cameras and five infrared laser-stripes to detect hazards; it could sense 20 3D-points per navigation step and its autonomy consisted of:

- Pose estimation
- Terrain Navigation
- Contingency Response
- Resource Management
- A "Find Rock" COMMAND
- A "Thread Needle" COMMAND to navigate between obstacles

In 2004 NASA *Mars Explorer* Rovers "*Spirit"* and *"Opportunity,"* also semi-autonomous tele-operated mobile robots, were capable of sensing 15,000 to 40,000 3D points per image and possessed the following autonomy:

- Pose estimation as a function of wheel rotation, accelerometer, and angular velocity
- Orientation sensing as a function of sun angle and gravity
- Terrain Navigation
- Obstacle avoidance

and in 2006 the following autonomy software upgrades were uploaded to these robots:

- A global path planner
- Visual target tracking
- On-board dust devil and cloud detection
- Auto approach & place instrument

And in 2010 an additional autonomy software upgrade was uploaded:

- AEGIS (Opportunistic Autonomous Exploration for Gathering Increased Science) system

In 2011, NASA will launch another Mar's mobile robot: the *Mars Science Lab* "*Curiosity"* which will navigate up to 5km from the landing site and find & sample scientific events[12]; and although it will still periodically receive commands from earth it will have the following autonomy:

- Global path planner
- Terrain prediction (for slip compensation)
- Autonomous Science to predict & detect novel science events
- Motion compensation while excavating/drilling with its robotic arm

In 2020, NASA and the European Space Agency (ESA) will launch a joint mission to explore Jupiter and its moons. The goal of this joint mission is to explore the Jupiter System then orbit Europa and Ganymede to characterize water oceans beneath their ice [2]. Figure 3 and 4 show these moons and Figure 5 shows cracks and holes in the surfaces where the relatively warm sub-surface oceans (warmed by the huge tidal forces caused by the extremely large mass of Jupiter) have reached the surface then froze. And as discussed in [6 and 28], many scientists now believe there is a possibility of life in these oceans.

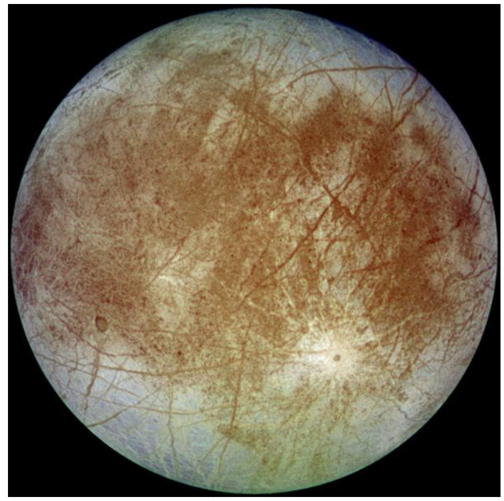

Figure 3. Jupiter's moon Europa [26].

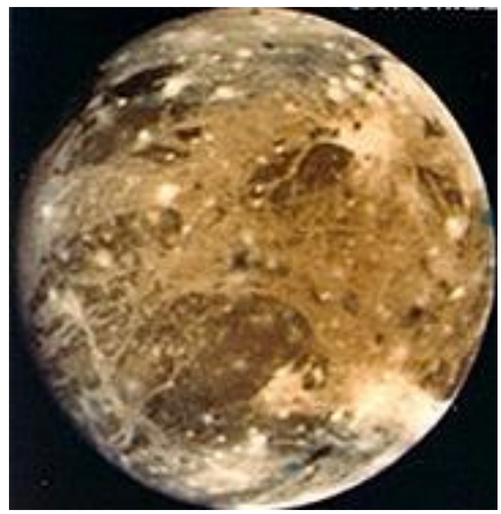

Figure 4. Jupiter's moon Ganymede [26].

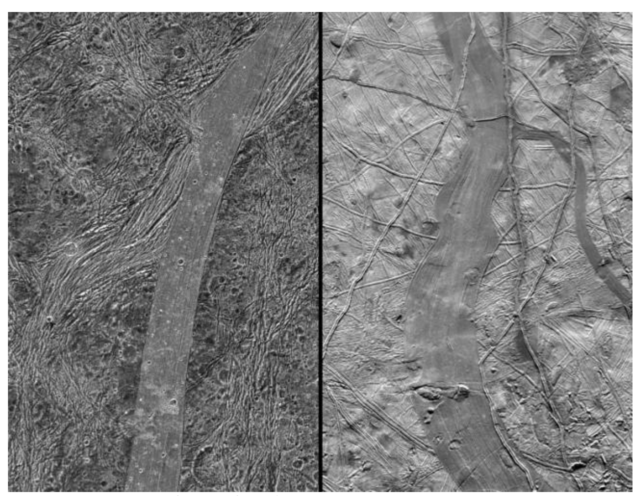

Figure 5. Surfaces of Jupiter's moons Ganymede and Europa showing cracks where relatively warm sub-surface oceans reach the surfaces then freeze [27].

