Robotics/Perception II

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Outline

- Sensors - summary
- Computer systems
- Robotic architectures
- Mapping and Localization
- Motion planning
- Motion control

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DARPA Challenges - application examples/challenges

2004 Grand Challenge - 240 km route in the Mojave Desert.

None of the vehicles finished the route. Sandstorm (Red Team,CMU) - 11.78 km of the course before getting hung up on a rock.

2005 Grand Challenge - Three narrow tunnels and more than 100 sharp left and right turns.

Vehicle	Team Name	Team Home	Time Taken (h:m)	Result
Stanley	Stanford Racing Team	Stanford University, Palo Alto, California	6:54	First place
Sandstorm	Red Team	Carnegie Mellon University, Pittsburgh, Pennsylvania	7:05	Second place
H1ghlander	Red Team	Carnegie Mellon University, Pittsburgh, Pennsylvania	7:14	Third place
Kat-5	Team Gray	The Gray Insurance Company, Metairie, Louisiana	7:30	Fourth place
TerraMax	Team TerraMax	Oshkosh Truck Corporation, Oshkosh, Wisconsin	12:51	Over 10 hour limit, fifth place

2007 Urban Challenge - 96 km urban area course, to be completed in less than 6 hours. Rules included obeying all traffic regulations while negotiating with other traffic and obstacles and merging into traffic.

2012 Robotics Challenge - ongoing focusing on humanoid robots.

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Anatomy of Robots

Robots consist of:

- Motion mechanism
  - Wheels, belts, legs, propellers, rotors
- Manipulators
  - Arms, grippers
- Sensors
- Computer systems
  - Microcontrollers, embedded systems
- Body/Frame

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Sensors

Summary of most commonly used sensor for mobile robots.

	Any weather	Any light	Detection in 15m	Fast response	Weight	Affordable
CCD Camera/stereo/ Omnidirectional/o. flow			👍	👍	👍	👍
Ultrasonic		👍		👍	👍	👍
Scanning laser		👍	👍	👍		👍
3D Scanning laser		👍	👍			👍*
Millimeter Wave Radar	👍	👍	👍	👍		

* scanning laser on a tilting unit

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Sensors - common interfaces

- analog - voltage level
- digital:
  - serial connections e.g.:
    - RS232
    - I2C
    - SPI
    - USB
  - pulse width modulation - PWM
  - …

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Computer systems

Many challenges and trade-offs!

- power consumption
- size & weight
- computational power
- robustness
- different operational conditions - moisture, temperature, dirt, vibrations, etc.

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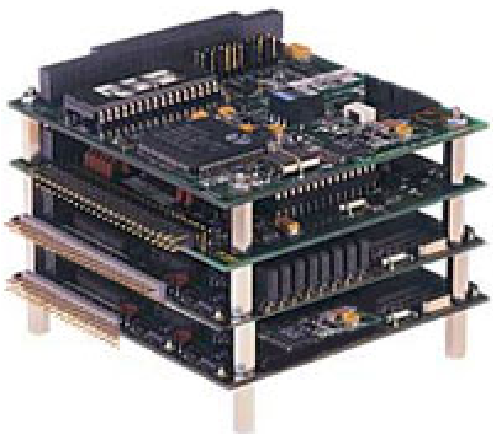
Computer systems cont'd

PC104 - standardised form factor

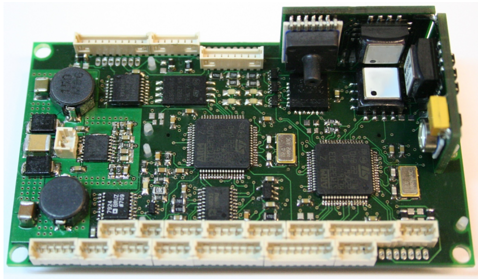
- industrial grade,
- relatively small size,
- highly configurable,
- >200 vendors world-wide,
- variety of components
- variety of processors

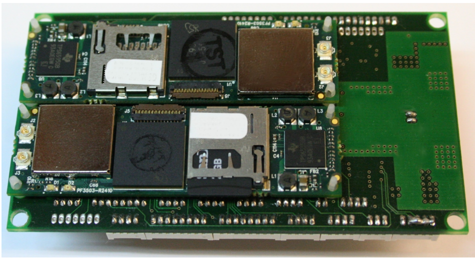


Computer systems cont'd

Custom made embedded systems

- with integrated sensor suite
- micro scale, light weight
- fitted for platform design

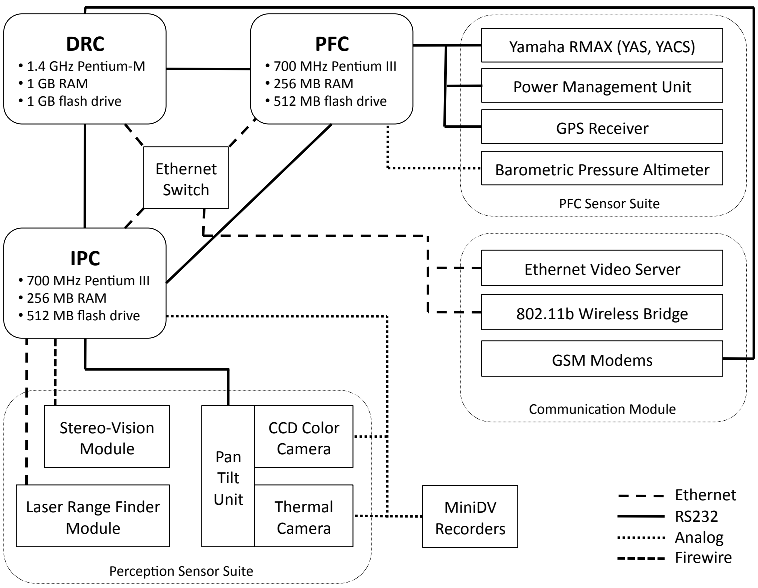




- application specific

Computer systems cont'd

Example system design:



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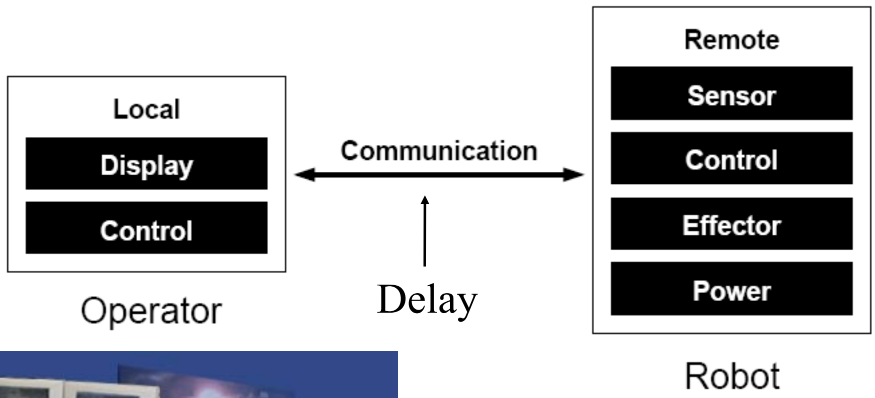
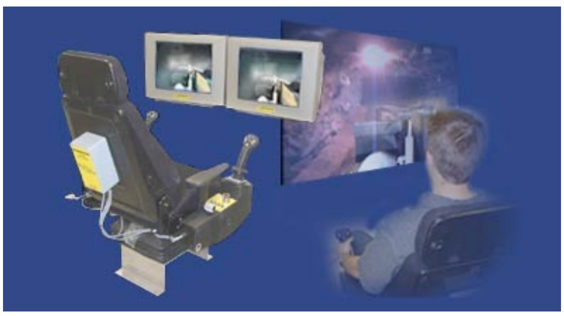
Telesystems/Telemanipulators





