“Sensor Fusion Techniques for Mobile Robotics”

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Saturday, September 3 (9h-10h30)
Sensor fusion techniques for mobile robotics

Monday, September 5 (9h-10h30)
Kalman filtering in sensor fusion

Outline

- ✓ Introduction
- ✓ Map building/ Localization
- ✓ Kalman filter
- ✓ SLAM
- ✓ Fault diagnosis

Multisensor data fusion

Technologies

Methodologies

How combine data and information from multiple sensors in order to improve accuracies and inference about the "environment"

To improve

Performances

Reliability

Multisensor data fusion is "new" for artificial intelligent systems

Background

Humans and animals have evolved the capability to use multiple senses ("natural sensors") to improve their capability to "survive" (to "evolve")!!!

Sight
Sound
Smell
Taste
Touch
data

The "brain"

In recent years sensors fusion has been deeply investigated in different fields of "sciences and engineering"

Example

Automatic landing guidance

E. D. Dickmanns, S. Werner, S. Kraus, and R. Schell, "*Experimental results in autonomous landing approaches by dynamic machine vision*, in Proceedings of SPIE - The International Society for Optical Engineering, volume 2220, pp. 304– 313, Orlando, FL, USA, 1994.

B. T. Sweet and C. L. Tiana, "*Image processing and fusion for landing guidance*, in Proc. of SPIE, volume 2736, pp. 84–95, 1996.

Automated target recognition

R. E. Bethel and G. J. Paras, "*PDF multisensor multitarget tracker*, IEEE Transactions on Aerospace and Electronic Systems, vol. 34, no. 1, pp. 153–168, 1998.

B. Bhanu, "*Automatic target recognition:state of the art survey*, IEEE Trans. Aerosp. Elect. Syst., vol. 22, no. 4, pp. 364–376, 1986.

Example ctd.

Monitoring of manufacturing processes

S. Chen and Y. W. Jen, "*Data fusion neural network for tool condition monitoring in CNC milling machining*, International Journal of Machine Tools and Manufacture, vol. 40, no. 3, pp. 381–400, 2000.

M. Yelverton, B. Cusson, T. Timmons, and K. Stoddard, "*Using automatic fault detection to improve diffusion furnace performance and reduce wafer scrap*, MICRO, vol. 17, no. 4, pp. 27–33, 1999.

Remote sensing

B. Haack and M. Bechdol, "*Multisensor remote sensing data for land use/cover mapping*, Computers, Environment and Urban Systems, vol. 23, no. 1, pp. 53–69, 1999.

D. Haverkamp and C. Tsatsoulis, "*Information fusion for estimation of summer MIZ ice concentration from SAR imagery*, IEEE Transactions on Geoscience and Remote Sensing, vol. 37, no. 3, pp. 1278–1291, 1999.

Example ctd.

Robotics

M. A. Abidi and R. C. Gonzalez, *Data Fusion in Robotics and Machine Intelligence*, Academic Press, 1992.

P.K.Allen,*Robotic object recognition using vision and touch*, Kluwer Academic Publishers, 1987.

Medical applications

A. I. Hernandez, G. Carrault, F. Mora, L. Thoraval, G. Passariello, and J. M. Schleich, "*Multisensor fusion for atrial and ventricular activity detection in coronary care monitoring*, IEEE Transactions on Biomedical Engineering, vol. 46, no. 10, pp. 1186–1190, 1999.

A. Hernandez, O. Basset, I. Magnin, A. Bremond, and G. Gimenez, "*Fusion of ultrasonic and radiographic images of the breast*, in Proc. IEEE Ultrasonics Symposium, pp. 1437–1440, San Antonio, TX, USA, 1996.

⋮

There are a lot of contributions proposed by the

- Aeronautics researchers community

- Manufacturing (Robotics) researchers community

Air Traffic Control

- redundant radar antennas
- GPS
- aircraft transponders
- altimeters
- …

Military applications:
- AWACS aircraft
- verify aircraft identity (Identify Friend and Foe)
- …