In 2009 the author taught a Ph.D. course in *"Advanced Robotics with Applications to Space Exploration"* at the University of Trento in Italy with an optional course project to design a fully autonomous rover for Jupiter's moon Europa. This assignment was defined as follows:

The mission objective is to explore an ocean confirmed in 2025 to be under the ice of Europa. Assume your launch is scheduled for 2040.

Also assume one of the following:

1. The ***Europa Jupiter System Mission*** scheduled for launch in 2020 discovers some very thin patches of ice (less than 200 meters thick) created by localized sub-surface thermal anomalies.
2. A mission concurrent to yours (but designed by others) has created craters on Europa's surface that have frozen over with approximately 200 meters of ice; but assume the ice will quickly freeze much thicker – and therefore a rapid execution of all mission operations is critical.

Your rover must be able to:

- Maneuver on the flat icy surface of Europa *(Assume some mobility is required even though main objective is getting below surface)*
- Drill through at least 200 meters of ice
- When liquid water is reached, either:
  - Act as an Unmanned Underwater Vehicle's (UUV), or
  - Deploy 100 very small networked UUV's (i.e., a "Swarm"). Assume they are only 10 centimeters long.
- Communicate with the UUV's if option (2) above is chosen
- Communicate with a base station that is also communicating with several orbiters, and earth. The base station is also assumed to be running a concurrent simulation to the rover's real-time code and will be building an environmental map simulation of the region of Europa being explored. This simulation information should also be communicated back to the rover, and then to UUV's if option (2) above is chosen; this is to help with exploration and preservation of the rover. Optionally, control a hyper-redundant manipulator attached to the rover to aid with exploration, digging, and/or deployment of small UUV's
- Withstand the extremely cold temperatures (-143C, -225F max)
- Power itself by some energy source other than the sun since incident solar radiation reaching Europa is minimal; propose a means of powering the rover.

Assume the launch vehicle and delivery system are designed by others. Begin your rover's trek on the surface by assuming that a successful orbiter and base station have been deployed; you may assume your rover is delivered to the surface by a different method (and location) than the base station. When estimating vehicle weight and maximum payload, consider that Europa's gravity is only 13.5% of Earth's.

Between 2000 and 2011, at Elizabethtown College in Pennsylvania, the author's students have created a line of fully autonomous mobile robots which have included sophisticated path-planning and obstacle avoidance using vision, GPS, Laser Range Finding (LADAR), ultrasonic sensors, and a digital compass; And various computing hardware and software have been experimented with including programming in C, Visual-Basic, Assembly language, and Labview. Algorithms have been developed for neural network detection of handwritten characters (for the robot to follow), and for exploration using local and global path-planning methods. A specialized wireless communication protocol was also developed for the IGVC (Intelligent Ground Vehicle Competition) shown in Figure 6 so that the robot can respond to a remote command center when not running in the fully autonomous mode.

Figure 6. Intelligent Ground Vehicle Competition (IGVC); an international competition held in the U.S. where Elizabethtown College has competed several times. All events require robots to be fully autonomous.

Figure 7. shows our fifth generation of fully-autonomous robots. Presently, the robot is being re-tooled for environmental sampling and integration with other environmental initiatives on campus. This includes adding a robotic arm for collecting environmental samples.

Figure 7. Fifth generation of Elizabethton College fully-autonomous mobile robots.

But What Is Intelligence ?

The concept of autonomy as it relates to machine intelligence can best be discussed in the context of understanding all mental abilities. Over the past fourteen years the author and his students at Purdue University, Elizabethtown College, and the University of Trento have developed a list of 42 mental abilities that can be consider when attempting to define what makes a machine intelligent or fully autonomous. Machine intelligence is typically broken into two main research fields: Symbolic Artificial Intelligence (AI) and artificial neural networks. Symbolic AI involves developing computer programs which use heuristics, inference, hypothesis testing, and forms of knowledge representation to solve problems. This includes "Expert Systems" and programming languages such as PROLOG and LISP, with the knowledge contained in the logic, algorithms, predicate calculus, and data structures [29]. An artificial neural network is a form of connectionist computer architecture (hardware or software) where many simple computational nodes are connected in an architecture *similar* to that of a biological brain. The typical network is trained (i.e., learns) by changing the strength (weight) of inter-neuron connections such that multiple input/desired-output pairs are satisfied simultaneously; the final set of network weights represents the compromises made to satisfy multiple constraints simultaneously [29-33]. In an attempt to simplify the discussion each of the 42 mental abilities in Table 1 have been grouped by abilities which are often related.

