# Gauging Intelligence of Mobile Robots

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## 1. Introduction

This chapter offers approaches for gauging the intelligence of a mobile robot and case studies as illustrations. The meaning of "Intelligence" varies greatly depending on the context in which the word is used. A general discussion on various perspectives for intelligence is provided. A framework consisting of an agent, an environment and a goal is provided for viewing intelligent behaviors. Three possible means of gauging performance of intelligent mobile robots are suggested. The first is a qualitative perception that is based on an extension of the Turing test for perceiving an unsuspecting UVS behavior as that of a person. The second is a quantitative measure where task-specific intelligence performance of a smart system is evaluated. The third is the comparative scale that gauges the difficulty of challenges against the intelligent skills of humans. Two case studies, one involving a commercially available robotic floor vacuum cleaner and the other autonomous competition mobile robots, are gauged using the suggested measures. Included in this chapter is a description of a key experiment which revealed that it requires the mind of at least a four-year-old child to successfully navigate an autonomous navigation course.

## 2. Intelligence

Gauging intelligence is one of the most challenging and controversial topics among researchers in the fields of artificial intelligence (AI) (Nilson, 1980), intelligent systems sciences and robotics (McCorduck, 2004). We can simplify the views by realizing that human intelligence is not the only kind of intelligence in nature (McCorduck 2004, Armand, 2005). One can think of non-human intelligence as found in processes and powers of biological systems, or what if we encounter extraterrestrial intelligence. There have been dramatic advances in the use of artificial intelligence in the commercial sector in recent years. Today's machines and computers incorporate some form of intelligence, albeit in different levels of sophistication. Realizing this, it is helpful to differentiate various kinds of intelligence: human, non-human, extraterrestrial, artificial, machine, etc.

***Presence and context of Intelligence.*** One often recognizes intelligence, when one sees it. The meaning of intelligence depends on whom or what the word is affiliated with. There is no single one-size-fits-all definition although an acceptable informal working definition is that: *Intelligence is a measure of an agent's ability to achieve goals in a wide range of environments* (Legg & Hutter, 2006). In practice, the definition would be better served by defining it with respect



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to its associated context and scope. For example, intelligent skills expected of a human driven vehicle versus that of an autonomous vehicle.

***Absence of Intelligence.*** One easily recognizes the absence of intelligence when something stupid or unintelligent happens. An autonomous vehicle that crashes into an unexpected obstacle in its path is a clear example of lacking a necessary intelligent reflexive response which would consist of sensory perception and reactive control action (Control Handbook, 1995). Now if the vehicle sees and avoids the obstacle but fail to complete an alternate path to its destination, assuming it is possible, then it lacks a sufficient intelligent decision and execution. Next if the vehicle does not learn from the environment and repeated experiences, then it lacks a higher intelligent cognition to learn and adapt. The reflexive response is a necessary part likened to the nervous system of a human, and the decision/execution and cognition is a sufficient part likened to the neural system. One recognizes an absence of intelligence when these necessary and sufficient factors of intelligence are not present.

***Natural Intelligence (NI).*** Natural intelligence, including biological and psychological intelligence, is usually associated with a creature's ability to maximize the chance of success in achieving its goal in a uncertain, complex, and, often, hostile environment. High intelligence traits deal with intricate thinking processes involving perception, reasoning, emotion, and action, for formulating and re-formulating a course of undertaking. Humans exhibit a most complex form of such traits that include yearning to communicate, organize, and succeed. On the other hand, low intelligence traits of simplest life forms, such as microbes, may involve mainly survival and reproduction.

***Human Intelligence.*** Psychologists still differ as to a precise definition of the comprehensiveness and functions of human intelligence. There are many definitions and theoretical models of human intelligence, and practical characterization of intellectual abilities can be controversial. Many associate human intelligence as a sum of specific clever abilities best displayed in specific situations in a timely manner. Human intelligence, at the minimum, has a capability to learn, understand, act, and adapt accordingly (Pinker, 1997).

***Survival and Adaptation.*** Natural intelligence emerges from competitive struggles for survival and gene propagation over millions of years. All forms of life may increase their intelligence over successive generations via evolution, instinct, and learning. In almost all the cases, survival of the fittest in a natural selection process is often ensured for species that are the most adaptive. As humans and microbes adapt in varying ways, it is clear that adaptation is an essential intelligence trait that ensures survivability.