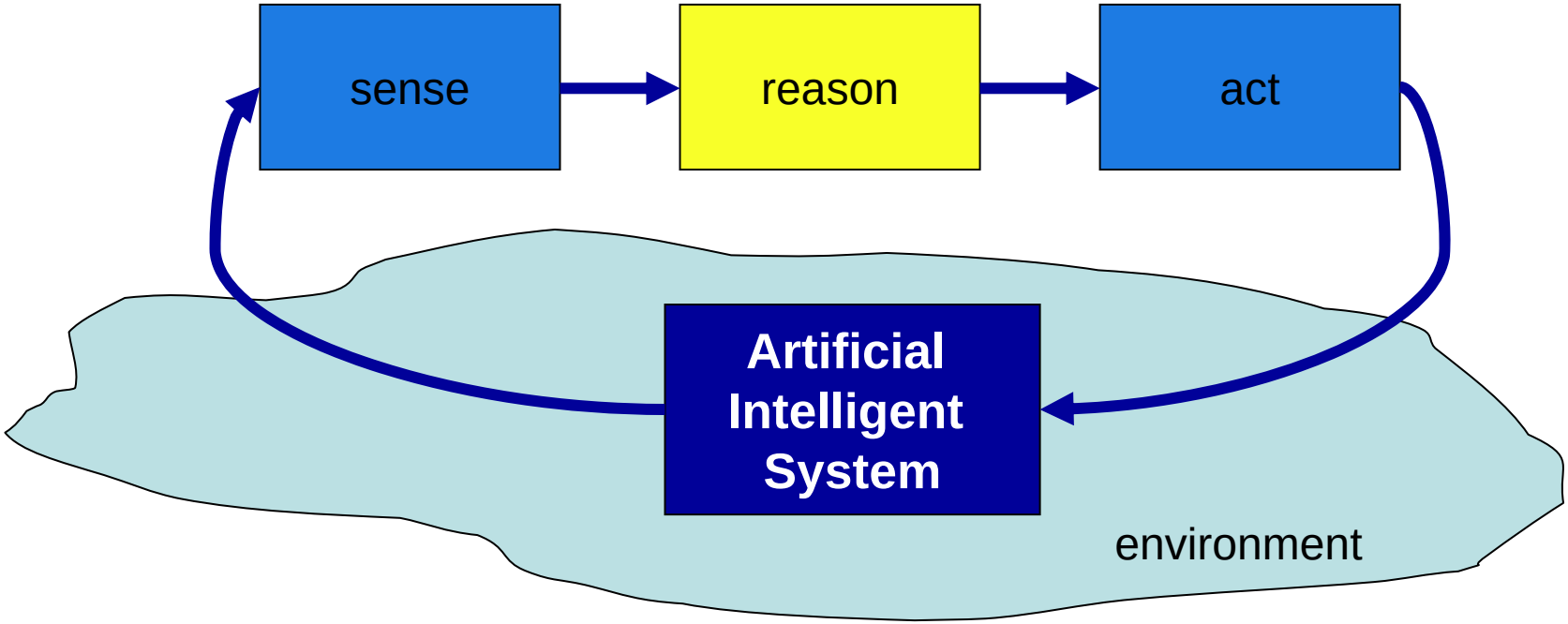
Autonomous robots

- to improve industrial automation
- manipulators
- mobile robots
- to simplify the interaction with the environment
- reliable information about the environment
- a network of robot sensors

Intelligent autonomous robots

In the framework
of Artificial Intelligent Systems

Control paradigm:



Artificial Intelligent Systems ⇒ **Robot systems:**

- **Manipulators**
- **Mobile bases**

Example:

Mobile robot

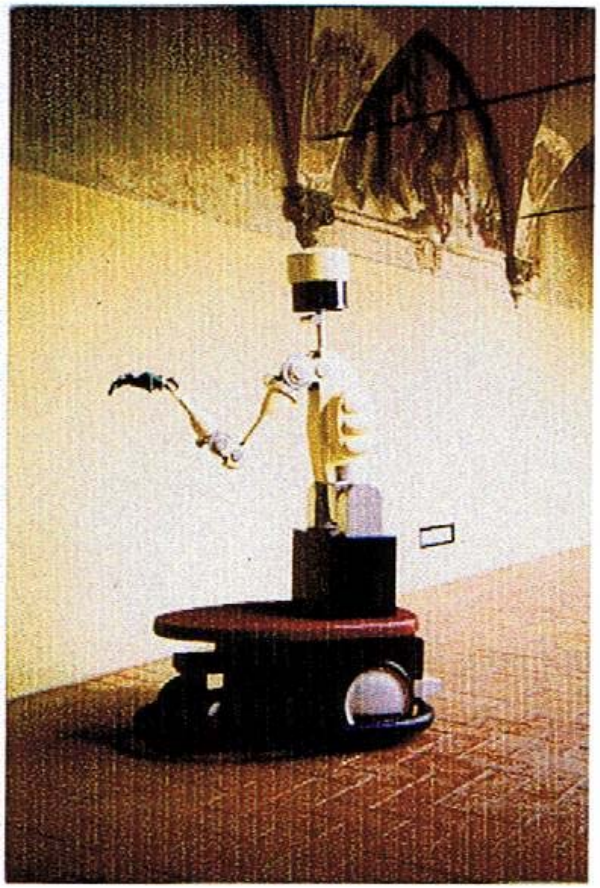
Mobile robots are not only "computer with wheels", but autonomous and "intelligent" agents with the integration and application of many technologies and methodologies.

An autonomous mobile robot integrates intelligence with perception and action.

A mechatronics device which is able to move and to act autonomously in the environment.

- ✓ Automatic Guidance Vehicle (AGV) for industrial applications AGV
- ✓ Assistive Mobile Base for rehabilitation applications (MOVAID. …) MOVAID
- ✓ Unmanned Vehicles for Underwater activities (UVU, ROV, …) ROV UVU
- ✓ Unmanned Vehicles for military use (land-mine detection, scouting, …) Scouting
- ✓ Air Unmanned Vehicles for disaster management systems (fair detection, …) Fair det.
- ✓ Planetary rovers (JPL rover, Mars Pathfinder, …) Rover
- ✓ Hard exploration (Polar robots, …) Polar
- ✓ Mobile base for maintenance and survey (cleaning, gardening, …)
- ✓ Entertainment robotics (RoboCup, Lego Dacta, Sony Entertainment robots, …) Robocup
- ✓ …

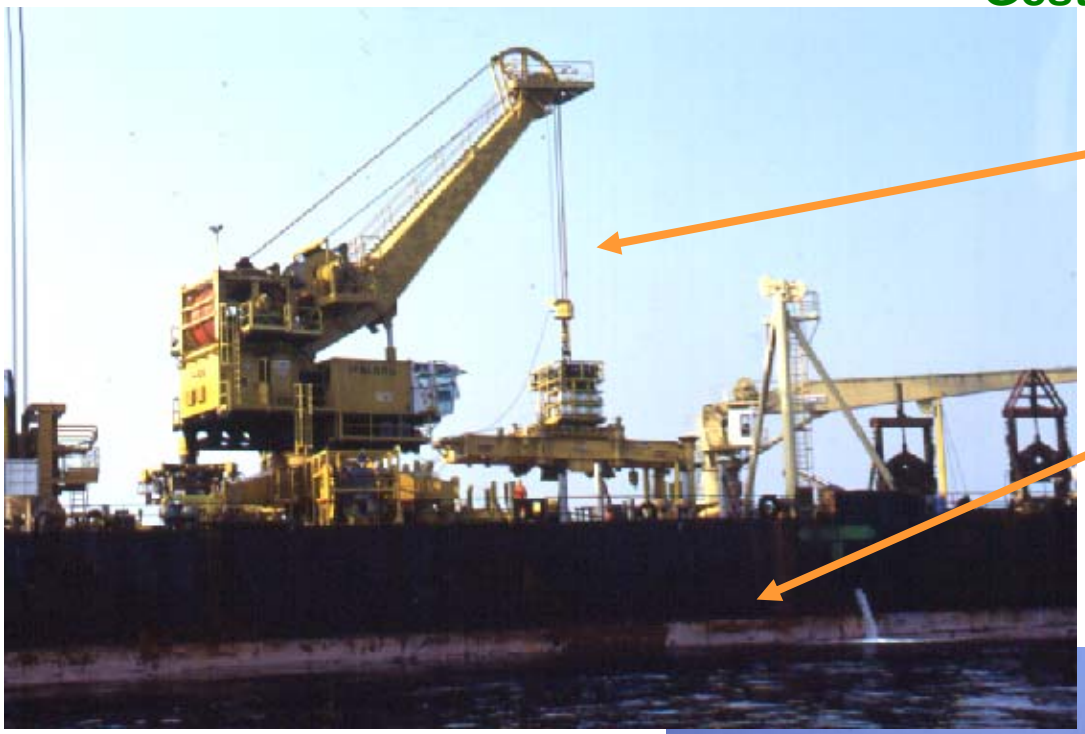
✓Automatic Guidance Vehicle (AGV) for industrial applications



