

<http://www.youtube.com/watch?v=3EeJClN5KYg>



Robotics

CS311, Spring 2013
David Kauchak


Some material adapted from slides from Zach Dodds

+ Admin

- Assignment 5 graded
- Exam #2 available later today
 - To be done by Sunday at midnight

+ What is a robot?

"I can't define a robot, but I know one when I see one."
--Joseph Engelberger (1966)



Justice Potter Stewart wrote in *Jacobellis v. Ohio* (1964), "I can't define pornography, but I know it when I see it."

Robot Defined

Word robot was coined by a Czech novelist Karel Capek in a 1920 play titled Rossum's Universal Robots (RUR)

Robota in Czech is a word for worker or servant



Karel Capek

Definition of robot:

Any machine made by one our members: Robot Institute of America ©

A robot is a **reprogrammable, multifunctional** manipulator designed to move material, parts, tools or specialized devices through variable programmed motions for the performance of a variety of tasks: Robot Institute of America, 1979

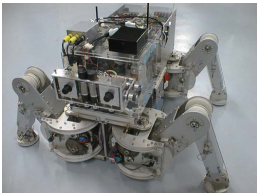
What is a Robot

Manipulator

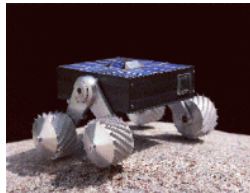


What is a Robot

Legged Robot



Wheeled Robot



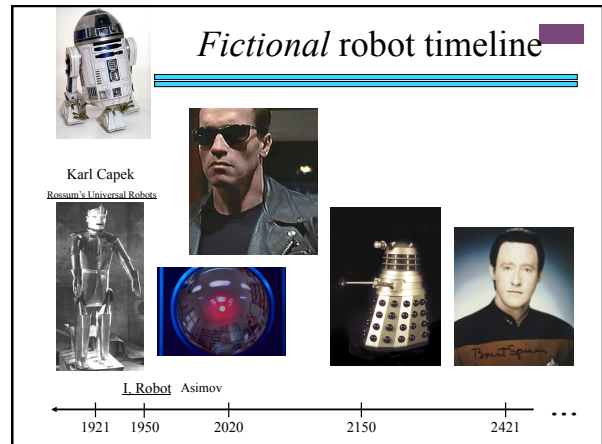
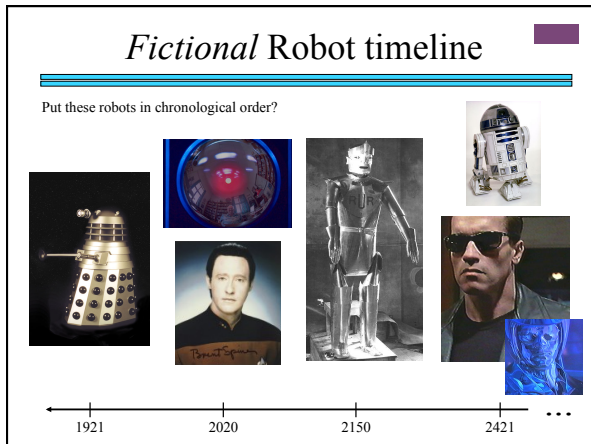
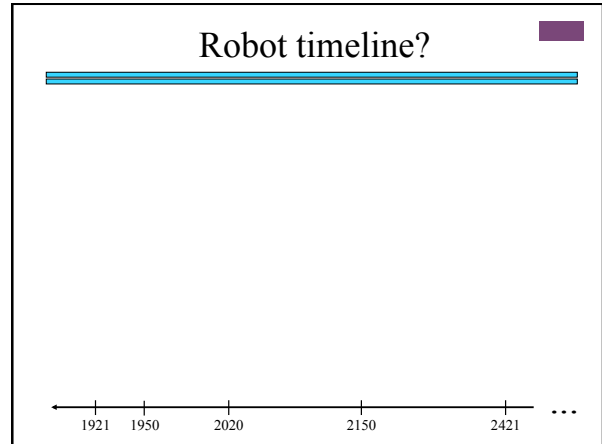
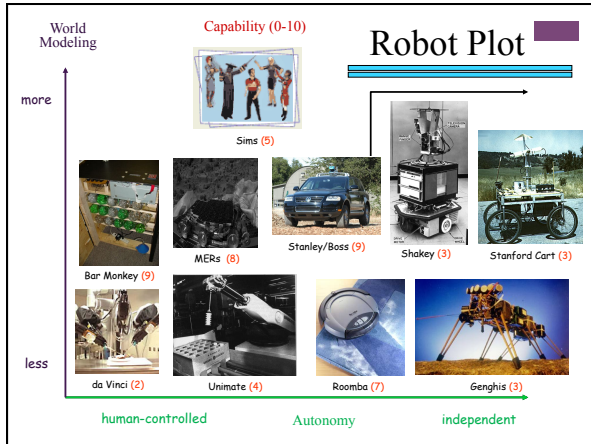
What is a Robot