***Relative Degree of Intelligence.*** While intelligence varies in complexity and ability to adapt, a measure of intelligence is often made by comparison to a norm of some sort. A means to gauge intelligence is to compare it with a known or expected level of competence. For instance, an intelligence quotient (IQ) is the ratio of individual intellectual performance over expected intellectual performance of a collection of individuals. Psychologists have developed many such scales for gauging human intelligence including children's cognitive capabilities.

***Eras of Intelligence.*** As knowledge advances with time and so does perception of intelligence. What might have been considered intelligent may not be viewed as intelligent now. A simple example is to contrast a person from 1900 to that from 2000.

***Technology and Intelligence Paradox***. As technologies advances, the concept of what intelligence must continue to evolve. Memory and computation which were once the hallmark of intelligence are now trivial tasks for a computational machine. The mentally demanding tasks of challenging games have been mostly reduced to heuristics searches. A child genius can recall volumes of information but so can a computer. There is an odd paradox that once a process or algorithm is understood, it tends not to be viewed as intelligent.

***Machine and Intelligence Paradox.*** Many of today's automation and/or robotic systems can handle extremely well the tasks considered difficult by human standard. Strangely enough, it is not easy to build machines that can handle certain situations considered easy by human. An example is the task of driving an automobile, where clever but simple decisions are often needed. Such paradox is not apparent before one actually attempt to build intelligent machines (Albus & Meystel, 2001). The paradox is what makes research on intelligent systems exciting

***Unmanned Vehicle Systems and Mobile Robots.*** Significant recent advances have been made in the field of autonomous/semi-autonomous (A/SA) unmanned aerial, ground, underwater, surface vehicles (UAV, UGV, UUV and USV). Because of complexities encountered in ground missions, progress in intelligent autonomous UGV systems is often considered to be most difficult. UGVs a.k.a. mobile robots presently pose challenges that the AI and intelligent systems communities can overcome and contribute significantly (Advanced robotics, 1996, Jones, et al., 1000, Martin, 2001).

***Magic and Technology.*** In The Wizard of Oz (1939), Dorothy Gale is swept away to a magical land in a tornado and embarks on a quest to see the Wizard who can help her return home. The Wizard turns out to be a professor who uses technology that to perform magic. An automatic door at our supermarkets would be magical to a person from the past or rural parts of the world. Indeed, intelligent mobile robots and bipedal humanoids wandering around performing useful tasks or possibly acting as adversaries to human beings may be construed by many as indistinguishable from magic.

## 3. Problem & Approach

The chapter presents possible means of gauging intelligence of mobile robots. The first is a qualitative perception that is based on an extension of the Turing test to perceiving an unsuspecting UVS behavior as that of a person. The second is a quantitative measure where task-specific intelligence performance of a smart system is evaluated and scored. The third is the comparative scale that gauges the difficulty of challenges against the intelligent skills of humans.

The chapter will present a framework consisting of an agent, an environment and a goal for considering the performance of a robot. Case studies involving a commercially available Roomba vacuum cleaner and mobile robots for the annual Intelligent Ground Vehicle Competition will be presented to illustrate the proposed gauging of intelligence. The chapter will describe an experiment which showed that the mind of at least a four-year-old child was necessary to successfully complete an autonomous navigation course.

## 4. Framework for Agent, Environment & Goal

An agent, an environment and a goal are three essential components for modeling an intelligent system. A mobile robot whose intelligence is question would be referred to as an *agent*; and the external environment, condition, problem or situation that it interacts with as the *environment*.

***Case Study A.*** Consider the iRobot Roomba robot (agent) whose goal is to vacuum floors (environment) that varies in sizes and shapes. It has a random cleaning pattern shown in

Figure 1. It also an ability to estimate the room size and so adjust its cleaning time, and to return to a Home Base for recharging before its battery is depleted