MOVAID: a robot for assistive applications

Scuola Studi Superiori S. Anna, Pisa

Prof. P. Dario

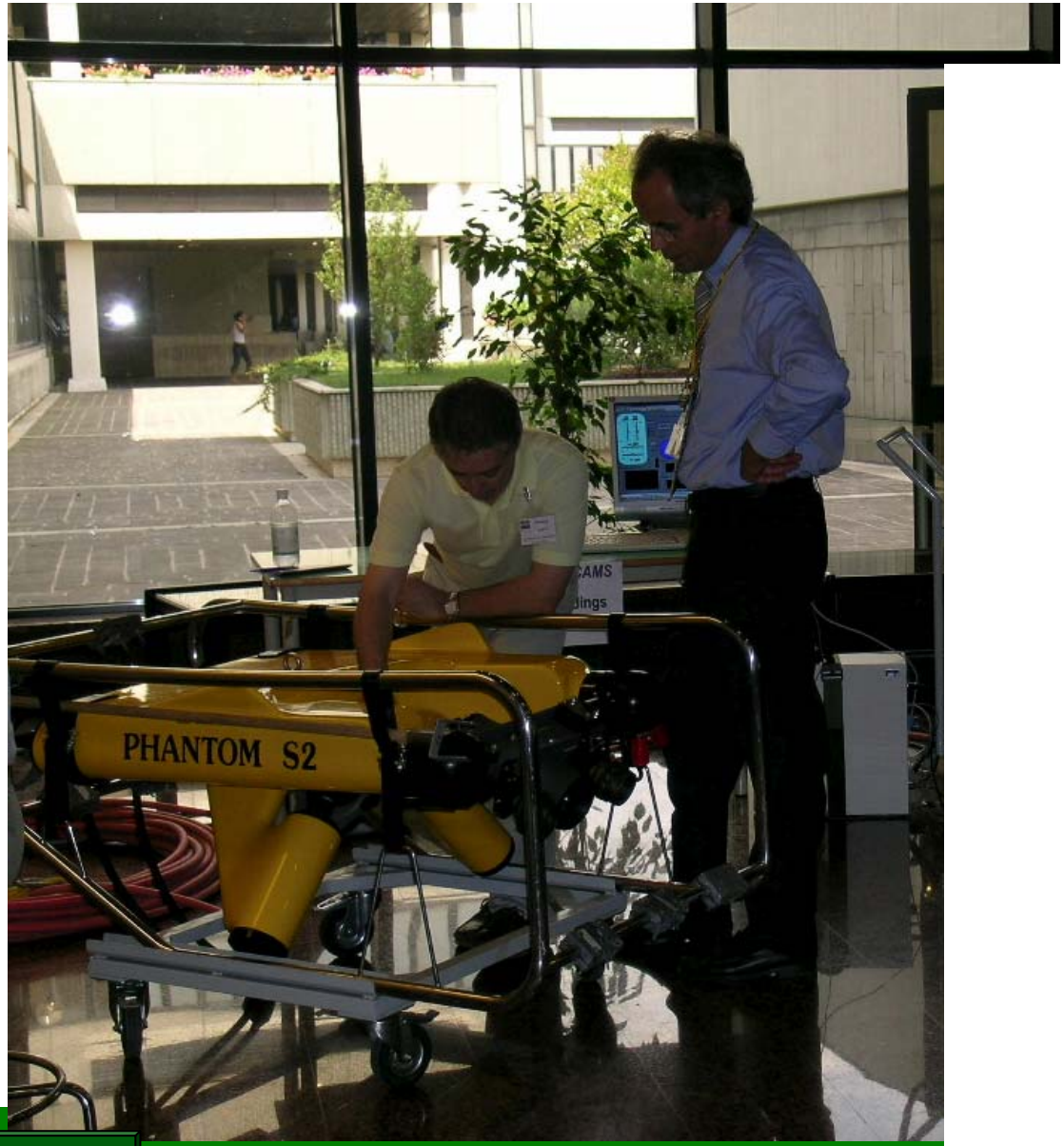


Supporting cable

Launching ship

Main frame

Underwater vehicle



QuickTime™ e un
decompressore TIFF (LZW)
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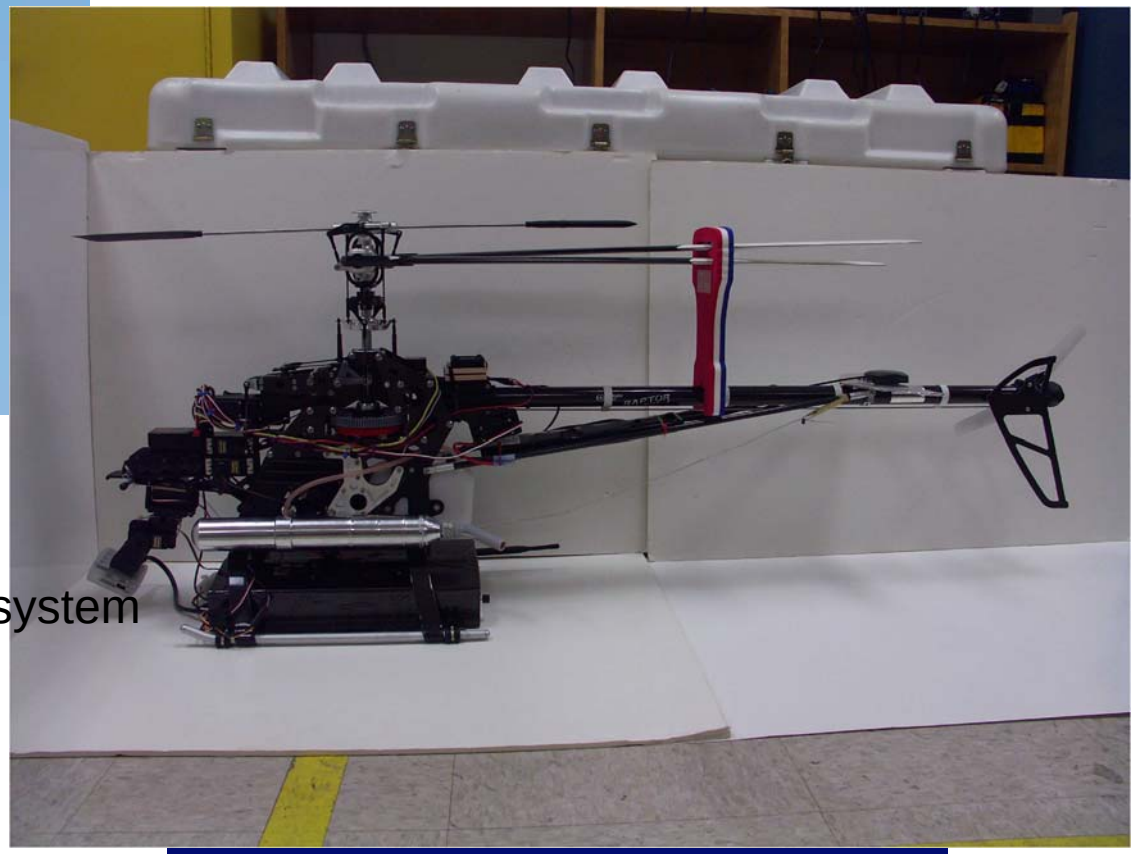
back