Video

Telepresence

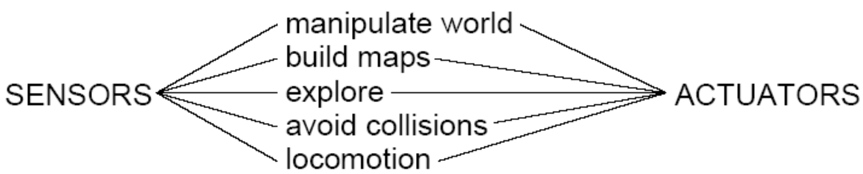
Experience of being fully present at live event without actually being there
- see the environment through robot’s cameras
- feel the surrounding through robot sensors

Realized by for example:
- stereo vision
- sound feedback
- cameras that follow the operator’s head movements
- force feedback and tactile sensing
- VR system

Reactive systems

SENSE ⟺ ACT

Robot responses **directly to sensor stimuli**.
Intelligence emerges from combination of simple behaviours.
E.g. - subsumption architecture (Rodney Brooks, MIT):
- concurrent behaviours
- higher levels subsume behaviours of lower layers
- no internal representation
- finite state machines

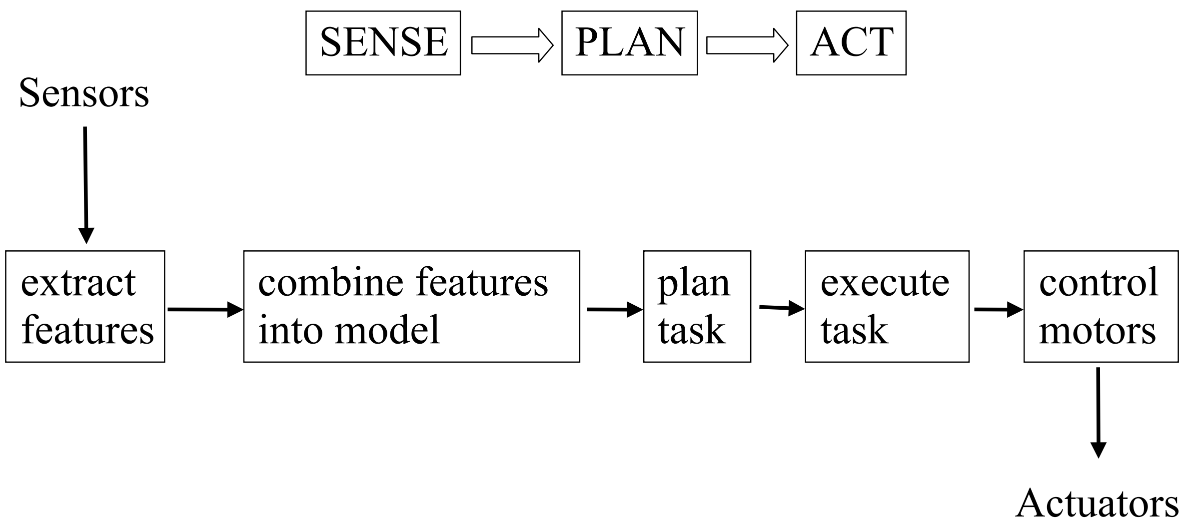


Video

Limitations of Reactive Systems

- Agents without environment models must have sufficient information available from local environment
- If decisions are based on *local* environment, how does it take into account *non-local* information (i.e., it has a "short-term" view)
- Difficult to make reactive agents that learn
- Since behaviour emerges from component interactions plus environment, it is hard to see how to *engineer* specific agents (no principled methodology exists)
- It is hard to engineer agents with large numbers of behaviours (dynamics of interactions become too complex to understand)

Hierarchical Systems



Hierarchical Systems (Shakey Example)

Shakey (1966 - 1972)

- Developed at the Stanford Research Institute
- Used STRIPS planner (operators, pre and post conditions)
- Navigated in an office environment, trying to satisfy a goal given to it on a teletype. It would, depending on the goal and circumstances, navigate around obstacles consisting of large painted blocks and wedges, push them out of the way, or push them to some desired location.
- Primary sensor: black-and-white television camera
- Sting symbolic logic model of the world in the form of first order predicate calculus
- Very careful engineering of the environment

Video

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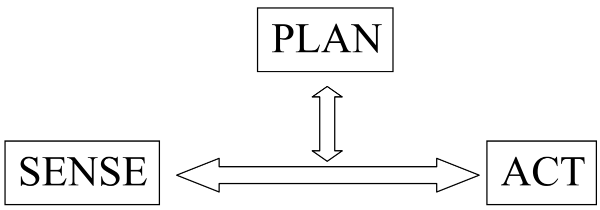
Hybrid systems (three-layer architecture)



Deliberative layer (planning)

Executive layer (sequencing)

Reactive layer (skills, control)

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Hybrid systems (Minerva Example)

Tour guide at the Smithsonian's National Museum of American History (1998)

high-level control and learning (mission planning, scheduling)
human interaction modules ("emotional" FSA, Web interface)
navigation modules (localization, map learning, path planning)
hardware interface modules (motors, sensors, Internet)

Table 1: Minerva's layered software architecture

Video

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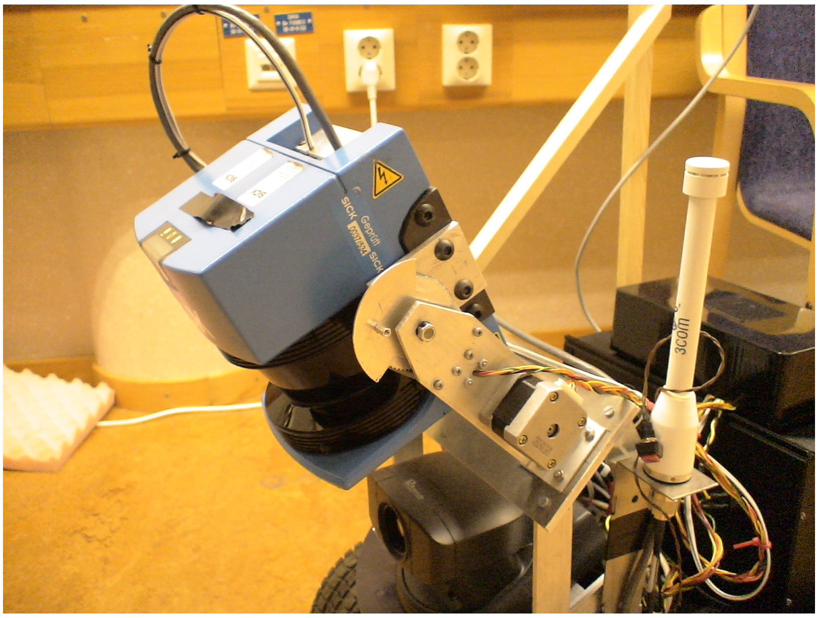
Autonomous UAV Technologies