Autonomous Underwater Vehicle



Unmanned Aerial Vehicle



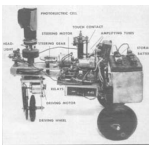
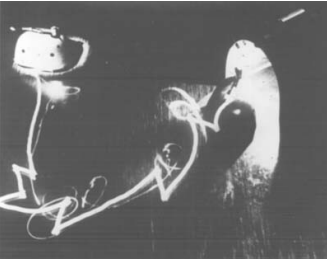


Real robot timeline

1951 1968 1976 1985 ...

Real robot timeline

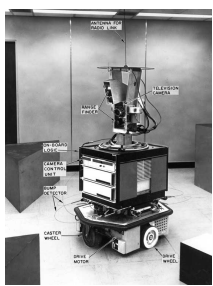
Tortoise "Elsie"

by Neurophysiologist Grey Walter

1951 <http://www.frc.ri.cmu.edu/~hpm/talks/revo.slides/1950.html> ...

Shakey



Nils Nilsson @ Stanford Research Inst.
first "general-purpose" mobile platform

Living Room (L) Kitchen (K)

sh tv sp

Bedroom (B)

rem

... 1968 ...

Robotics's Shakey start

START

$At(sh,L) \wedge At(sp,K) \wedge At(rem,B) \wedge At(tv,L)$

Go(L,B)

Go(L,K)

Push(tv,L,B)

Push(tv,L,K)

$At(sh,K) \wedge At(sp,K) \wedge At(rem,B) \wedge At(tv,K)$

$At(sh,L) \wedge At(sp,L) \wedge At(rem,L) \wedge At(tv,L)$

GOAL

ACTIONS

Go(from,to)
Preconditions: $At(sh,from)$
Postconditions: $At(sh,to)$

Push(obj,fr,to)
Preconditions: $At(sh,fr) \wedge At(obj,fr)$
Postconditions: $At(sh,to) \wedge At(obj,to)$

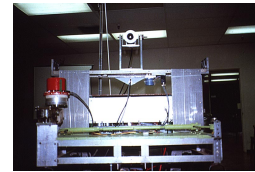
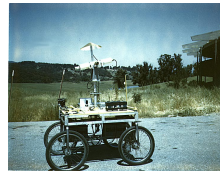
+ Shakey in video

<http://www.youtube.com/watch?v=qXdn6ynwpiI>

Stanford Cart: SPA

Hans Moravec @ SAIL

"functional" task decomposition
"horizontal" subtasks



1976

Cartland (outdoors)







Cartland (indoors)



“Robot Insects”

Rodney Brooks @ MIT

“behavioral” task decomposition →
“vertical” subtasks

SENSING

planning and reasoning

identify objects

build maps

explore

wander

avoid objects

ACTING

... ————— | 1985 | ————— ...

+ Robotics

What are the challenges?
How do these relate to AI?

+ AI

- Search
 - planning
- Game playing
- CSPs
- Bayesian
- HMMs
- Machine learning
 - neural nets
- Knowledge representation
- Natural Language processing
- Computer vision

Autonomy/behavior

how much of the world do we need to represent internally ?

Robot Architecture

how should we internalize the world ?

what outputs can we effect ?

what inputs do we have ?

what algorithms connect the two ?

how do we use this “internal world” effectively ?

Robot Architecture

how much / how do we represent the world internally ?

As much as possible!

SPA paradigm

```

    graph LR
      sense[sense] --> plan[plan]
      plan --> act[act]
    
```

Not at all

Reactive paradigm

Task-specific

Behavior-based architecture

As much as possible.

Hybrid approaches

history...