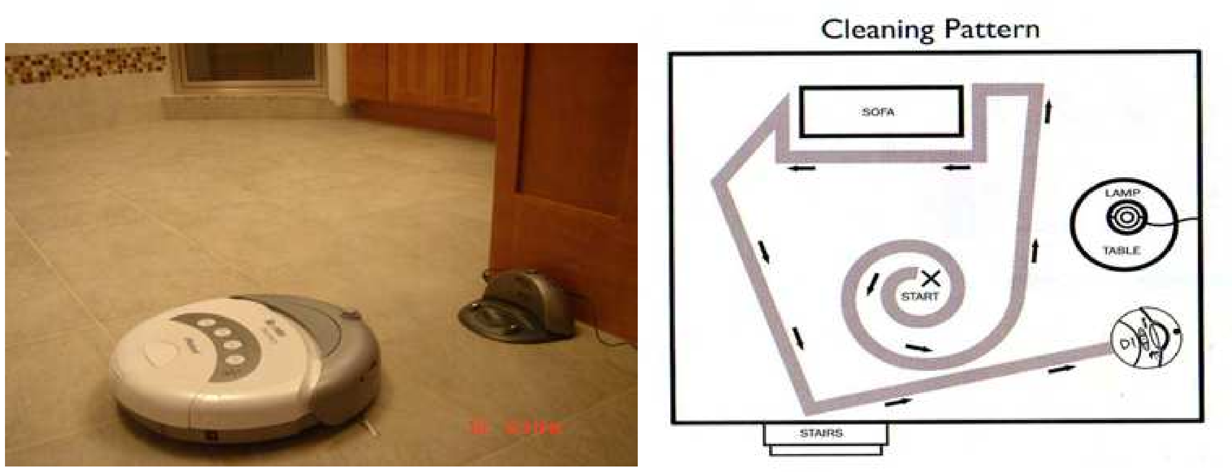



Fig. 1. The Roomba, its environment and cleaning pattern.

***Case Study B.*** Next consider an annual Intelligent Ground Vehicle Competition vehicles and its challenges. A typical technology make-up for an autonomous IGVC vehicle to implement intelligent control schemes is shown in Figure 2. (See www.igvc.org for more details)