Laser Range Finder



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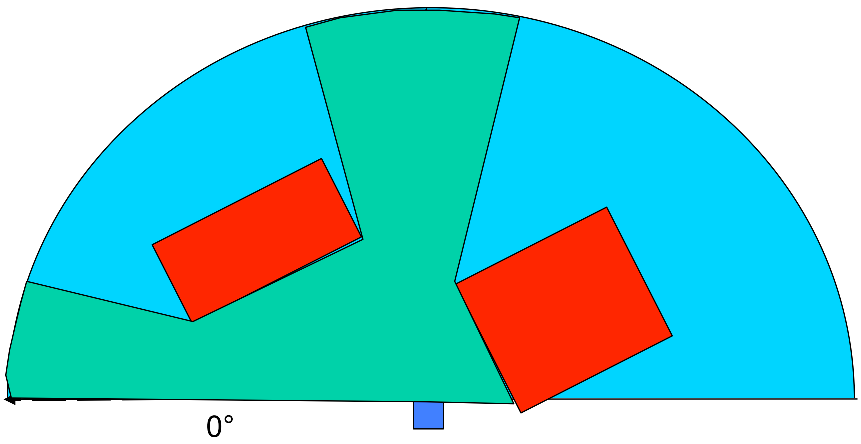
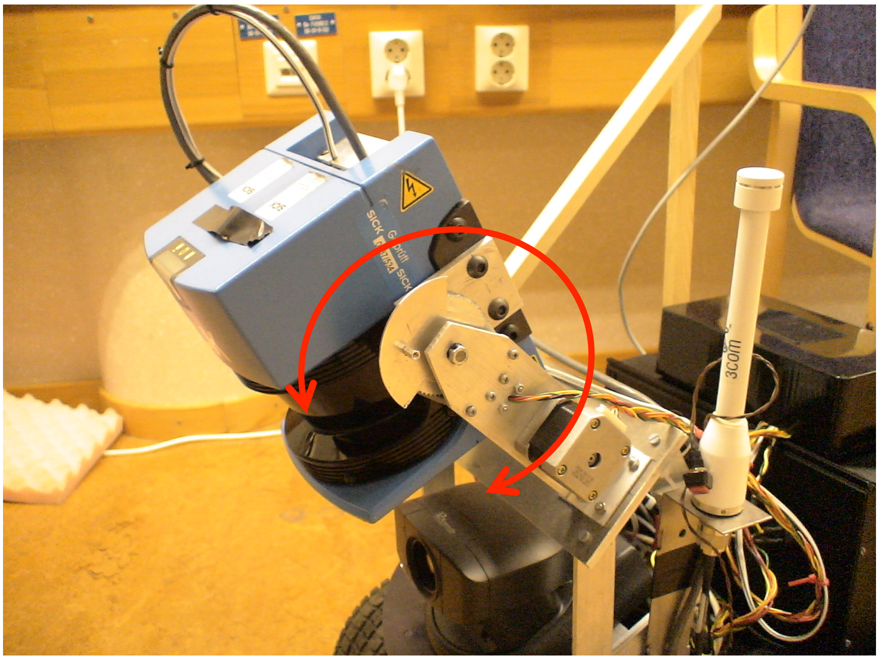
Laser Range Finder - the principle



View from top

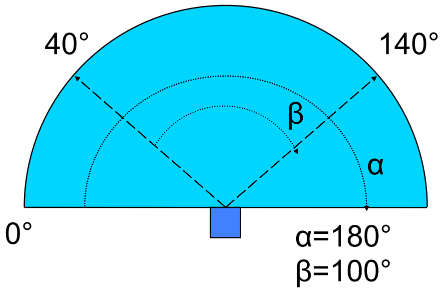
Video

Laser Range Finder - the principle cont'd



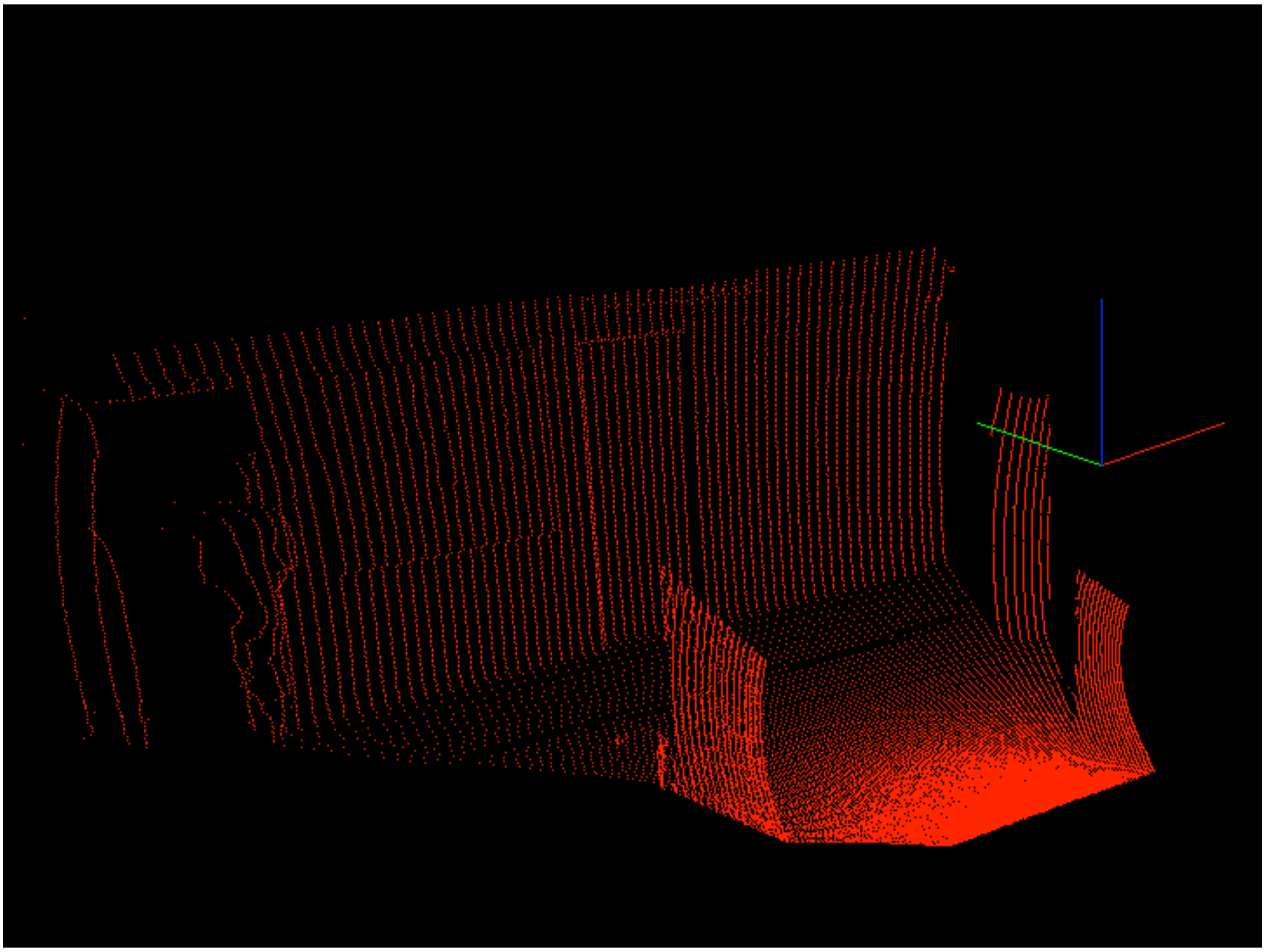
SICK LMS Resolution Modes

Angular range	Angular resolution
0°..100°	1°
0°..100°	0.5°
0°..100°	0.25
0°..180°	1°
0°..180°	0.5°



View from top

Mode	Measurement Range
mm mode	0..8191mm = 8.191meters
cm mode	0..8191cm = 81.91meters