(1) Acquire and retain knowledge, (2) Solve problems are often assessed for humans by standardized tests such as the SAT exam for U.S. college entrance. Most any computer can solve problems and retain knowledge; they only differ in memory capacity, method of storage, method of solving, and class of solvable problems.

(3) Learn and adapt: Humans easily learn and adapt to new environments and stimuli, and do so in both real-time and evolutionary time. Conventional computers have great difficulty with this. A human programmer is almost always needed to modify the programs. Traditional symbolic AI is somewhat adaptable to new input, however artificial neural networks are much better at this -- with an ability to generalize when presented new inputs. They can also learn very quickly when embedded in hardware [14, 19, 34].

(4) Motor coordination, (5) Acquire energy, (6) Protect self: These have been referred to as "Mobility", "Acquisition", and "Protection" [35] and are essential for the survival of most animals. These have been somewhat implemented by conventional and *intelligent* machines (e.g., robotic motor control, power supplies, firewalls).

(7) Sensory processing, (8) Real-time thought, (9) React instinctively, (10) Anticipate, (11) Predict: Most animals sense their surroundings and think quickly and often instinctually what to do. They therefore can anticipate and predict. With the exception of instinct, conventional and *Intelligent* machines can also do these things; however neural networks outperform symbolic AI when dealing with new stimuli and can be much faster (especially if embedded in hardware [14]). They can also predict by extrapolating known information.

MENTAL ABILITY		MACHINE INTELLIGENCE		Comments
		Can Symbolic AI Program do?	Can Artificial Neural Network do?	
1	Acquire & retain knowledge	yes	yes	
2	Solve problems	yes	yes	
3	Learn and adapt	somewhat	yes	Evolution
4	Motor coordination	somewhat	somewhat	Survival
5	Acquire energy	somewhat	somewhat	Survival
6	Protect self	somewhat	somewhat	Survival
7	Sensory processing	yes	yes	
8	Real-time thought	yes	yes	
9	React instinctively	not yet	not yet	
10	Anticipate	yes	yes	
11	Predict	yes	yes	
12	Communicate	yes	yes	
13	Generalize	somewhat	yes	
14	Associate	somewhat	yes	
15	Recognition patterns	somewhat	yes	
16	Robust under partial failure	no	yes	
17	Autonomous thought	somewhat	somewhat	
18	Drive to reproduce	not yet	not yet	
19	Stability, predictability	yes	somewhat	Uncertainty
20	Multitask	somewhat	yes	
21	Abstraction	no	somewhat	
22	Intuition	not yet	not yet	
23	Common sense	not yet	not yet	
24	Manipulate tools	yes	yes	Evolution
25	Heuristics	yes	no	
26	Inference	yes	somewhat	
27	Hypothesis testing	yes	no	
28	Self-discipline & control	somewhat	somewhat	
29	Ethical behavior	somewhat	somewhat	Trained
30	Selective awareness	yes	yes	Filtering
31	Open to inspection	yes	somewhat	
32	Emotions	not yet	not yet	
33	Imagination	not yet	not yet	
34	Creativity	not yet	not yet	
35	Passion	not yet	not yet	
36	Playfulness	not yet	not yet	Evolution
37	Empathy	not yet	not yet	
38	Courage	not yet	not yet	
39	Leadership	not yet	not yet	
40	Self awareness	not yet	not yet	
41	Awareness of mortality	immortal?	immortal?	
42	Group psychology	somewhat	somewhat	Network

Table 1. Subjective assessment of the ability of two kinds of machine intelligence to reproduce human mental abilities.

(12) Communication: Animals, conventional computers, and *intelligent* machines all communicate. However nothing comes close to what humans can do with natural language processing. Traditional symbolic AI has been attempting this for decades, however neural networks have had more recent success in speech recognition including the difficult understanding of "context"[29-33]. The most recent success in this field is the IBM supercomputer **"Watson"** which in 2011 dominated the TV show jeopardy against two all-time human champions. This was done by combining the rule-based methodology of traditional Symbolic AI with a statistical, distributed narrowing of possible target-answers by using methods similar to the underlying learning principles of artificial neural networks [36].

(13) Generalize: Generalize is *"to derive or induce a general principle or concept from particulars"[37]*. Animals do this well. Conventional computers don't; they give very specific responses to very specific inputs. Symbolic AI can only do this to the extent the program has been built with variations to consider. Neural networks are very good at this; with the ability to generalize such that outputs are produced which "best fit" (i.e., classify) a set of inputs (even when they differ from what the network was trained with).