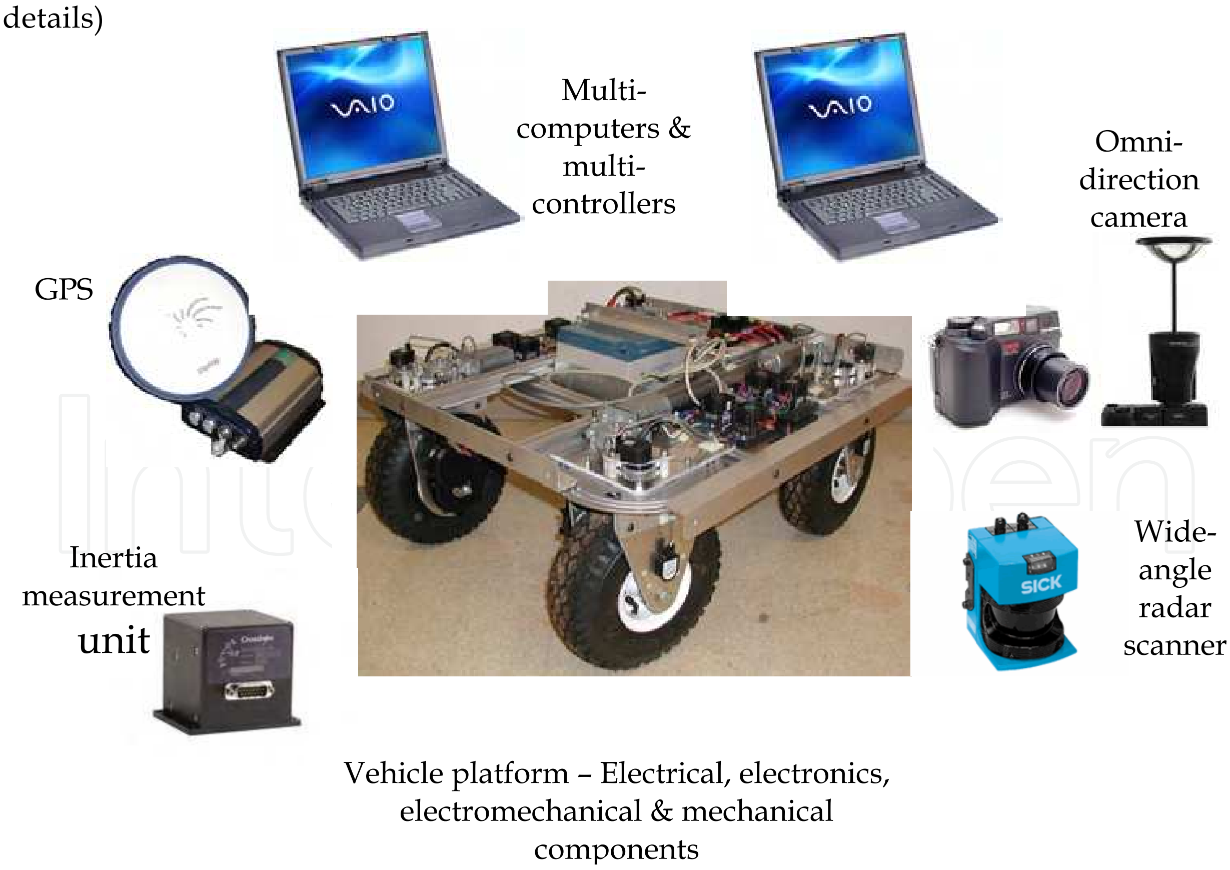



Fig. 2. Typical technology make-up of an IGVC vehicle.

The IGVC environments and goals consist of 1) Autonomous Challenge Event (ACE) where an agent must negotiate around an outdoor obstacle course in a prescribed time while staying within the 5 mph speed limit, and avoiding the random obstacles and escaping traps along the track (Figure 3), 2) Navigation Challenge Event (NCE) where agent autonomously travel from a starting point to a number of target destinations (waypoints or landmarks) and return to home base, given only a map showing the coordinates of those targets (Figure 4).

Fig. 3. Obstacle traps and lane for ACE.

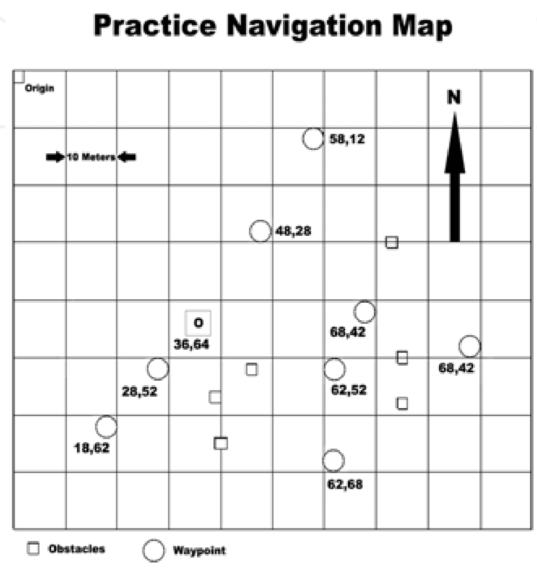



Fig. 4. Waypoints and obstacles for NCE.

## 5. Gauging of Intelligence

The Turing test for AI essentially asserts: If you unknowingly communicated with a computer via text messages, and perceived that you have communicated with a person, then the computer has demonstrated a certain level of artificial intelligence. Turing also predicted that by the end of the century we would be able to speak of machine that thinks. Indeed, many of today’s automated technology have surpassed the test and are capable of communicating with us better than a real person could.
A simple extension of the Turing test to IUVS can be asserted as follow:

> *If you perceive that a computer controlled system performs as well as a human would, then the system has demonstrated a certain level of intelligent system behavior.*

In this qualitative perception, the communication could be entirely by means of observation by human observers.
***Example.*** A car passed you by, stopped at red traffic lights, sped up on green, and drove safely through the thick of traffic, as though there was a person driving it. If that car was driven by an intelligent control system, then you have just witnessed an IUVS in action. ***Second example.*** A jetliner with 400 passengers landed smoothly during a blizzard. As they were leaving the plane, the passengers, having endured a rough flight, thanked the captain for the safe landing. The captain smiled, pondering the fact that the aircraft had autonomously landed itself using a new automatic landing control system.

***Occam's razor.*** One of the fine judgments in this intelligence test is to see if the agent employs a simplest and effective solution to a problem at hand that has several different possible alternatives consistent with observed environment data. For example, a simple left-right turn that allows the agent to return to the original should be preferred over a more elaborate alternate path. An agent that chooses the former would generally be considered rational and intelligent than if it chooses the latter. This common sense of embracing the less complicated option is known as Occam's razor, and is identified with intelligent behavior.
***Case A.*** In the case of the Roomba, qualitative perception questions related to the goal would include: i) Does the agent perform (clean/vacuum) like a person would? ii) Is estimation of room size and adjustment of sweeping time noticeable? iii) Does it return to the Home Base? The answers are as follows: i) The agent does not clean like a person; its random cleaning pattern does not follow the principle of Occam's razor. ii) Sweeping time, even if adjusted accordingly, is not noticeable. iii) The agent does return to the Home Base to recharge its battery, and this is an outstanding feature of the Roomba.
***Case B.*** In the case of the IGVC, the qualitative perception questions related to the goal would include: i) Does the agent perform (navigate) the autonomous challenge course like a person would? ii) Does the agent perform (traverse) the navigation challenge course like a person would? iii) Does the agent perform (follow) the autonomous challenge course like a person would? The answers are as follows: i) Winning vehicles/agents do navigate like a person would. ii) In this case, winning agents traverse the navigation challenge course much faster than a person would since the computers can interpret the GPS data with ease. iii) Winning agent does follow the leader but not as well or smoothly as a person would.