Robots in Iraq and Afghanistan

Air Unmanned Vehicles for disaster management systems (fair detection, …)

vision system

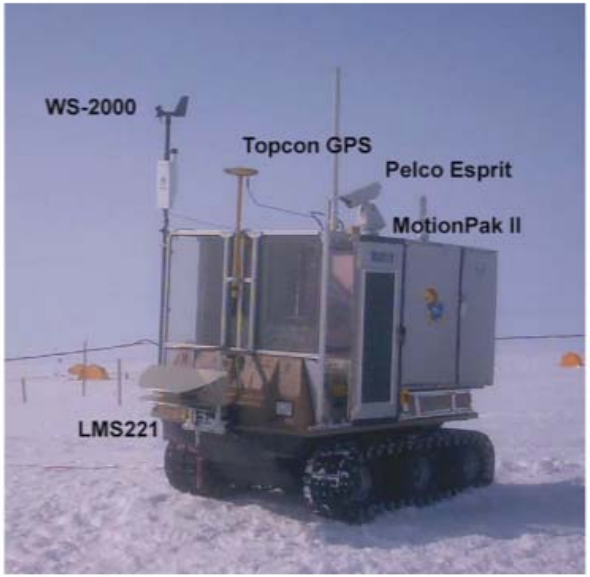


University of South Florida- Tampa

Planetary rovers (JPL rover, Mars Pathfinder, …)