(14) Associate, (15) Recognize patterns: All animals do this well; however no animal surpasses the human's ability to associate concepts and memories. Conventional computers do this in a very limited way; they can associate by correlating data and can recognize the simple encoded patterns of bit-streams input by humans and other machines. Symbolic AI programs do this better, but are still limited by the fixed structure (i.e., the "*state-space*" is fixed regardless of how efficiently it is searched). Neural networks are very good at association – with an ability through generalization to associate patterns such as never-seen hand-written characters to recorded ASCII representations. Neural networks are widely used for recognizing image and speech patterns [30-33].

(16) Robust under partial failure: Evolution has insured that animals can often continue to function when one or more subsystems fail (including parts of the brain). Conventional computers can't do this to any significant degree; even a simple one-bit error in program execution can sometimes cause a system to "lock-up." Symbolic AI programs running on conventional computers are also likely to not function when the underlying computer system fails. Neural networks are very robust under partial failure and have the ability to partially function when some neurons or inter-neuron connections fail [30-33].

(17) Autonomous thought: With the exception of programming dictated by genes, most animals are free to make their own decisions. Conventional computers and symbolic AI programs can be considered to somewhat help facilitate autonomy in machines; however, since they typically respond in a pre-programmed way without significant learning, their contribution is limited. A neural network's ability to learn, generalize, and deal with never-seen input is a very important part autonomous thought.

(18) Drive to reproduce: Humans are free to make their own decisions (including suppressing the urge to reproduce). *Intelligent* machines do not yet reproduce on their own. But it's not beyond the realm of possibility that someday far in the future fully-autonomous *intelligent* machines could decide to reproduce.

***(19) Stability and Predictability*:** There is a definite degree of uncertainty associated with human behavior. "*physics has managed to incorporate uncertainty into its prospectuses, and there is no reason to believe that the scientific study of behavior cannot successfully incorporate a "biobehavioral uncertainty principle" as well…..Intrinsic variability not only removes the spectra of absolute predictability, but may provide a basis for admitting more fully into scientific discourse the concept of free will…. behavior is fundamentally exploratory" [38]*. Conventional computers and symbolic AI don't have this problem (or virtue). They simply respond in a pre-programmed way. Neural networks however can produce unexpected results; especially when dealing with never-seen input.

(20) Multitask: The evolution of most biological life has led to brains with multiple subsystems working in a coordinated fashion; some performing basic system regulation (e.g., pulmonary, respiratory, temperature, and motor control), some pre-processing information before relaying it to higher reasoning centers (e.g., visual cortex), and some performing higher reasoning. Conventional computers are becoming better at multitasking, with multiple CPU's (Central Processing Units) and subsystems performing tasks simultaneous to the functioning of the CPU's. Examples are DMA (Direct Memory Access), and graphics-board processors [39-42]. Also many computing systems are becoming distributed with relatively simple computing being embedded (FPGA's ASIC's, and microcontrollers) and the more complex computing being done by separate more-powerful parts (microprocessors, array-processors, physics-engines, vector-register units, etc.) [39-44]. It's important to note that "multitasking" in computer industry nomenclature can sometimes imply a time-sliced use of a CPU and not *true* simultaneous, parallel functionality. This is one reason to be careful when comparing human performance with typical uni-processor computer performance. When discussing brain performance, one must consider the brain's high degree of parallelism and pre-processing, and its ability to combine highly-focused parts into an inter-woven collective. For example, in [45] "Concept Neurons" are show to be so specific that one single neuron was identified in a test-subject to be specifically created to recognize the actress Jennifer Anniston; however the typical human brain can coordinate billions of neurons. This is accomplished by creating specialized clusters of neurons for the various mental abilities listed in Table 1, and this distributed thought is needed for self awareness [43]; but in some humans the degree of localization and distributed communication is different. For example Autism is believed to be related to a lack of communication between the brain's hemispheres. A study of one Autistic Savant in [45] showed that the lack of communication between the hemispheres meant no preprocessing of information and therefore an inability to understand metaphors; however this also allowed the test-subject to be extremely focused on individual tasks such that they could, for example, *photographically* memorize two pages at once while reading, and they could memorize 50000 zip codes. Also in [45] it was shown that many scientists have highly developed localized (but somewhat isolated) regions of the brain, with shorter connection lengths between neurons allowing localized intense processing. There cerebral cortex was also shown to have a typically higher density of neuron connections; however most scientists (the author included) would probably object to being compared to a type of Savant. Man-made multitasking is typically only found in symbolic AI programs when written for multi-processor machines, but multitasking is a significant part of artificial neural network learning. IBM *"Watson"*[36] is a new step in multitasking both hardware and software.