### 5.2 Quantitative Measure

***Task Specific Intelligence.*** Because of the limitation in system capability, the scope of expected intelligent behavior for a UGV would always have to be task specific in nature. This allows one to set up a goal for the IUVS, define expected challenges, guess potential uncertainties, and measure success in task completion. The task specific intelligence problem should pose a goal of the task along with its expected challenges, uncertainties in challenges, and a measure of success.
***Case A.*** Questions related to Quantitative Measure would ask for a score, say from 0 to 10, for the agent's performance in achieving the goal. Quantitative Measure questions would be: i) How clean is the vacuumed area? ii) How well does it cover areas, avoiding obstacles? The answer is: i) 10 out of 10 clean for the bathroom floor shown in the Figure. ii) 9 out of 10 for reaching areas that it can navigate to; 1 out of 10 for getting entangled with a loose item.
***Case B.*** An elaborate scheme for scoring Quantitative Measure of IGVC agent performance is described on www.igvc,org. *Qualitative Measure for the Autonomous Challenge Event:* Judges will rank the entries that complete the course based on shortest adjusted time taken. In the event that a vehicle does not finish the course, the judges will rank the entry based on the longest adjusted distance traveled. Adjusted time and distance are the net scores given by judges after taking into consideration penalties, incurred from obstacle collisions, pothole hits, and boundary crossings. *Measure of success for Navigation Challenge*: Vehicles may seek the waypoints in any order, and the

vehicle actually reaching the most waypoints in the allotted seven minute run time will be the winner. If a vehicle fails to come within two meters of a target, it will not be judged to have reached that target.

### 5.3 Comparative Scale

***Comparative Scale against Human Capability.*** As robotics and automation systems replace humans in carrying out all sorts of tasks, one may think of calibrating the levels of difficulty or challenges in the tasks against the skill capability of a person. In this way, one could gauge the intelligence of a robotics system to, say, the sensory-motor-decision skills of a qualified person. The person's qualification could provide a scale for rating the intelligence level required of a task.

***Case A.*** There is no experimental data to establish the Comparative Scale for a Roomba. But it is safe to conjecture that the vacuuming agent has an equivalent skill set of a three year old child.

***Case B.*** An experimental investigation into Comparative Scale for the autonomous challenge event was performed at the 1997 IGVC, held on the campus of Oakland University on May 28 - June 2, 1997. During the competition, experiments were conducted with the help of kindergarten children from the Lowry Child Care Center at Oakland University. The idea was to determine the performance and capability of children of ages two through six years in completing the course. The experimental data would provide a scale for gauging the performance of IGVC agents.

*Experiment*. In the field experiment, the children took turns driving a battery-powered cart (similar in size to the competition vehicles) around a 630 foot autonomous obstacle course. A camera recorded the driving behavior and head movements of the kids during the test. The videotape recorded the kids' initial driving reaction to the obstacle course and, in many cases, their improved driving skills that emerged from learned experience.

*Subject samples.* Twenty-two children participated. They were classified by age in Table 1 and labeled as 2X, 3X, 4X, 5X and 6X, where X is a letter in the alphabet. The experiment was assisted by a medical doctor (co-author), a day care provider from the Center, and the parents of the children. Prior to the experiment, a brief survey on each of the children was also conducted so that their background might be factored into consideration when interpreting their maneuvering skills. To check for presence of sensory-motor skill in the children sample, each child was tested by having him or her sketch a "figure of a person" on a paper. A sample of the sketches in Figure 5 showed that each child demonstrated some minimal necessary sensory-motor capability for the challenge at hand. The children's prior experience in driving a toy car and playing video games was also noted as shown in Table 1. However, the experience appeared to be irrelevant to the driving ability demonstrated in the field at this time.