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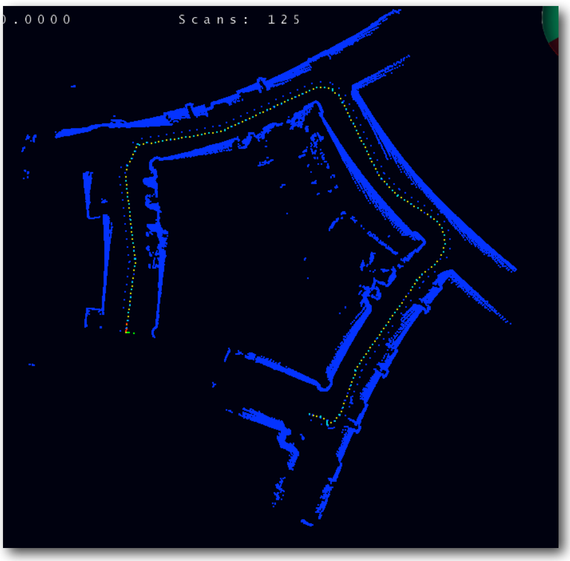
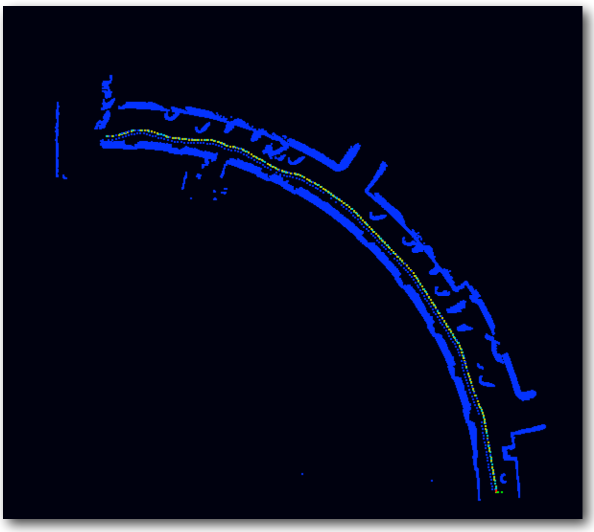
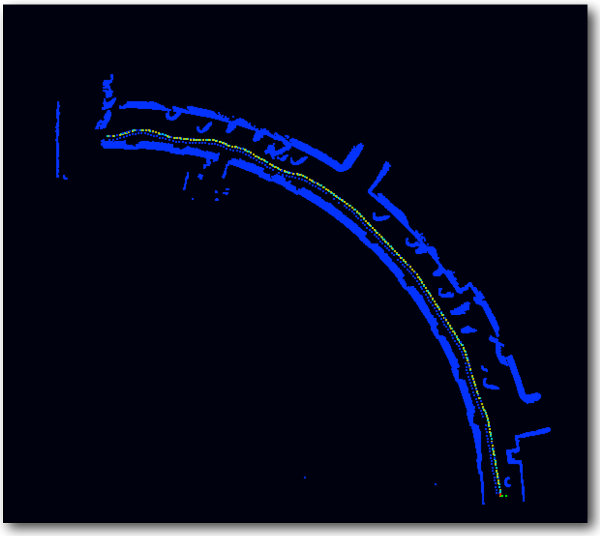
Mapping





Based only on odometry + range data

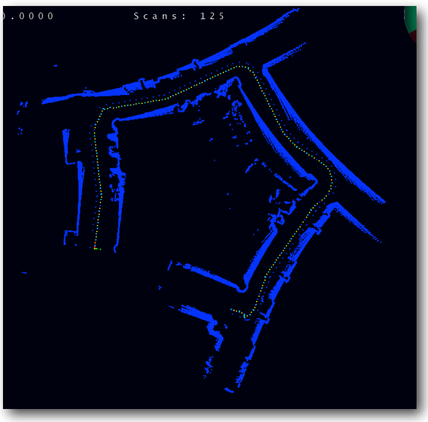
Mapping cont’d

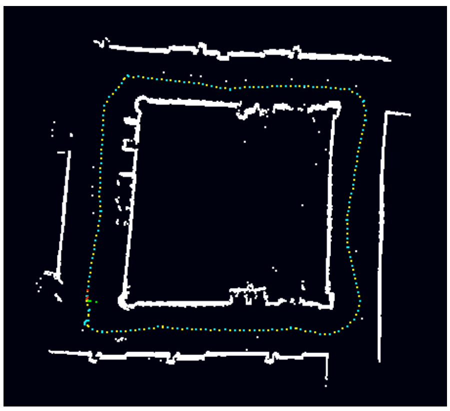


Based only on odometry + range data + matching

3D Mapping video

Mapping cont’d





Based only on odometry + range data + matching

Robotic perception

Robot perception viewed as **temporal inference from sequences of actions and measurements** → dynamic Bayes network of first order Markov process

Example: **localization** - holonomic robot with range sensor, estimate pose while moving

$\vec{x}_t = (x_t, y_t, \theta)^T$ not observable current state

$\vec{a}_t = (v_t, \omega_t)^T$ known action

$\vec{o}_t = (range1, range2, \cdots)^T$ observable sensor reading

$\mathrm{Bel}(\vec{x}_t) = \mathrm{p}(\vec{x}_t | \vec{o}_{1:t}, \vec{a}_{1:t-1})$ current belief state (captures past)

next belief state? → Bayesian inference problem

Recursive filtering equation

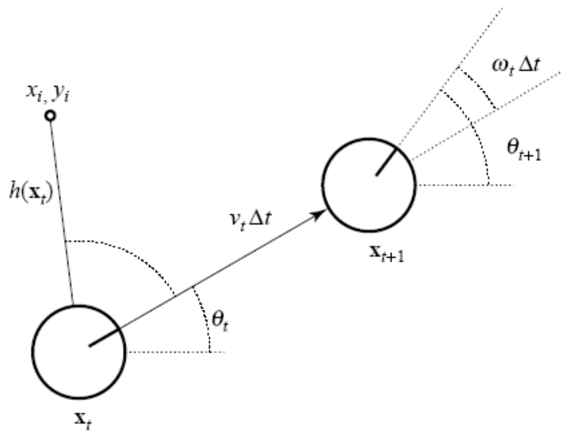
$$\mathrm{Bel}(\vec{x}_t) = \alpha \underbrace{\mathrm{p}(\vec{o}_t | \vec{x}_t)}_{\text{sensor model}} \int \underbrace{\mathrm{p}(\vec{x}_t | \vec{x}_{t-1}, \vec{a}_{t-1})}_{\text{motion model}} \underbrace{\mathrm{Bel}(\vec{x}_{t-1})}_{\text{previous belief state}} d\vec{x}_t$$

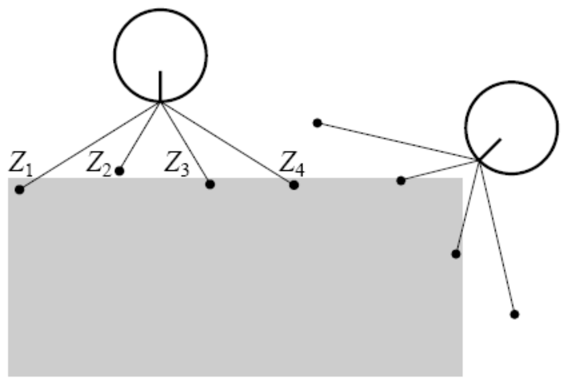
using Bayes' rule, Markov assumption, theorem of total probability

Motion model: deterministic state prediction + noise

Sensor model: likelihood of making observation o_t when robot is in state x_t

Motion and sensor model





Assume Gaussian noise in motion prediction, sensor range measurements

Localization algorithms

Particle filter (Monte Carlo localization):

- belief state - a collection of particles that correspond to states
- belief state sampled, each sample weighted by likelihood it assigns to new evidence, population resampled using weights