(21) Abstraction, (22) Intuition, (23) Common sense: Abstract is: "*having only intrinsic form with little or no attempt at pictorial representation or narrative content" [37]*. Intuition is: *"Knowing without conscious reasoning" [37]*. Combining these definitions can yield insight into the more complex workings of the human brain (i.e., partially defined or disconnected thoughts could lead to higher reasoning). Conventional computers and symbolic AI programs simply respond in a pre-programmed way. The ability of neural networks to learn by repeatedly modifying inter-neuron connection weights until a compromise is reached could be thought of as a form of abstraction. Common sense is: *"Sound and prudent but often unsophisticated judgment" [37]*. Some very analytical people are sometimes said to not have common sense; perhaps the need for highly focused logic and "sophisticated judgment" to prove a hypotheses could hinder the ability think in a whole-brain fashion – even if an abstract, intuitive, and somewhat unsophisticated thought could lead to a better common-sense answer.

(24) Manipulate tools: Although a spider can design and construct elaborate webs, it is not likely to envision extensions of its appendages (i.e., tools) to do so. Manipulating tools is exclusive to more evolved animals and is attributed to humans becoming bipedal; allowing our front "feet" to become hands for manipulating tools. Conventional and *intelligent* computational systems can also manipulate tools by creating signals to send to actuators (e.g., motors, etc.), which in turn position and orient tools. This is a definition of robotic-arm control. Not only what a robotic arm holds, but the arm itself can be considered a tool for the computer to realize manipulation of the physical world around it.

(25) Heuristics, (26) Inference, (27) Hypotheses testing: Most animals don't consider every possible way to react to a situation before acting (i.e., an exhaustive search); they instead apply heuristics to more efficiently select an action. They also recognize when one scenario infers another, and can solve problems by testing multiple hypotheses to result in one solution. Conventional computer programs only somewhat do this. Symbolic AI programs (especially "Expert Systems") can do all of these things [29]. Most neural networks however are not well suited for the step by step process needed to apply heuristics or hypothesis test, but can somewhat infer results for given input data (including never-seen input).

(28) Self-discipline & Impulse control, (29) Ethical behavior: Despite genetic, instinctual, programmed animal "drives," humans can override their programming to maintain a level of self-restraint, and can even develop a set of rules (i.e., ethics and values) to maintain civilization. Conventional computer programs are incapable of these things; however symbolic AI programs can incorporate all of the rules (and therefore ethics and values) of a given human. Also, you could train a neural network to respond "ethically" to given situations.

(30) Selective awareness (filtering): Most humans have the ability to focus on a task while ignoring distractions such as extraneous noise or motion around them. They are also able to find images semi-obscured by camouflage or clutter. Conventional computer programs and symbolic AI programs can achieve this through pre-processing of input data by using signal and image processing techniques. Also, several types of neural networks, with their ability to generalize and deal with never-seen input, can perform very well when given "fuzzy" input [30-33].

(31) Open to inspection: Despite many years of scientific advances in understanding both the biological and behavioral function of human brains, tracing mental thoughts is still less "exact" then tracing the execution of a conventional or symbolic-AI program. Neural networks however are less open to inspection than AI programs because of the many compromises made in changing inter-neuron weight values during the training (learning) phase (i.e., to satisfy many input/desired-output pairs simultaneously).

(32) Emotions, (33) Imagination, (34) Creativity, (35) Passion, (36) Playfulness: The ability to feel, to imagine and create, to have passions and ambitions, and to experiment through playful curiosity are still primarily human traits; Play also seems to have contributed to human evolution: *"Given that the adaptiveness of behavior itself derives from an evolutionary process in which variability and play are absolutely essential .....playfulness is indeed not only to be enjoyed but to be accorded high value for its fundamental role in the success of all* *organisms, including human" [38].* No man-made device is yet capable of these things.

(37) Empathy, (38) Courage, (39) Leadership: The ability to empathize with the feelings of others, to take risks including self-sacrifice for the benefit of others, and to display leadership qualities (e.g., vision, compassion, motivation of others) are still primarily human traits. No man-made device is yet capable of these things. However, simple programmed responses to perceived human emotion are now possible [46].