*Results.* Figure 5 shows a montage of snapshots from the recorded experiment in progress. The photos A, B, & C demonstrate some of the challenges on the obstacle course. Photos D and G give an idea about unsuccessful attempts by a two-year-old. Photos E and H illustrate that three-year-olds have some problem steering and maneuvering the obstacle course. The obstacles often prove to be challenging even for some of the four-year old children, as evident in Photo F. Photo I shows a child receiving instructions; the child quickly learned how to handle the equipment. Table 1 describes the observations that support the experimental results and the photos.

The two-year old child had no idea initially on what to do, how to drive or steer the cart and about the objective of the experiment. In about 10 minutes, the child learned to drive the cart with the pedals. He held the steering wheel only as a support. The child did not achieve the objective of the obstacle challenge. Three-year old children could understand the objective of the challenge, and drive the cart properly. However, this age group had difficulty with motor skills, cart control, and accuracy. For the objective of the IGVC contest course, none of three-year-olds finished the course. Children of age four and above had little difficulty finishing the course. Two kids in this age group made some mistakes, but they all outperformed any of the robotic vehicles that competed in the IGVC. The five- and six-year-olds had a blast test-driving the obstacle course.

| ID | Age (Yr/Mo) | Driven a toy cart? | Video games hrs/wk | Observation on driving and maneuvering skills[1] |
|---|---|---|---|---|
| 2A | 2/10 | N | 4 | Initially clueless; manage to only throttle after 10 mins. |
| 3D | 3/3 | Y | 0 | Hit two obstacles hard; did not finish course |
| 3B | 3/7 | Y | 0 | Touched lines 6 times; did not finish |
| 3E | 3/7 | N | 0 | Touched lines 2 times; did not finish |
| 3A | 3/9 | N | 0 | Went out-of-bound at 315', did not finish |
| 4I | 4/4 | Y | 1 | Hit one obstacle; finished course |
| 4B | 4/7 | N | 1 | Finished course in 2:17 minutes (slow) |
| 4D | 4/8 | N | 3 | Touched a boundary line; hit one obstacle; finished |
| 4G | 4/8 | N | 1 | * |
| 4H | 4/8 | Y | 0 | Finished course in 2:35 minutes (slow) |
| 4J | 4/8 | N | 3 | * |
| 4E | 4/9 | N | 0 | * |
| 4F | 4/11 | N | 0 | * |
| 5C | 5/1 | Y | 7 | Touched an obstacle; finished course |
| 5F | 5/1 | N | 0 | * |
| 5G | 5/4 | N | 0 | Finished course in 2:32 minutes (slow) |
| 5A | 5/9 | Y | 0 | * |
| 5D | 5/9 | Y | 0 | * |
| 5B | 5/11 | Y | 1 | * |
| 5H | 5/11 | N | 3 | * |
| 6D | 6/1 | N | 0 | * |
| 6E | 6/2 | Y | 2 | * |
| 6C | 6/4 | Y | 0 | * |
| 6A | 6/7 | Y | 0 | * |
| 6B | 6/11 | Y | 0 | * |

" * " entries indicate the child had no problem in completing the obstacle course under two minutes.

Table 1. Driving and maneuvering performance of children from the obstacle course experiment.


Fig. 5. Hand sketches used to confirm presence of sensory-motor capabilities.