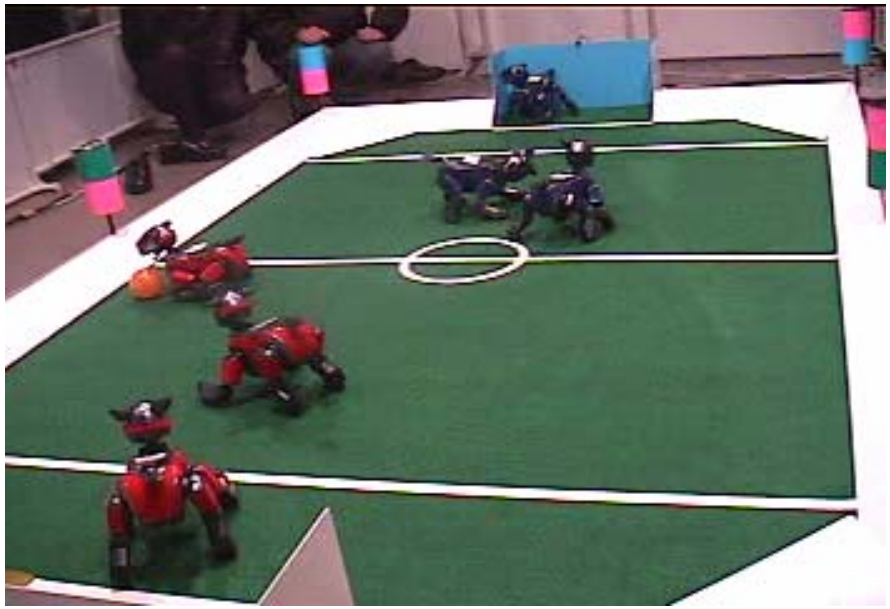
PRISM

Hardware Integration: External

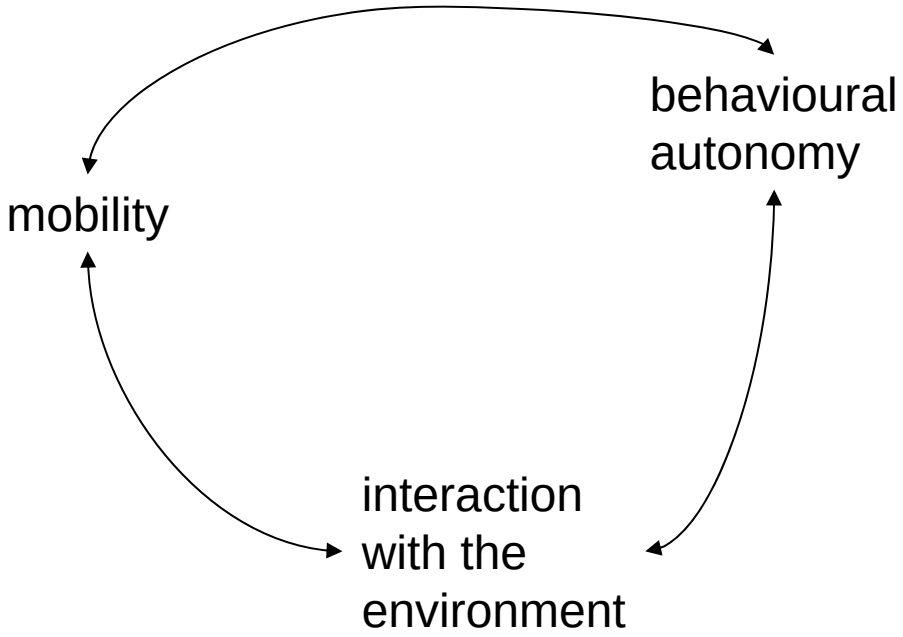


Information and Telecommunication Technology Center

University of Kansas



Mobile robot



Mobile robot

mobility → control

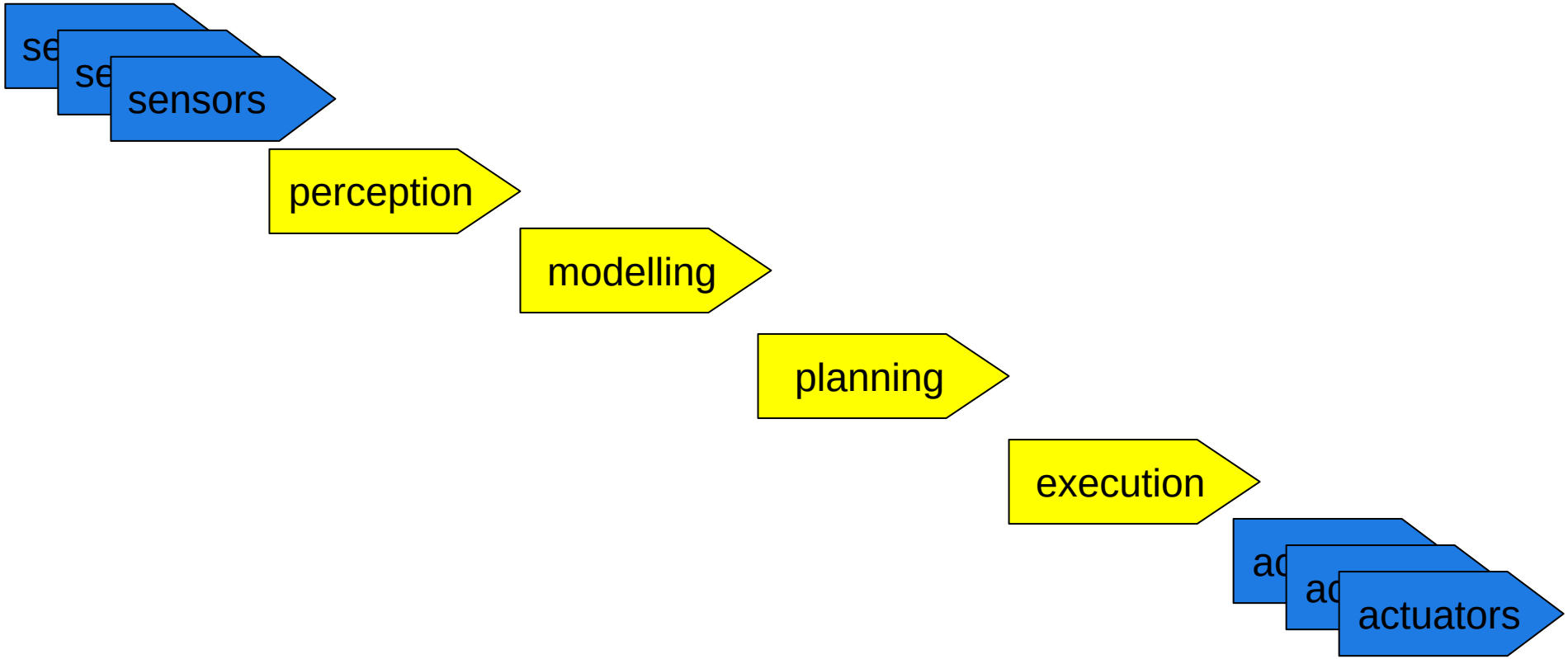
behavioural autonomy → • reasoning • decision making

interaction with the environment → • sensing • modelling

Mobile robot

The classical Control Paradigm:

sense-reason-act



Performances are improved by the reduction of the gap between perception and action:

- parallel processing of sensor data
- to reduce the importance of the world modelling
- to limit symbolic reasoning

New control architecture:
- different levels
- independent modules
- direct access to sensor data and actuators
- reduced interactions between modules

☺ In robotics (mobile robotics) an important aspect is the integration, optimization of the sense capabilities !!!

☺ The fusion of sensor data for improving the autonomy and reliability of mobile robots.

- Base localization
- Obstacle detection
- Cooperative task

…

INTERACTIONS with the ENVIRONMET

Intelligent autonomous robot

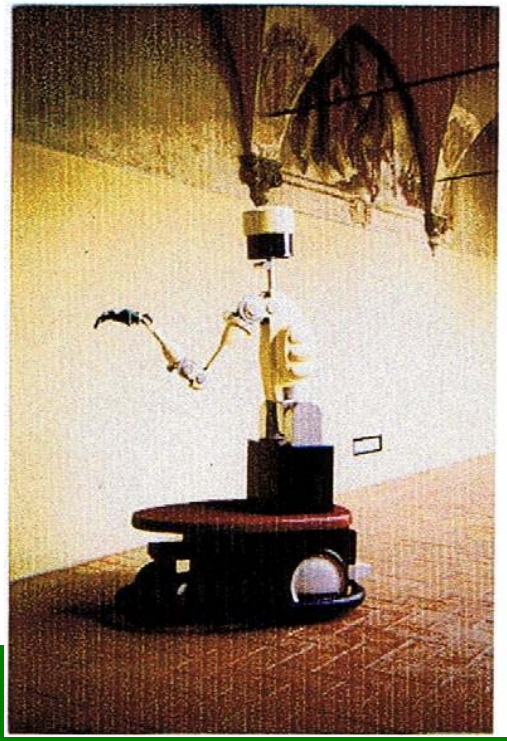
Where am I? ⇨ Localization problem

Where am I going? ⇨ Localization and/or place recognition problem

How do I get there? ⇨ Path planning problem

⇩

sensors



MOVAID

Sensor := it is a device that, in a given environment A, produces an information V at the time t :

uncertainty (noise)

$$S(A,t) = \{ V(t), \varepsilon(t) \}$$

datum

The range of uncertainty is a priori known (a priori estimated)

It is possible to associate a probability to the sensor reading (there are many causes to alter the sensor reading)

P(S,A,t) = < prob. that the distance of V(t) from the physical value measured in A is less than $\varepsilon(t)$ >

P(S,A,t) depends on $\varepsilon(t)$ and it is unknown (in many cases)!!!