(40) Self-Awareness & Conscious, (41) Awareness of mortality: Humans can see themselves, their lives, their influence on others, their influence on the future, and their mortality. And as mentioned above when discussing multitasking, it takes the collective integration of many mental abilities to achieve self-awareness; moreover the human "conscious" can even lead to out-of-body experiences where there is a perceived disconnect between the physical world and the perceived world of the mind. The research in [45] showed the following:

- Conscience lags six seconds after related neurons fire
- A virtual *self* outside of your body can be created
- The virtual self can react to virtual stimuli (in a gaming environments).
- There is a perceptual part of the brain where proprioception (awareness of your position and orientation in space) contributes to the creation of a virtual self.
- Conscious "self-awareness" is needed for complex decision making and full autonomy; with all parts communicating.

This can all be easily related to the "Pose Estimation" required for robot autonomy. It now seems possible that perhaps someday *intelligent* machines could become self-aware. And becoming aware that they are not mortal would then be a simple realization as long as there is an ample supply of replacement parts.

(42) Group Psychology: Humans can play, work, raise children, and wage war as teams. They can also collectively share beliefs. Networked conventional computer programs and *intelligent* machines, especially if implemented with parallel processing architectures, have the potential to implement the equivalent of group psychology.

A significant problem to solve is multitasking manmade subsystems as efficiently and elegantly as the human brain. The degree of parallelism (DOP) needed to be comparable to a human brain is not yet available. Multitasking is typically only found in symbolic AI programs when written for multi-processor machines. However, since multitasking is a significant part of artificial neural networks where learning occurs between the many simple computational nodes, perhaps someday a MPP (Massively Parallel Processing) supercomputer could be built with billions of nodes (like the human brain), instead of just thousands (to-date). It could then be subdivided into clusters for each mental ability (or selected groups of abilities) of Table 1 to implement an artificial neural network to rival all of the functionality of the human brain.

Another hurdle to overcome in building *intelligent* machines (including fully-autonomous robots) that rival humans is choosing an architecture that is either structurally similar to, or merely produces results in a *similar fashion* to the human brain (i.e., "bottom-up" vs. "top-down" design). Figure 8 and 9 illustrate these models. Most artificial neural networks are top-down designs which learn and can be trained to react to external stimuli such that they mimic certain biological brain function. They learn by repeatedly applying mathematics to change inter-neuron connection strengths (weights) until the outputs converge to desired tolerances. The network is trained (i.e., learns) by changing the strength of connections such that multiple input/desired-output pairs are satisfied simultaneously; the final set of weights represents the compromises made to simultaneously satisfy the constraints. A major problem in implementing this is that these computations require many mathematical matrix and vector manipulations, but are often run on typical von-Neumann type uni-processor machines that have a "bottle-neck" forcing non-parallel computations. SMP (Symmetric Multi-Processing) machines can improve performance; however the best machines for these calculations are MPP or vector-register supercomputers, or embedded application-specific highly parallel systems – especially those which can provide learning in real-time. The all-digital vector-register neural network processor (with on-chip learning) proposed in [34] by the author is one example of this. The "bottom-up" approach is to build a man-made system which functions like a biological brain at the circuit-level. This theory discussed in [14] is to build artificial dendritic trees as RC analog circuit elements (i.e., built with resistors and capacitors) that produce signals close to those propagating through the dendritic tree inter-neuron connections of the human brain. Fig. 10 is a VLSI chip built by the author to implement this theory. It has 64 neurons built from approximately 10,000 transistors on a 2mm x 2mm silicon die. Even though the semiconductor industry continues to find ways to increase the number of transistors per unit area, the chip-area required to include billions of neurons (like that of the human brain) would need to be millions of times larger than a typical chip. One reason for this is that our brains are three-dimensional whereas integrated circuits are mostly two-dimension (despite multiple levels of layerization). Another problem is connecting all of these neurons since the wire routing would be in mostly two dimensions. Even with several layers of metallization (for wires), it would be extremely difficult to connect billions of neurons (with each requiring thousands of connections to other neurons). Perhaps the most difficult problem to overcome with this type of implementation is mimicking human learning where inter-neuron connections are not only strengthened or weakened during learning, but are often grown. Wires on chips need to be fixed, or at-best of variable resistance, and considering the required extensive connectivity between billions of neurons, this would likely take many years to be realized.