Sense - Plan - Act

Shakey

SENSING

perception

world modeling

planning

task execution

motor control

ACTING

```

    graph LR
      sense[sense] --> plan[plan]
      plan --> act[act]
    
```

Stanford Cart

MERs

... 1968 1976 ... - 2009 ...

Mars Exploration Rovers

Labels: Pancam (pair), Navcam (pair), Front Hazcam (pair), Instrument Deployment Device (IDD), In-situ instruments (APXS, MB, MI, RAY), Rover Equipment Deck (RED), CHH Antenna, Low Gain Antenna (LGA), High Gain Antenna (HGA), Solar Arrays, Warm Electronics Box (WELB), Rocker-Bogie Mobility System.

Sense - Plan - Act "deliberative" architecture

Mars Science Lab

2011 - lasers, lifebio, and maybe nuclear-powered

Robot Architecture

how much / how do we represent the world internally ?

As much as possible!

SPA paradigm

```

    graph LR
      sense[sense] --> plan[plan]
      plan --> act[act]
    
```

Not at all

Reactive paradigm

```

    graph LR
      sense[sense] <--> act[act]
    
```

stimulus - response

Task-specific


Behavior-based architecture

As much as possible.


Hybrid approaches

Biological Inspiration

Ethology: describing animal behavior



Getting to the ocean?



Digger wasps' nest-building sequence

AI reasoning systems abstract too much away: *frame problem*
 "The world is its own best model"

sense


↔

act

Decision-making is based only on current sensor inputs.

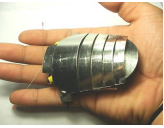
Analog reactive robots

"Tortoise" Gray Walter
Valentino Braitenberg
Mark Tilden commercial products...
"BEAM"

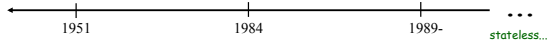


"light-headed" behavior

<http://people.cs.uchicago.edu/~vladimir/vb/robots/>



<http://ham.fdn.cambridge.ac.uk/robotics/act/microary.htm>
robot made from Playstation pieces...!



1951 1984 1989- ...

stateless...

Robot Architecture

how much / how do we represent the world internally ?

As much as possible!

SPA paradigm

sense

→

plan

→

act

Not at all

Reactive paradigm

sense

↔

act

stimulus - response == "behavior"

Task-specific

Behavior-based architecture

}

Subsumption paradigm

Potential Fields

} different ways of composing behaviors

As much as possible.

Hybrid approaches

Behavior-based control

Behavior a direct mapping of sensory inputs to a pattern of task-specific motor actions

sense

↔

act

extinguish →
approach →
wander →

little explicit deliberation except through system state

"Vertical" task decomposition

SENSING

planning and reasoning

identify objects


build maps

explore

wander

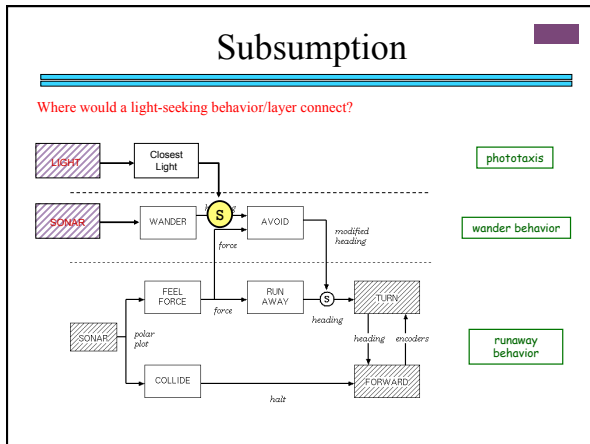
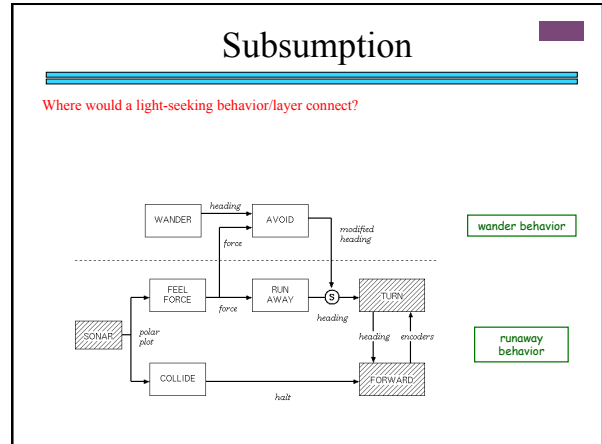
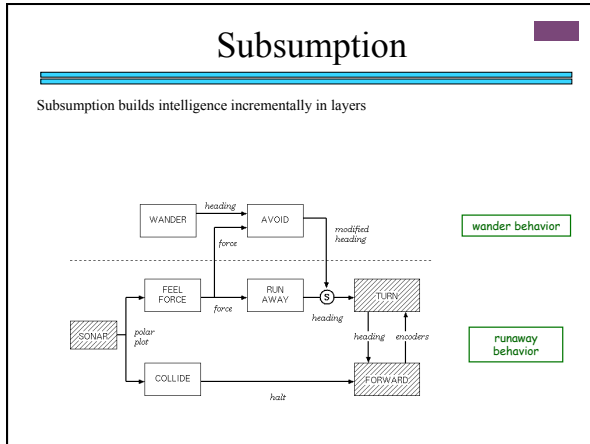
avoid objects