Information from sensors is: uncertain

erroneous

incomplete

Many sensor measurements are uncertain.

The true physical sensing device does not operate in practice as we have modelled it. Systematic errors and random errors. Uncertainty and Erroneous are often used interchangeably in this context.

They depend on the parameter variations and uncertainties

Incompleteness := a single sensor cannot sense all information.

The information from sensors is incomplete, erronous and uncertain!!!

It is necessary to FUSE redundant information from multiple senors!!!

Multiple sensors should measure (partly) the same information to REDUCE the errors and the uncertainty in this information and to solve the problem of incomplete information.

Main features of a sensor:

- ✓ Accuracy: how correct the sensor reading is
- ✓ Repeatability: how consistent the measurements are in the same circumstances
- ✓ Resolution: granularity of results (e.g. 1cm resolution)

To improve the accurancy a general solution is based on the integration of many different sensors

Independent sensors used in a proper combined way are able to increment the capability for acquiring information on the environment.

Complementary sensors

Competitive sensors

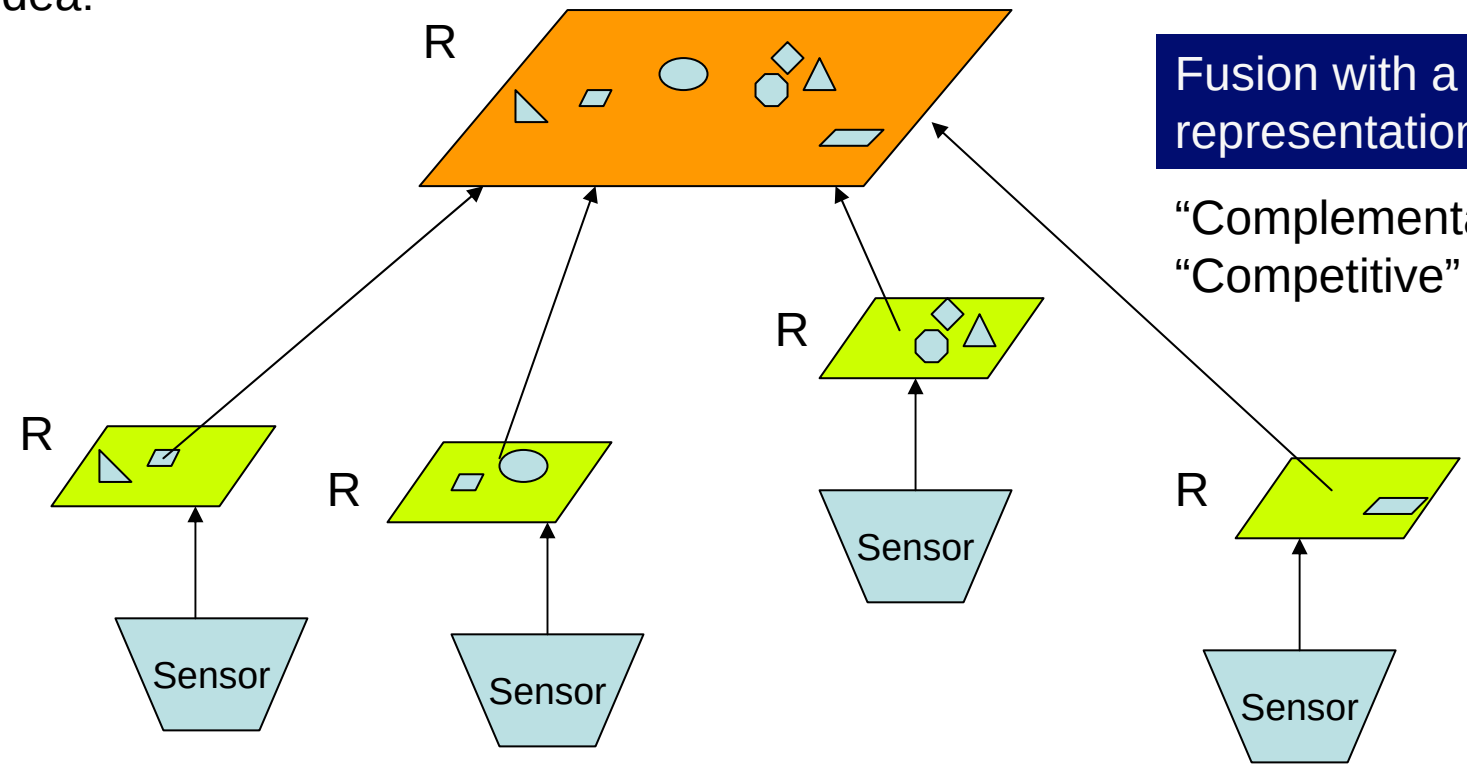
Cooperative sensors

Virtual sensors

How do we combine the sensor readings?

Multiple sensors data fusion

The idea:

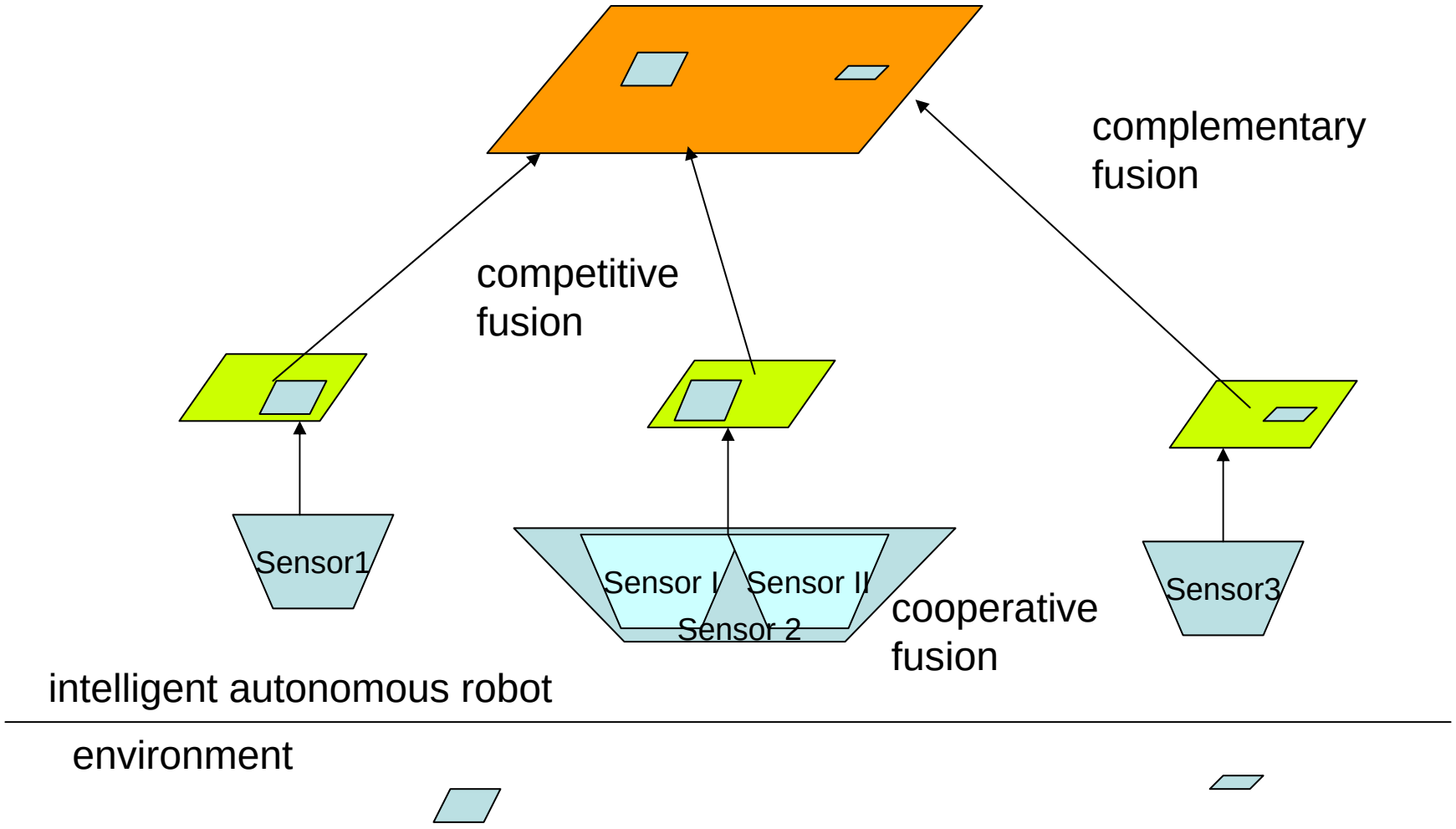


Fusion with a common representation

"Complementary" and "Competitive" fusion

intelligent autonomous robot

environment


complementary fusion
competitive fusion
Sensor1
Sensor I
Sensor II
Sensor 2
cooperative fusion
Sensor3
intelligent autonomous robot
environment

Classification by types of sensors data

Complementary fusion:

fusion of several disparate sensors which give partial information of the environment (this procedure resolves incompleteness of sensor data)

Competitive fusion:

fusion of uncertain sensors data from several sources (devices) (this procedure resolves uncertain and erroneous of sensor readings)

random and systematic errors are reduced

Cooperative fusion:

fusion of different sensors where one sensor uses the observation of the other sensors for generating the observation (stereo vision systems)

R. R. Brooks and S. S. Iyengar, *Multi-Sensor Fusion: Fundamentals and Applications with Software*, Prentice Hall, 1999

Classification by levels of representation

Signal level:

fusion is performed by the combination of the signal of a group of sensors; the signal can be modelled as random variables corrupted by uncorrelated noise; the fusion is an estimation procedure.

Feature level:

fusion is performed at the feature level; feature represents the sensor information; it increases the reliability of the processing results; the procedure involves the extraction of representation features from multiple sensor information; the fusion is based on a probabilitic procedure.

R. R. Brooks and S. S. Iyengar, *Multi-Sensor Fusion: Fundamentals and Applications with Software*, Prentice Hall, 1999

Symblic level:

the information from multiple sensors are integrated at the highest level of abstraction (symbol level); it is a patter recognition.

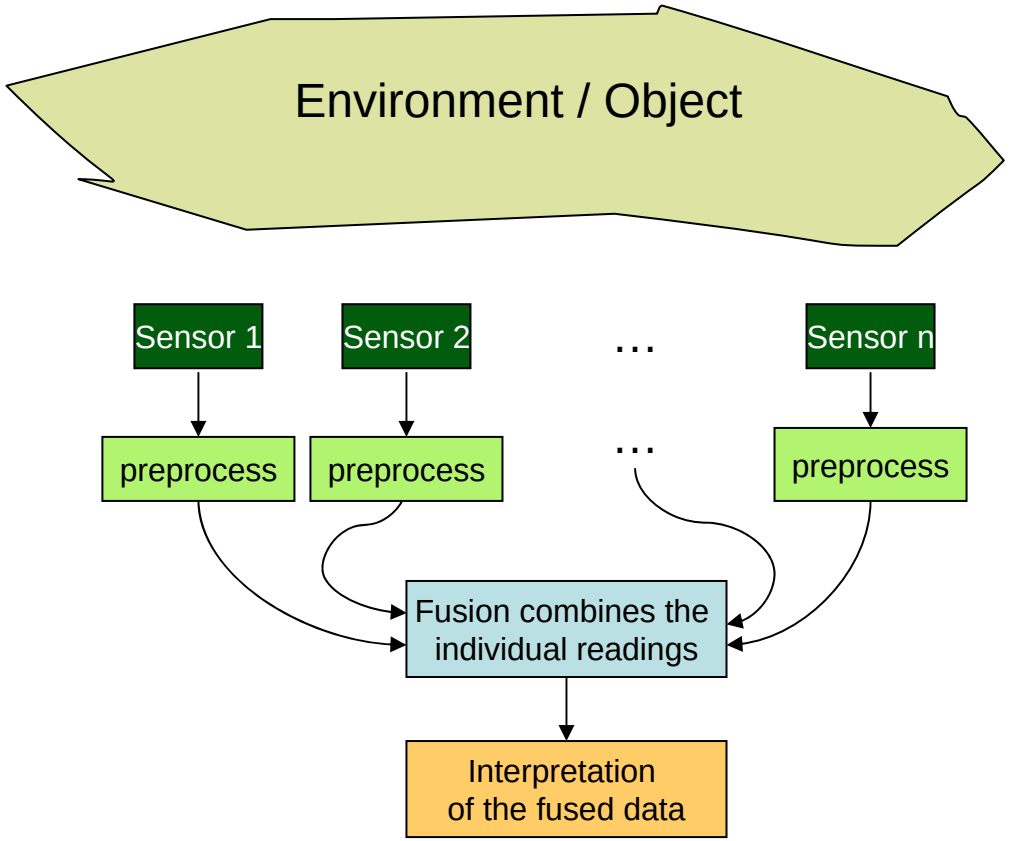
Classification by architectures

Centralized architecture:

The the computable data from many sensors is combined (fusion) and evaluated by the system (interpretation) in a centralized solution.