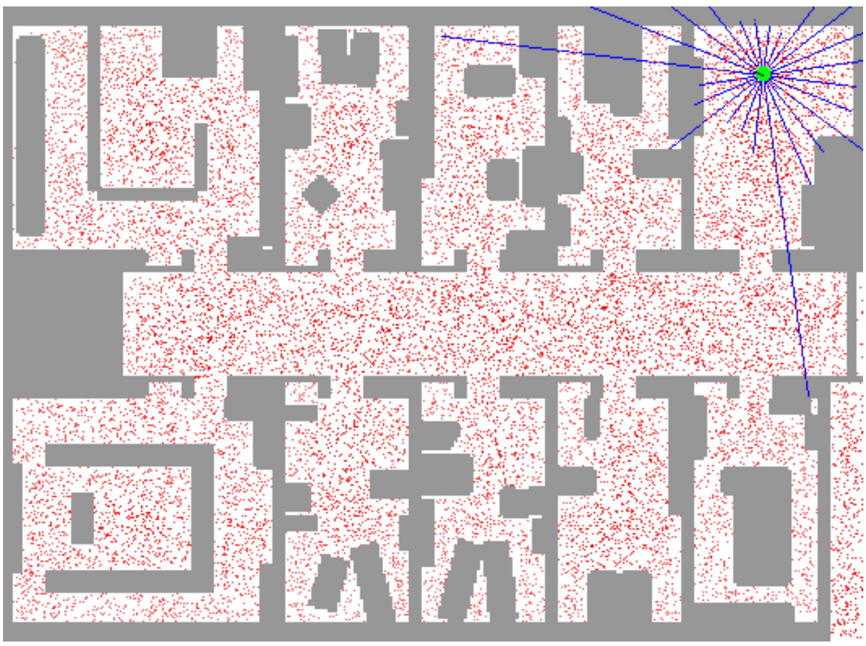
Kalman filter:

- belief state - a single multivariate Gaussian
- each step maps a Gaussian into a new Gaussian, i.e. it computes a new mean and covariance matrix from the previous mean and covariance matrix
- assumes linear motion and measurement models (linearization →extended KF)

Global Localization (Particle Filter Examples)

$$\mathrm{Bel}(\vec{x}_t) = \alpha \underbrace{p(\vec{o}_t|\vec{x}_t)}_{\text{sensor model}} \int \underbrace{p(\vec{x}_t|\vec{x}_{t-1},\vec{a}_{t-1})}_{\text{motion model}} \underbrace{\mathrm{Bel}(\vec{x}_{t-1})}_{\text{previous belief state}} \, d\vec{x}_t$$

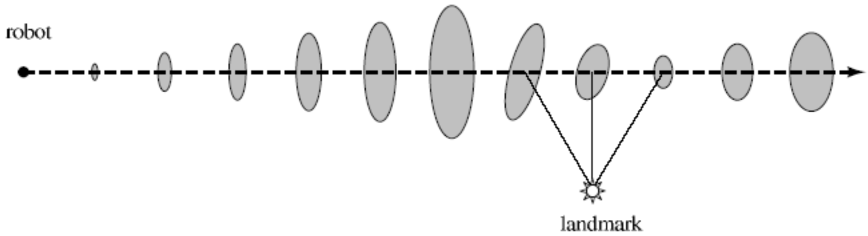
Global Localization (Particle Filter Examples; sonar vs laser)



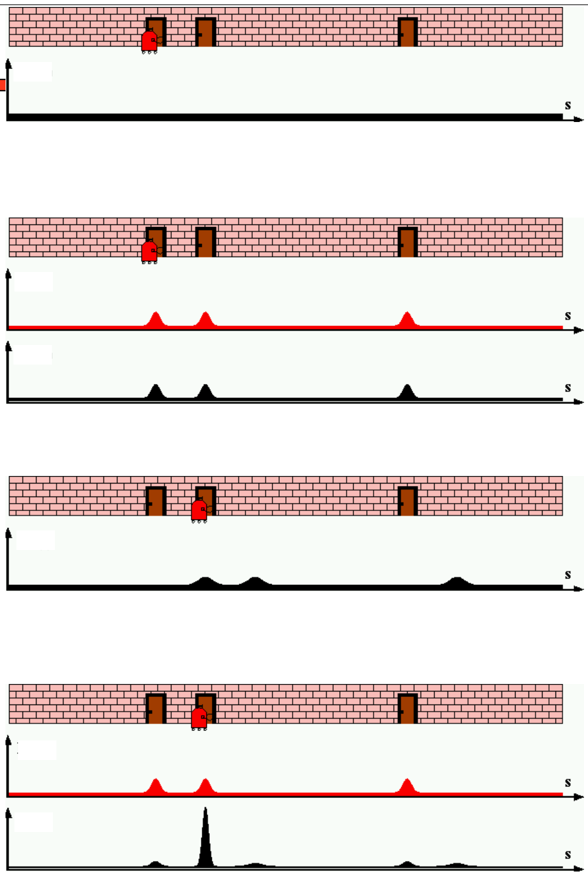
Video_sonar

Video_laser

Extended Kalman Filter (EKF) - example



EKF example



SLAM

Localization: given map and observed landmarks, update pose distribution

Mapping: given pose and observed landmarks, update map distribution

SLAM: given observed landmarks, update pose and map distribution

Probabilistic formulation of SLAM:

add landmark locations $L_1, \ldots, L_k$ to the state vector, proceed as for localization

Problems:

- dimensionality of map features has to be adjusted dynamically
- identification of already mapped features

Laser-based SLAM Video Distributed SLAM Video

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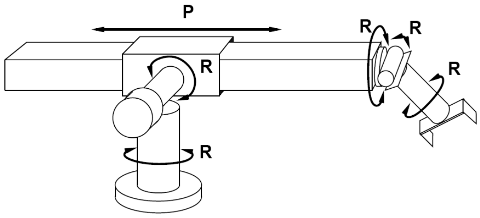
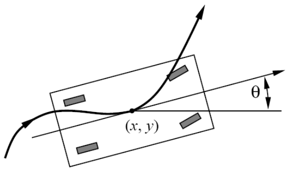
Degree of freedom (DOF)

One DOF for each independent direction in which robot can move



Configuration of robot specified by 6 numbers => 6 DOFs

Non-holonomic: number of effective DOFs less than controllable DOFs



Car has 3 effective DOF and 2 controls =>non-holonomic

Motion Planning

Motion types:

- point-to-point
- compliant motion (screwing, pushing boxes)

Representations: configuration space vs workspace

Kinematic state: robot's configuration (location, orientation, joint angles), no velocities, no forces

Path planning: find path from one configuration to another

Problem: continuous state space, can be high-dimensional

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Motion Planning - representations

Workspace - physical 3D space (e.g. joint positions)

Robot has rigid body of finite size

Well-suited for collision checking

Problem: linkage constraints (not all workspace coordinates attainable) makes path planning difficult in workspace

Configuration Space - space of robot states (e.g. joint angles)

Robot is a point, obstacles have complex shapes

Problem: tasks are expressed in workspace coordinates, obstacle representation problematic