ACTING



Genghis

... 1985 ...

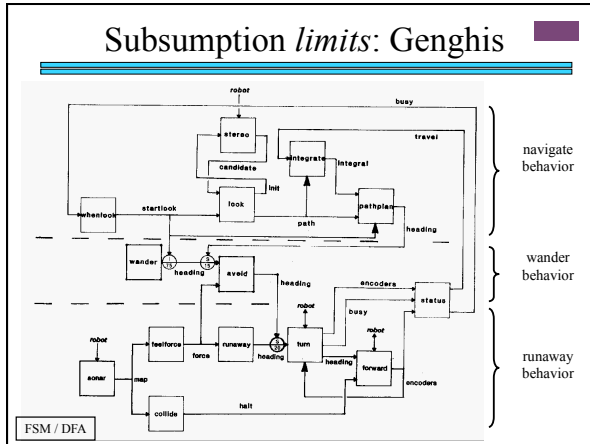


Subsumption - Limits


Reaching the end of the subsumption architecture and purely reactive approaches.

Herbert, a soda-can-collecting robot
<http://www.youtube.com/watch?v=YiNKuwiVYm0>

Success of behavior-based systems depends on how well-tuned they are to their environment. This is a huge strength, but it's also a weakness ...



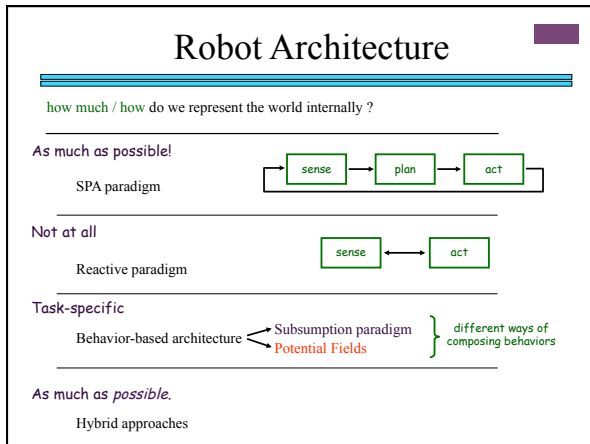
Unwieldy!



Larger example -- Genghis

- 1) *Standing* by tuning the parameters of two behaviors: the leg "swing" and the leg "lift"
- 2) *Simple walking*: one leg at a time
- 3) *Force Balancing*: via incorporated force sensors on the legs
- 4) *Obstacle traversal*: the legs should lift much higher if need be
- 5) *Anticipation*: uses touch sensors (whiskers) to detect obstacles
- 6) *Pitch stabilization*: uses an inclinometer to stabilize fore/aft pitch
- 7) *Prowling*: uses infrared sensors to start walking when a human approaches
- 8) *Steering*: uses the difference in two IR/range sensors to follow

57 modules *wired* together !




Potential Fields

Potential fields compose simple behaviors by *adding* the outputs that each sensor/input sends the robot

Individual potential fields (motor schemas) contain state

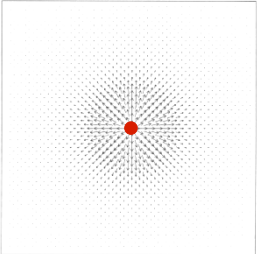
A sequencing process (FSM/ DFA) updates the potential fields and/or decides which ones to run next...