Keeping it simple

Since the Apollo missions of the 1960's NASA has known that simplicity is extremely important when creating reliably machines to send into space. The Mars robots of the recent decades are good examples of this. Despite integrating increasing complexity and autonomy, the following computer specifications illustrate NASA's wisdom on keeping it simple:

1996 ***"Sojourner"***
- 100 **k**Hz Intel 80C85 CPU
- 512 Kbytes of RAM
- 176 Kbytes of flash memory

2004 ***"Spirit"*** *and* ***"Opportunity"***
- 20-MHz IBM RAD6000 CPU
- 128 Mbytes of RAM
- 256 Mbytes of flash memory

2011 ***"Curiosity"***
- 200-MHz IBM RAD750 PowerPC
- 256 Mbytes of RAM
- 2 Gbytes of flash memory

Spirit, *Opportunity*, and *Curiosity* all use the *VxWorks* REAL-TIME Operating System to run many parallel tasks without all of the typical storage and resource-hogging needs of today's common operating systems. This efficiency of processing can be contrasted with present-day human obsessions with attempting to multitask too many things simultaneously. In [47] it was shown that even MIT students who believed they are capable of extreme multitasking scored much lower than they should have on tasks that require focused attention. In [47], an analogy was made to a well trained muscle needing less energy to do a task; it was shown that despite much brain activity (distributed throughout the brain) when web-searching, a sample task of focused reading of a book (with much less overall brain activity) yielded much better test scores for comprehension. A "Mental Ability Filter" was created by the brain [47].

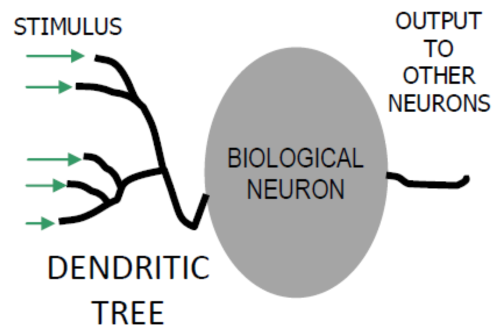

Figure 8. "BOTTOM-UP" *biological* model learns by strengthening, weakening, or growing new connections. Stimulus is from the environment and other neurons.

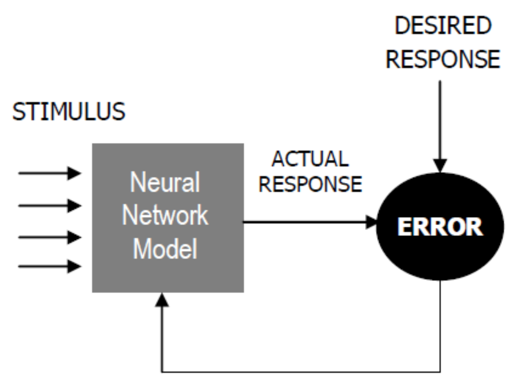

Figure 9. "TOP-DOWN" *psychological* model learns by adapting to minimize error. Preset stimulus is applied during learning ("training"). New stimulus from the environment is applied after training completed (i.e., to react to with ideally zero error)

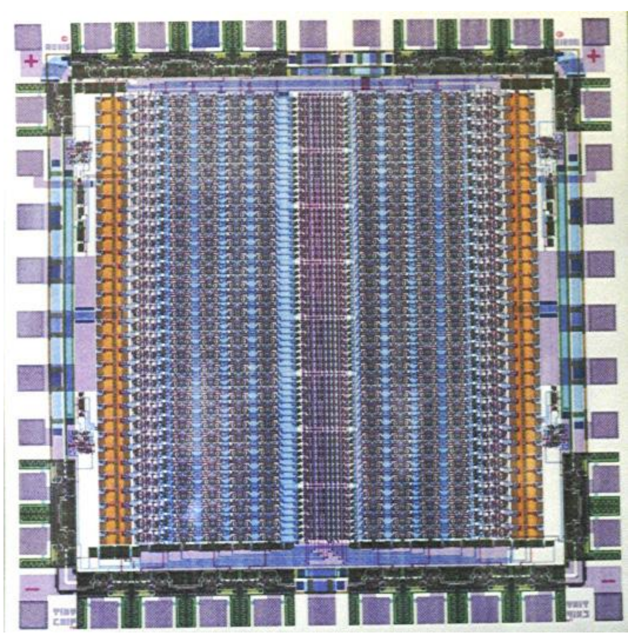

Figure 10. A "Bottom-Up" Artificial Neural Network Chip. (Wunderlich, 1992)

Grasping in the Dark

Robots can sometimes become overwhelmed with sensory information that inhibits their progress. Global path-planners can certainly help with this problem as was the case in 2006 when an upload of new global path-planning software was needed to free the Mar's rover from getting stuck due to multiple conflicting commands [12]. Another strategy to overcome this problem is to create "attractors" that virtually *pull* a mobile robot or robotic arm into and through noisy, crowded, or un-charted environments [16]. This concept is illustrated in Figure 11 where the robotic arm needs to have an educated guess where to go; else it becomes completely overwhelmed by obstacle avoidance commands repelling every elbow away from the walls of the enclosure. Fully autonomous robots will be needed to explore distant places like Jupiter's moon Europa, and the ability to "grasp in the dark" at virtual temporary goals could help improve the robot's ability to explore.