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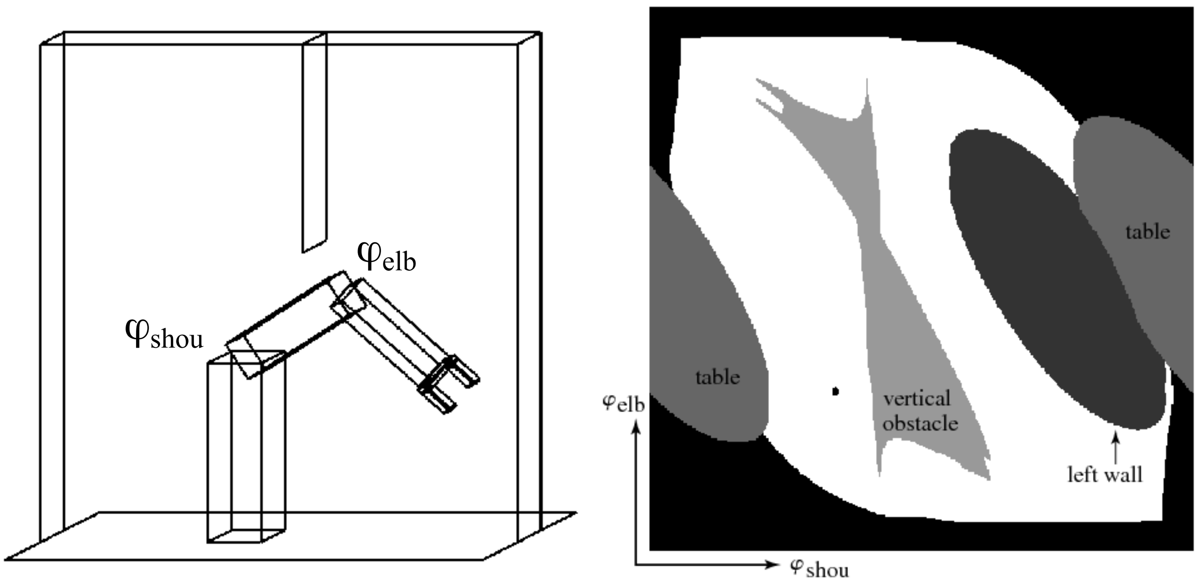
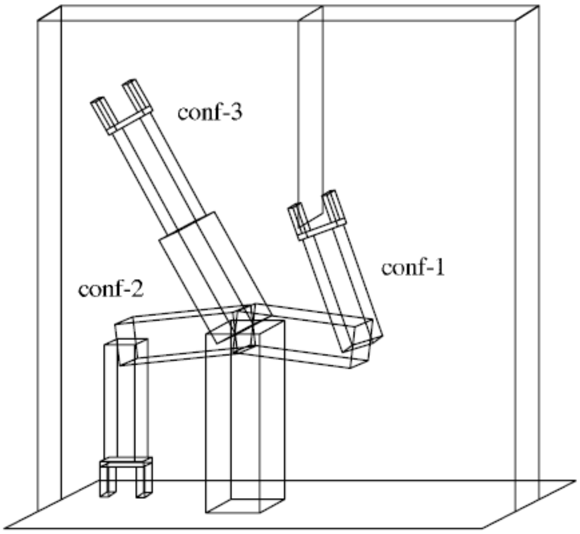
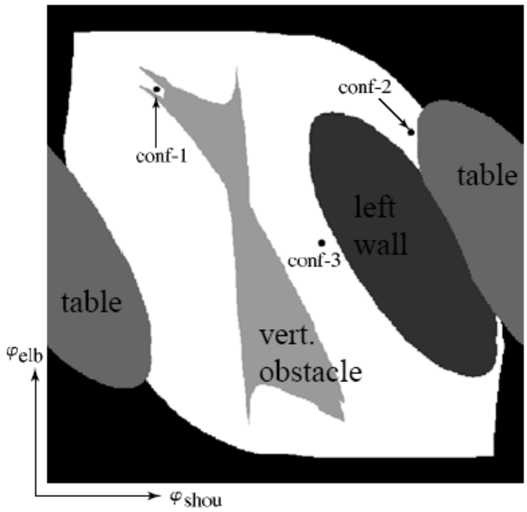
Workspace vs. Configuration Space



Workspace vs. Configuration Space





Motion Planning - representations

- Free space (attainable configurations) ->occupied space (not attainable configurations, obstacles)
- Planner may generate configuration in configuration space, apply inverse kinematics and check in workspace for obstacles

Inverse kinematics (often hard and ill-posed problem)

Workspace → Configuration Space

Configuration Space → Workspace

Kinematics (simple, well-posed problem)

Path Planning

Basic problem: convert infinite number of states into finite state space

Cell decomposition:

- divide up space into simple *cells*,
- each of which can be traversed “easily”

Skeletonization:

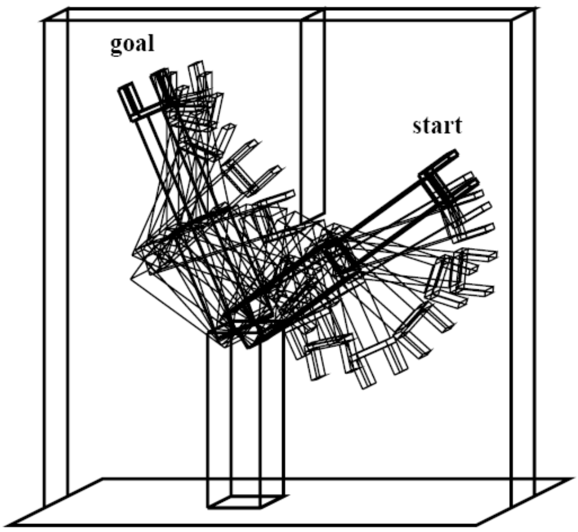
- identify a finite number of easily connected points/lines
- form a graph such that any two points are connected by a path

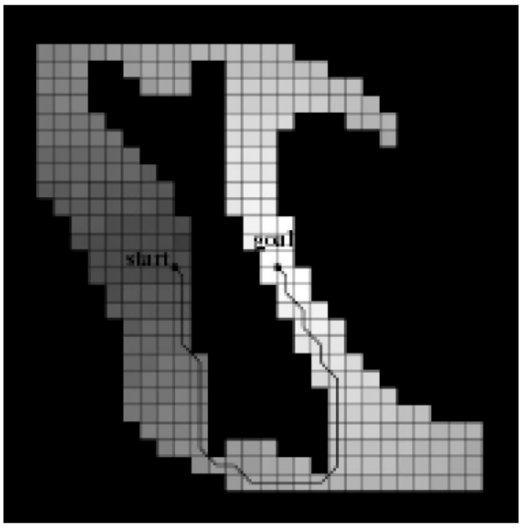
Graph search and colouring algorithms

Assumptions: motion deterministic, localization exact, static scenes

Not robust with respect to small motion errors, does not consider limits due to robot dynamics

Cell Decomposition





Grayscale shading - cost from the grid cell do the goal

Cell Decomposition

Problem: may be no path in pure free space cells

Soundness

(wrong solution if cells are mixed)

vs.

Completeness

(no solution if only pure free cells considered)

Solution: recursive decomposition of mixed (free+obstacle) cells or exact decomposition

Doesn't scale well for higher dimensions

Skeletonization

Visibility graphs: find lines connecting obstacle vertices through free space, build and search graph; not for higher dimensions

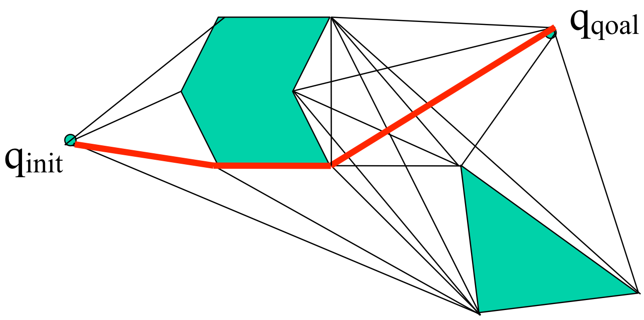
Voronoi graphs: find all points in free space equidistant to two or more obstacles, build and search graph; maximizes clearance, creates unnecessarily large detours, does not scale well for higher dimensions

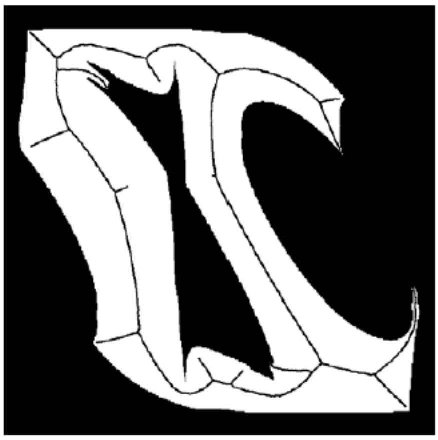
Probabilistic roadmaps:

- generate randomly large number of configurations in free space, build graph (construction phase)
- search graph (query phase)