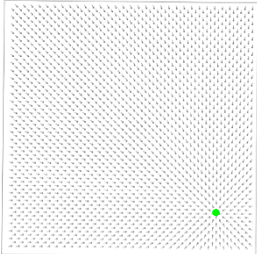
Ron Arkin @ Georgia Tech

Motor Schemas / Potential Fields

Direct mapping from the environment to a control signal



obstacle-avoiding schema

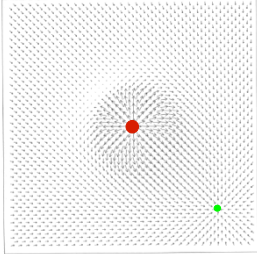


goal-seeking schema

note that the complete environmental vector fields are only for visualization!

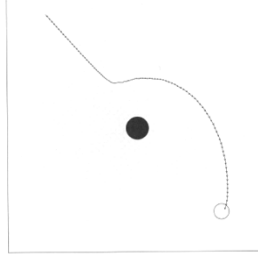
combine?

Behavior Summer

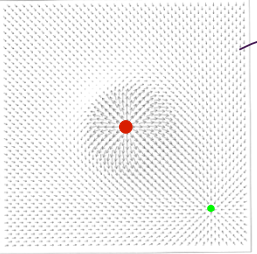


vector sum of the avoid and goal motor schemas

path taken by a robot controlled by the resulting field

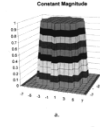


Implementation details

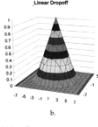


the extent to which potential field force drops off with distance...

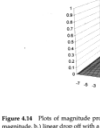
what crucial assumption is being made here?



Constant Magnitude



Linear Dropoff

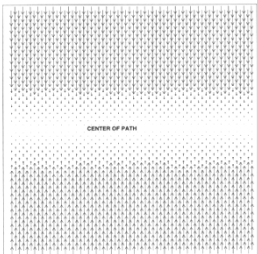


Exponential dropoff

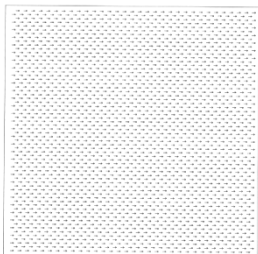
Figure 4.10 Plots of magnitude profiles for a field of radius 5 units: a) constant magnitude, b) linear drop off with a slope of -1, and c) exponential drop-off.

corridor-following schema(s)?

Additional behavior primitives



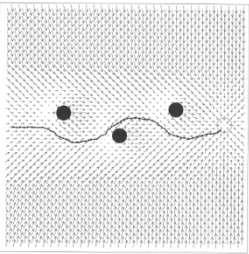
corridor-centering schema



go! schema

A more complex task

Direct mapping from the environment to a control signal



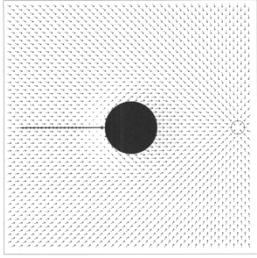
larger composite task

How many individual fields are summed in this task?

Not necessarily all at one time!

Local minima

A potential-field-based system can get stuck!



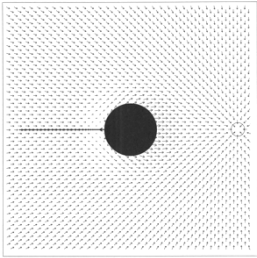
the problem

What would happen if a robot came in in the middle on the left?

a solution?

Local minima

A potential-field-based system can get stuck!



the problem

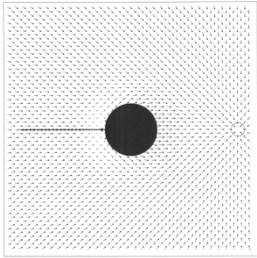
Why is the "local minimum" problem, as illustrated to the left, *not* likely to actually cause a robot to get stuck in practice?

robots controlled by summing goal/obstacle potential fields *can* get stuck in practice -- draw an example of an environment with both obstacle(s) and goal(s) in which getting stuck might actually occur.