A. Staying inside the lane and avoid obstacles.

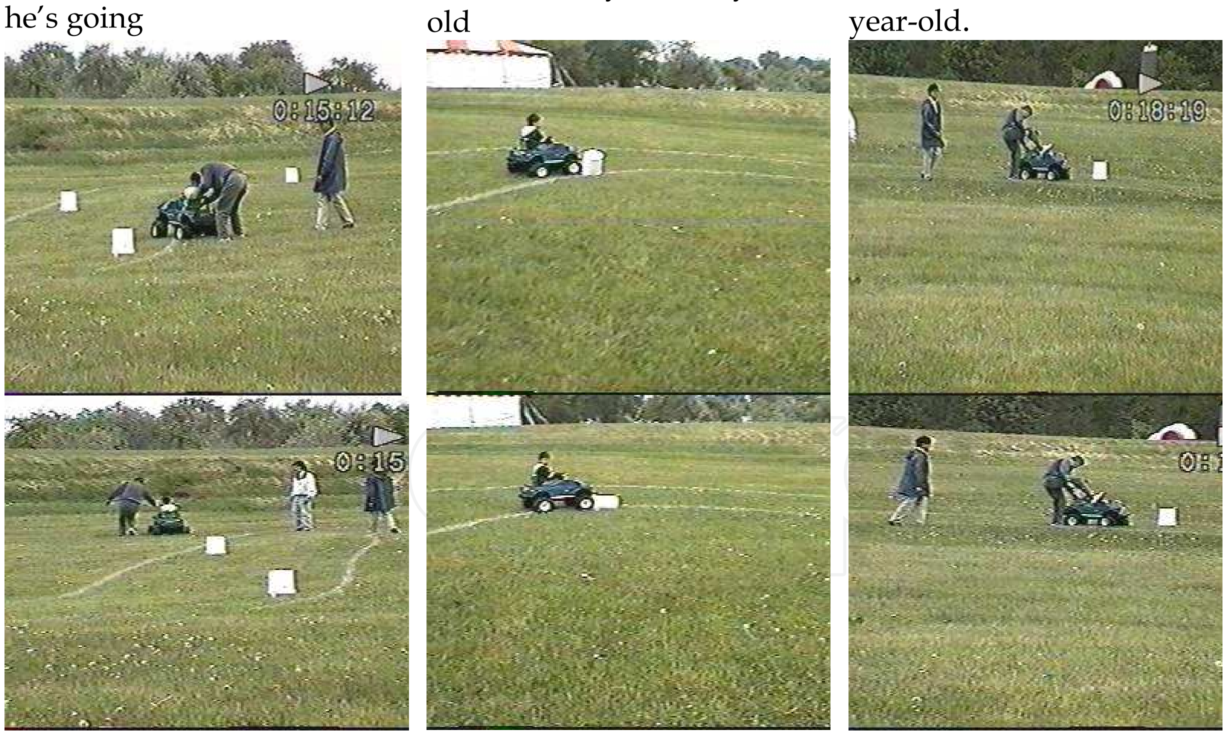
B. Maneuvering over a ramp (simulated bridge)

C. Overcoming a sand pit (increased resistance)

D. A two year old not paying attention to where he's going

E. Steering off the lane with two wheels by a three-year-old

F. The challenge is intensive even for a four-year-old.



G. Steering out of bounds several times by the two-year-old

H. A three-year-old hitting an obstacle

I. Instructions from the parent on how to use the throttle

Fig. 6. Field experiments in which children were challenged to complete the obstacle course at the IGVC.

*Conclusion.* An important conclusion from the experiment is that children approximately four-years old and above can handle the obstacle course. By virtue of comparison, a UVS that successfully completes obstacle course may be said to have an equivalent intelligent sensory-motor and control skill of a four-year old child.

## 6. Conclusion

The paper illustrates three means for gauging the intelligence of mobile robots: The ***qualitative perception*** of intelligence based on extending Turing test to the systems at hand; the ***quantitative measure*** that gauges task-specific intelligence from its performance in uncertain environments; the ***comparative measure*** that calibrates difficulty levels of what the system has to do against levels of human skills. The framework of an agent, an environment and a goal was applied to two case studies was helpful in gauging the intelligence of the mobile robots. An important field experiment reveals that the autonomous obstacle course challenge in the IGVC requires the ***sensory-motor-decision skill*** of at least a four-year old. As frontiers of and education efforts on IUVS are being pursued, it is necessary and worthwhile to consider means for improving as well as gauging the intelligence of the systems.

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This book covers many aspects of the exciting research in mobile robotics. It deals with different aspects of the control problem, especially also under uncertainty and faults. Mechanical design issues are discussed along with new sensor and actuator concepts. Games like soccer are a good example which comprise many of the aforementioned challenges in a single comprehensive and in the same time entertaining framework. Thus, the book comprises contributions dealing with aspects of the Robotcup competition. The reader will get a feel how the problems cover virtually all engineering disciplines ranging from theoretical research to very application specific work. In addition interesting problems for physics and mathematics arises out of such research. We hope this book will be an inspiring source of knowledge and ideas, stimulating further research in this exciting field. The promises and possible benefits of such efforts are manifold, they range from new transportation systems, intelligent cars to flexible assistants in factories and construction sites, over service robot which assist and support us in daily live, all the way to the possibility for efficient help for impaired and advances in prosthetics.



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