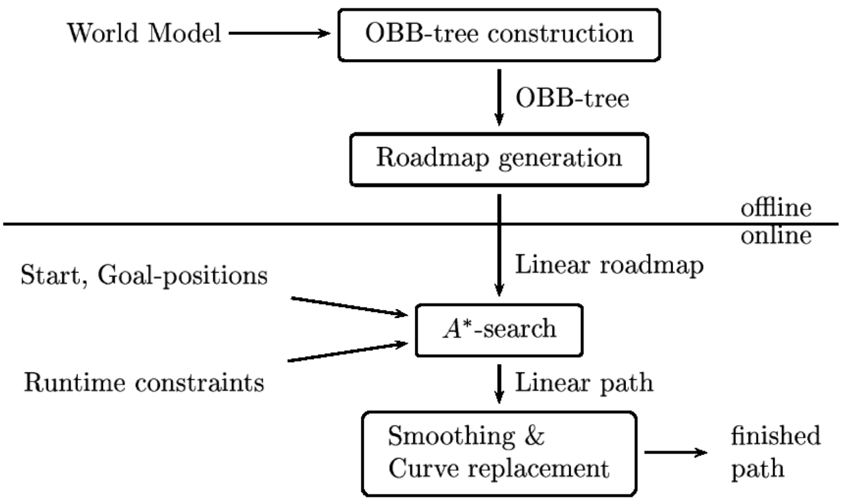
scales better to higher dimensions but incomplete

Visibility and Voronoi Graph

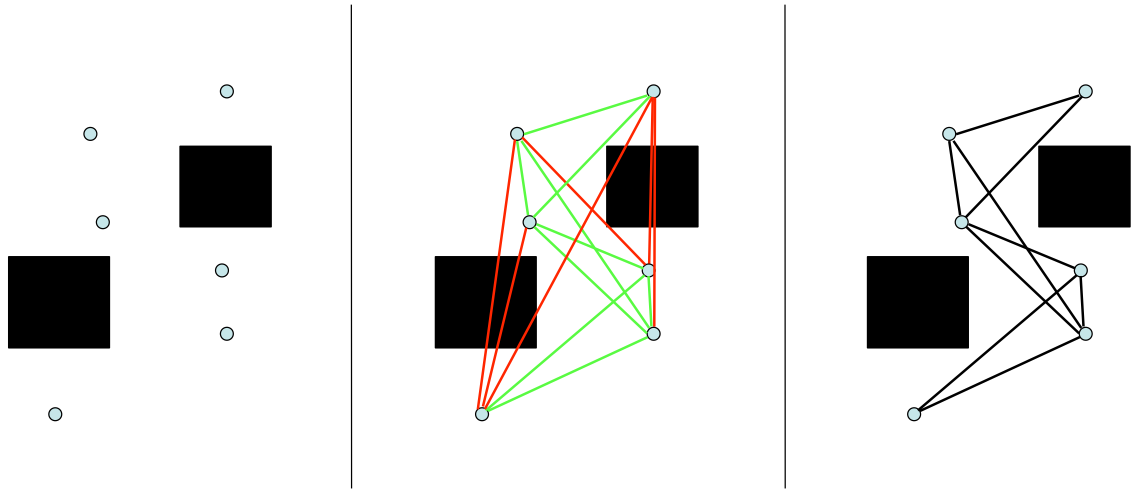




Probabilistic Roadmaps (PRM planning procedure example)



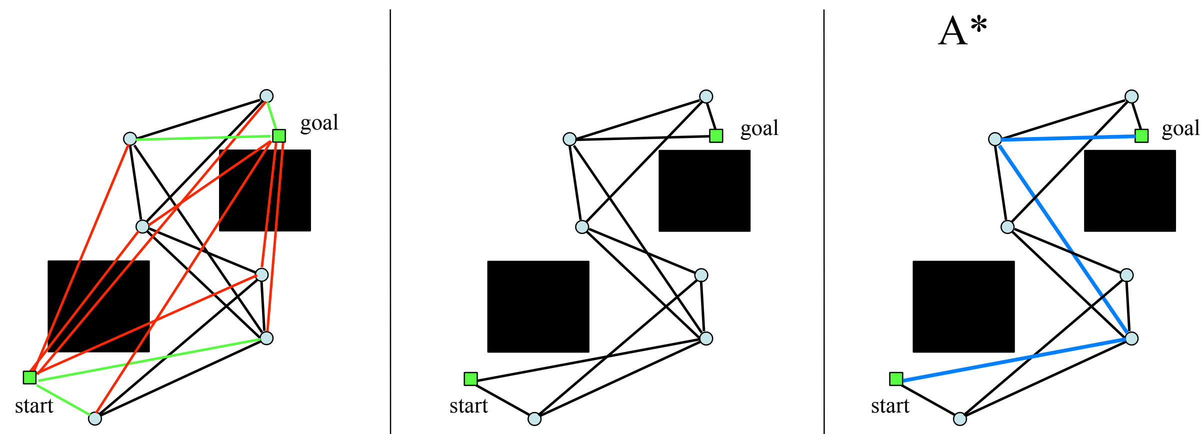
Probabilistic Roadmaps
(PRM planning procedure example: Construction phase)



Generate random configurations

Make connections

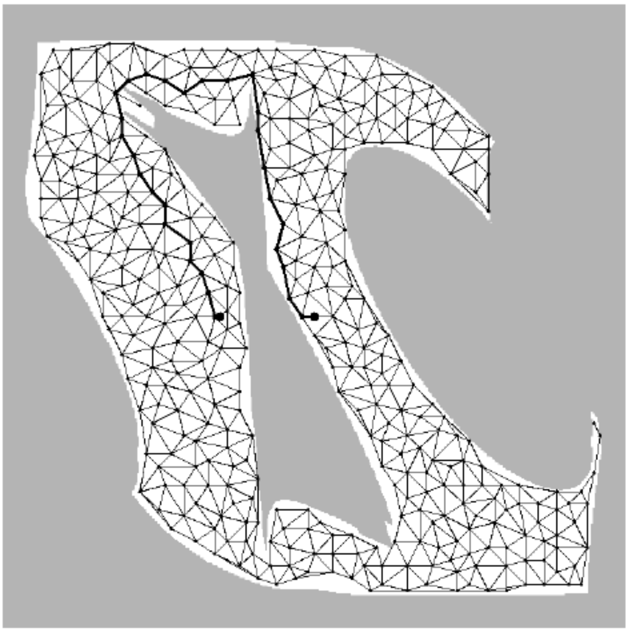
Probabilistic Roadmaps
(PRM planning procedure example: Query Phase)



Add start and goal configurations to the roadmap

Curve Replacement & Smoothing

Probabilistic Roadmaps



Potential Fields

Additional cost function in connectivity graph:
potential grows when closer to obstacles
Maximises clearance from obstacles while minimising path length:

- creates safer paths

Problem: choosing appropriate weights

Motion Control

- Path following involves forces: friction, gravity, inertia,
- Dynamic state: kinematic state + robot's velocities
- Transition models expressed as differential equations
- Path planner assumes robot can follow any path
- Robot's inertia limits manoeuvrability

Problem: including dynamic state in planners makes motion planning intractable

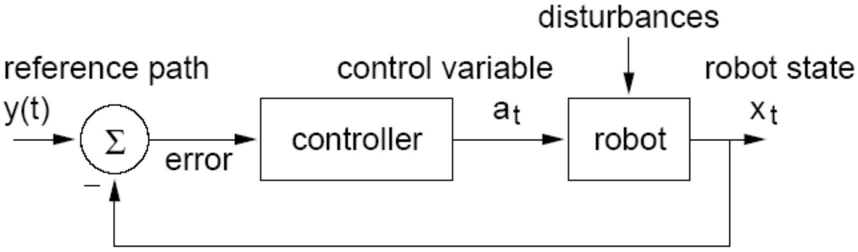
Solution: simple kinematic planners + low-level controller for force calculation