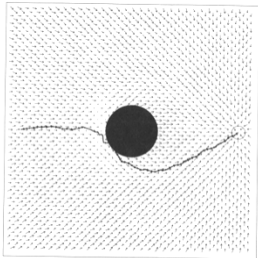
Suggest how a robot might overcome the problem of getting stuck in such cases...

Local minima

A potential-field-based system can get stuck!



the problem



a solution

Bigger deadends...

How to get out of larger wells ?

The diagram shows a robot (black circle) at the end of a long horizontal passage. A path is shown starting from the robot, moving left, then up, then right, and finally down to a goal (black circle) at the bottom right. The path is labeled with 'Magnitude 0.80 Direction 0.445' at the start and 'Goal' at the end.

Bigger deadends...

uses memory of where the robot has been

The left diagram is identical to the one in the previous slide. The right diagram shows the robot's path as it moves back and forth in the dead-end, eventually finding a way to turn back and exit the passage. The path is labeled with 'Magnitude 0.80 Direction -0.053' at the start and 'Goal' at the end.

past-avoiding motor schema

Another example

Keeping away from past locations...

The left diagram shows a robot in a maze with a path that loops back to a previously visited area. The right diagram shows the robot's path as it explores the maze, avoiding previously visited areas. The path is labeled with 'Magnitude 0.80 Direction -0.136' at the start and 'Goal' at the end.

Pfields in Practice


Stealthy navigation @ USC (Ashley Tews, Gaurav S. Sukhatme, and Maja J. Mataric)

The image shows a 3D perspective view of a robot (red dot) navigating through a complex environment. The path is shown as a green line. The environment is represented by a grid of black and white pixels. The path is labeled with 'Magnitude 0.80 Direction -0.136' at the start and 'Goal' at the end.

part of the potential field... What's going on here?

Docking with potential fields

Why might a simple attractive force not be sufficient for docking (plugging-in, etc.)?

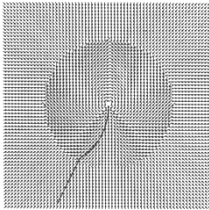



example goals

How does the idea of docking, e.g., with an electrical outlet change the requirements for a potential field?

Docking with potential fields

The key insight is the need to establish an approach *direction*



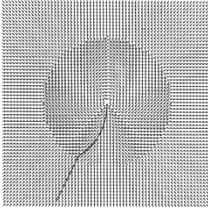


example goals

Figure 4.25 Docking potential field showing path of robot entering from slightly off course.

Docking with potential fields

The key insight is the need to establish an approach *direction*



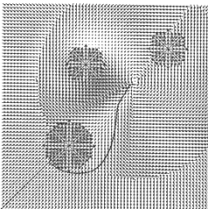


Figure 4.25 Docking potential field showing path of robot entering from slightly off course.

Figure 4.26 Visualization of the docking behavior with obstacles.

+ Review

- Machine learning
 - general learning concepts
 - supervised vs. unsupervised
 - features/feature-based problems/feature space
 - bias/variance
 - overfitting
 - hyperplanes/linear separability
 - Supervised learning
 - applications
 - approaches
 - k-NN
 - decision trees
 - NB
 - SVM (large margin classifiers)
 - Ensemble approaches (boosting)

+ Review

- Machine learning (continued)
 - unsupervised learning
 - application
 - issues
 - number of clusters
 - flat vs. hierarchical
 - soft vs. hard clustering
 - approaches
 - k-means
 - EM
 - word alignment
 - clustering (mixture of gaussians)
 - spectral clustering (min-cut)

+ Review

- Neural networks (Machine learning?)
 - perceptrons/neurons
 - activation functions (threshold vs. sigmoid)
 - perceptron learning
 - multi-layer networks
- Knowledge representation
 - basic logic
 - ontology
 - NELL

+ Review

- CSPs
 - problem formulation
 - variables
 - domain
 - constraints
 - why CSPs? applications?
 - constraint graph
 - CSP as search
 - backtracking algorithm
 - forward checking
 - arc consistency
 - heuristics
 - most constrained variable
 - least constrained value
 - ...

+ Review

- Natural language processing
 - Applications
 - Problem areas
 - Why it's hard?
 - Machine translation setup

+ Guest speaker

- Rodney Brooks
 - Professor at MIT (was previous director of CSAIL)
 - Founder of iRobot
- <http://www.youtube.com/watch?v=B79D9nW2AFA>