Conclusions and Future Research

Robot autonomy needs to be carefully designed to protect life, property, and robots; however excessive constraints can prevent discovery, or even halt all progress. Full or autonomy requires maximum adaptability. A future goal for our autonomous mobile robots is to develop fully integrated local and global path planning; with complex environmental maps developed from data continuously collected from the real-time local path planner. We will also be investigating the "attractors" presented above for 'grasping in the dark" when confronted with what would otherwise be overwhelming obstacles. We hope to combine various aspects of machine intelligence while considering the mental abilities presented in Table 1. This may involve developing separate artificial neural networks for various mental abilities (or groupings of abilities), then connecting them with one "global-oversight" neural network to reach compromises and arbitrate conflicting signals. Research may then be extended to test simulated human brain models (Artistic, Scientific, Autistic, or Asperger's). Network clusters could be separated from a working collective to simulate certain human conditions; And re-establishing connectivity in varied ways (e.g., optimal delays, etc.) could lead to natural and physical science discoveries (including robot autonomy). Future inter-disciplinary collaborations could relate engineering, computer science, psychology, and possibly even occupational therapy where a simulation of Sensory Integration" could be shown to be related to a lack of commutation between regions of the brain; which often leads to a "sensory overload" from not being able to process everything while attempting focused tasks; and as discussed above, this can be easily applied to autonomous robot path-planning. Possible discoveries in optimal combinations of localized focused thought with simultaneous, but not disruptive, communication between processing centers could be applied to machine intelligence algorithms. Future research may also investigate how sensory "noise" over time can cause cognitive or computing interference that can't be filtered and possibly may intensify inhibition of mental or computing capabilities; this could be shown to be due to the difficulty in internalizing, isolated, and integrated noise into the global conscious of the human mind, or into the global path-planner of an autonomous robot. The ability of a human or machine intelligence to "compromise" may require special coding or even structural changes. All localized processing may need to communicate and settle to one solution despite conflicting conclusions. Localized frequently-reinforced processing may be resistant to change; especially since localized areas may perform best when narrowly focused without distraction. New communication connections may be needed. The ability to change (i.e. plasticity) of human and machine minds in autonomous robots may require new measures to ensure optimal learning and adaptively. Robot autonomy needs to be designed to be safe, but without excessive constraints that could prevent discovery, or even halt all progress.

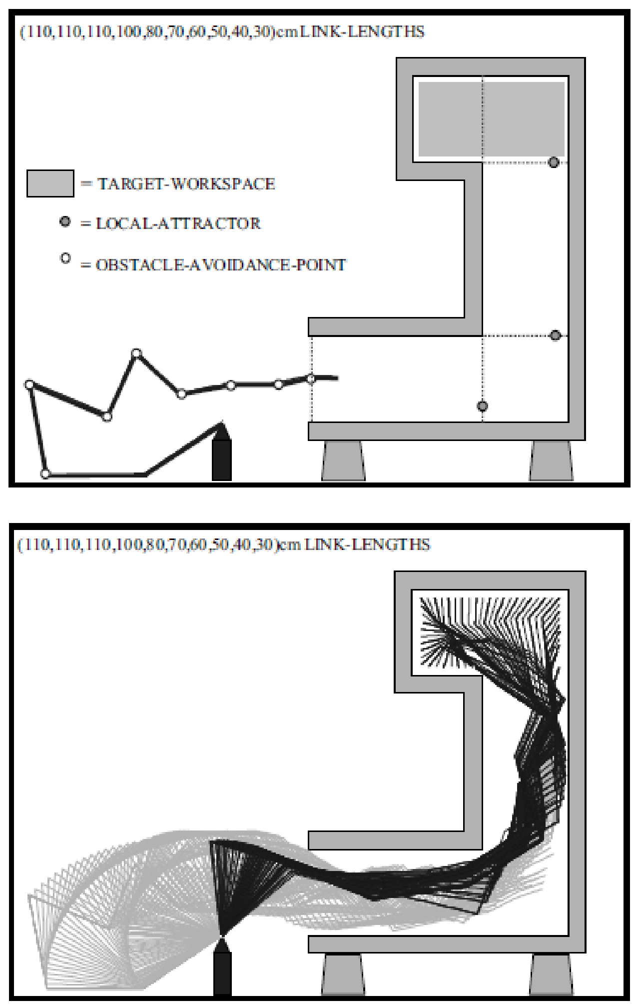

Figure 11. A robotic arm "grasping in the dark" [16]

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