Other solution: motion control without planning: potential field and reactive control

Controllers

- Techniques for **generating robot controls in real time** using feedback from the environment to achieve a control objective
- Reference controller: keep robot on pre-planned path (reference path)
- Optimal controller: controller that optimizes a global cost function, e.g. optimal policies for MDPs
- Stable: small perturbations lead to bounded error between robot and reference signal
- Strictly stable: able to return to reference signal

Closed-loop control

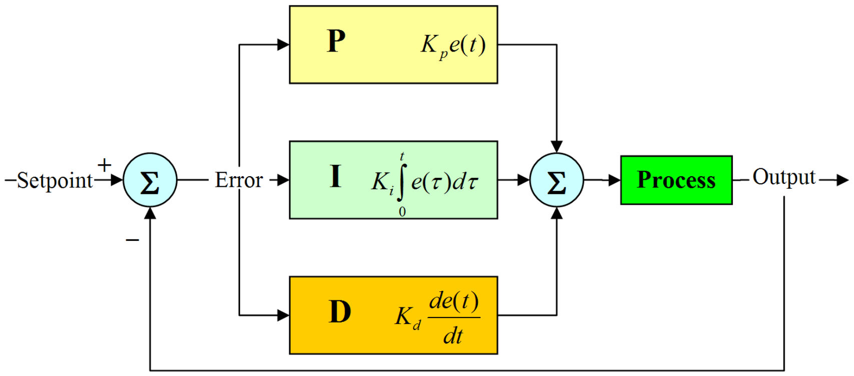


Performance of controller:

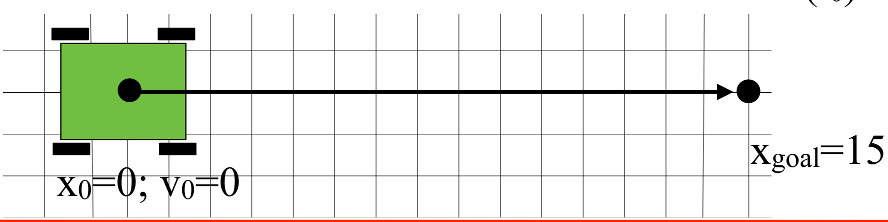
- stability
- overshoot ← inertia
  - steady-state error ← friction
- rise time
  - settling time

P controller: $a_t = K_P(y(t) - x_t)$ K_P gain parameter

PID Example



$e(t_0) = x_{goal} - x_0 = 15$



Closed-loop control

PD controller: $$a_t = K_P(y(t) - x_t) + K_D \frac{\partial(y(t) - x_t)}{\partial t}$$

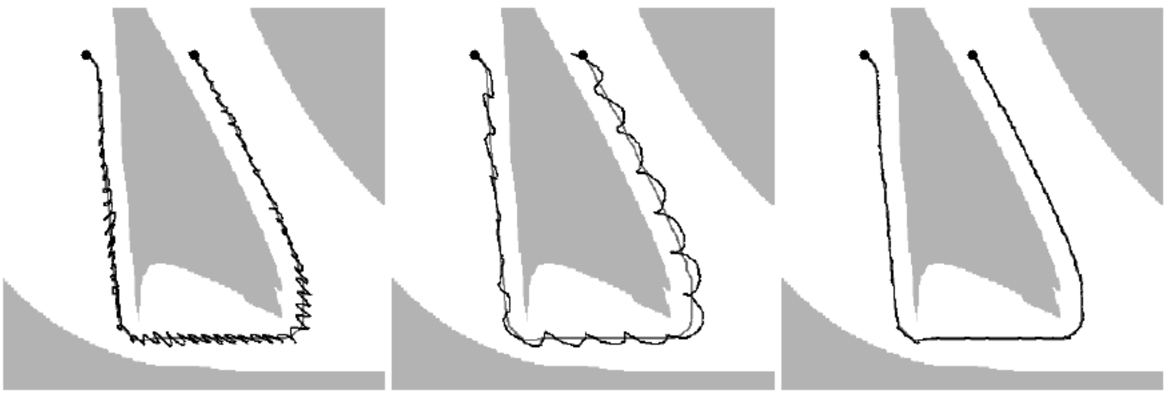
- decreases overshoot
- decreases settling time

PID controller:

$$a_t = K_P(y(t) - x_t) + K_D \frac{\partial(y(t) - x_t)}{\partial t} + K_I \int (y(t) - x_t)\, dt$$

- eliminates steady-state error

Closed-loop control



P control $K_P = 1.0$

P control $K_P = 0.1$

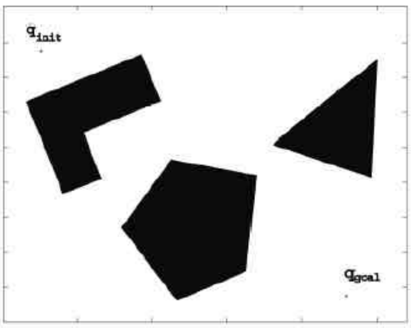
PD control $K_P = 0.3,\ K_D = 0.3$

Potential Field Control

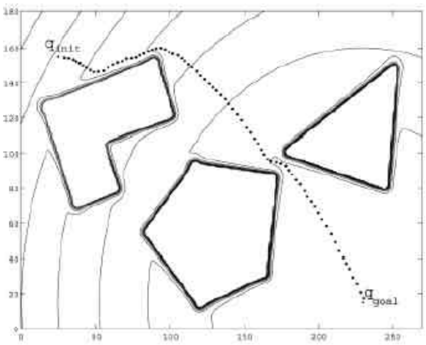
- Motion planning: pot. field as additional cost function
- Generating robot motion directly: superpose potential field of obstacles with field generated by an attractive force, follow the gradient
- Efficient calculation possible, especially compared to path planning
- Problem: local minima, only kinematic method

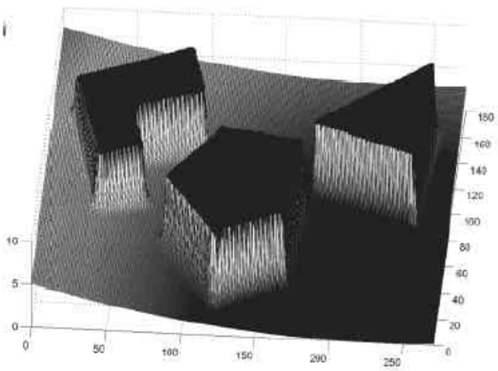
Video

Potential Field Control



- Robot is treated as a *point under the influence* of an artificial potential field.
- Generated robot movement is similar to a ball rolling down the hill
  - Goal generates attractive force
  - Obstacle are repulsive forces





Siegwart, I. Nourbakhsh

Reactive Control

Before: model of environment required (reference path, potential field)

Problems with model based approaches:

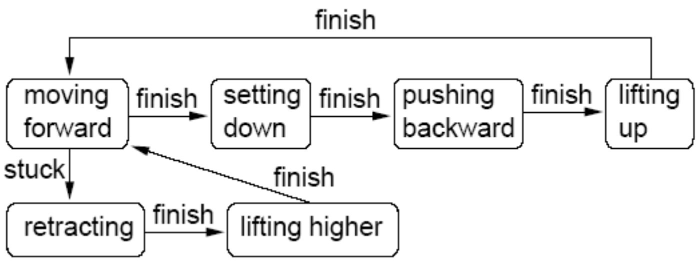
- accurate models are difficult to obtain, especially in complex or remote environments
- computational difficulties, localization errors

→ reactive control

Event driven systems (↔transformational systems) →finite state machines

Environment feedback plays crucial role in the generated behavior

Reactive Control



Emergent behavior: behavior that emerges through interplay of (simple) controller and (complex) environment

Characteristic of great number of biological organisms

Video

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