The sensing process in many cases can be decomposed in:

- detection
- preprocessing
- fusion
- data interpretation



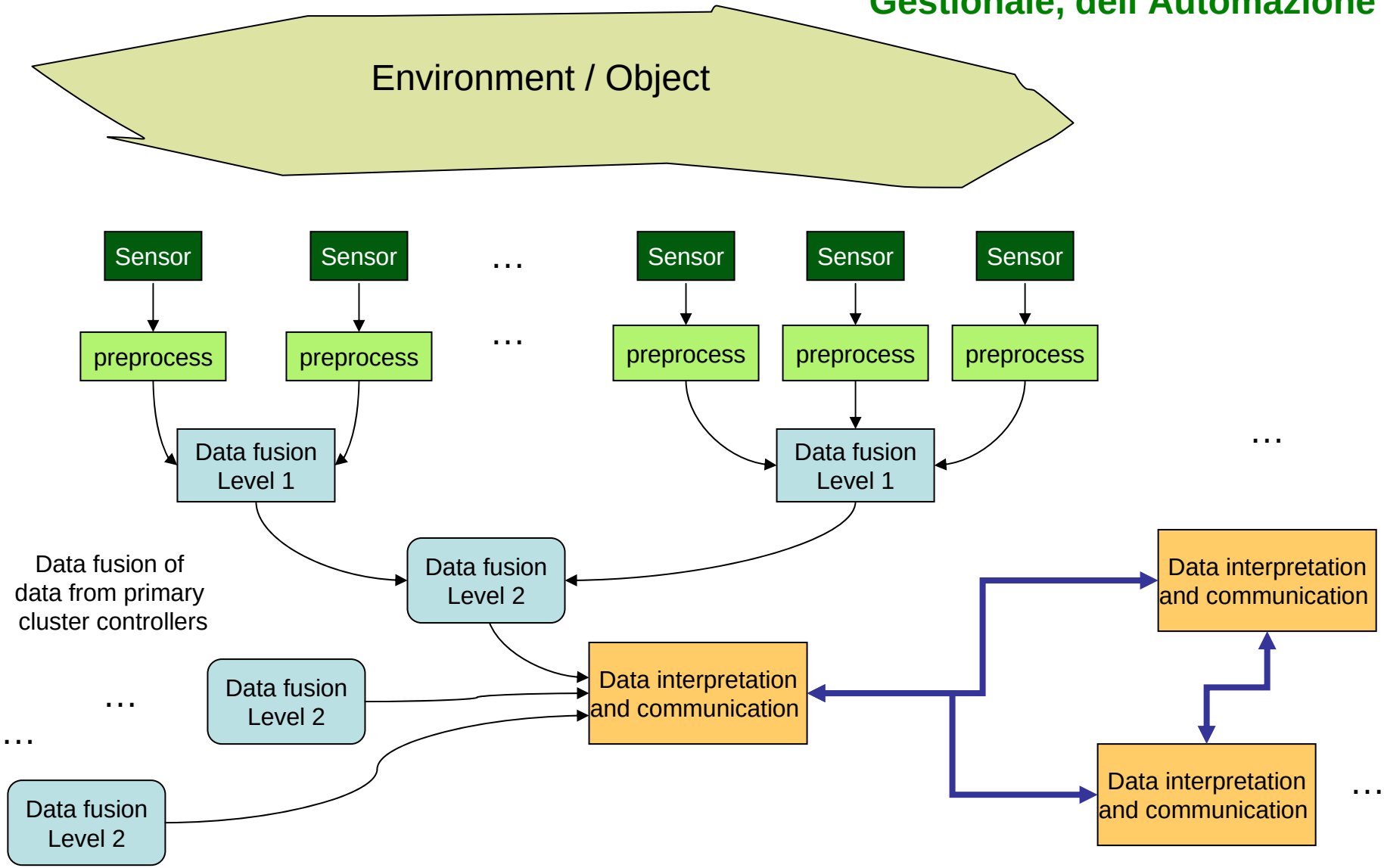
R. R. Brooks and S. S. Iyengar, *Multi-Sensor Fusion: Fundamentals and Applications with Software*, Prentice Hall, 1999

Decentralized architecture:

The sensors are connected, forming clusters; each cluster has a number of sensors collecting redundant information and the related data are fused in first level cluster controller; this cluster controller transmits the fused data to another cluster controller that is a part of a network; finally the data are interpreted in a distribute architecture where local data interpretation modules are connected by a local area network.

To reduce the amount of data to be transmitted and to increase the reliability (fault tollerance)

R. R. Brooks and S. S. Iyengar, *Multi-Sensor Fusion: Fundamentals and Applications with Software*, Prentice Hall, 1999


Environment / Object
Sensor
Sensor
…
Sensor
Sensor
Sensor
preprocess
preprocess
…
preprocess
preprocess
preprocess
Data fusion Level 1
Data fusion Level 1
…
Data fusion of data from primary cluster controllers
Data fusion Level 2
Data interpretation and communication
Data fusion Level 2
…
…
Data fusion Level 2
Data interpretation and communication
Data interpretation and communication
…

Classification by mathematical representation

There are a lot of mathematical techniques for developing different fusion solutions.

In this summer school some significant examples will be presented and discussed.

My contribution is to recall the Kalman filter approach for sensor fusion in mobile robots, that is strictly related to our research activity in this field.

Part 2: “Map building”

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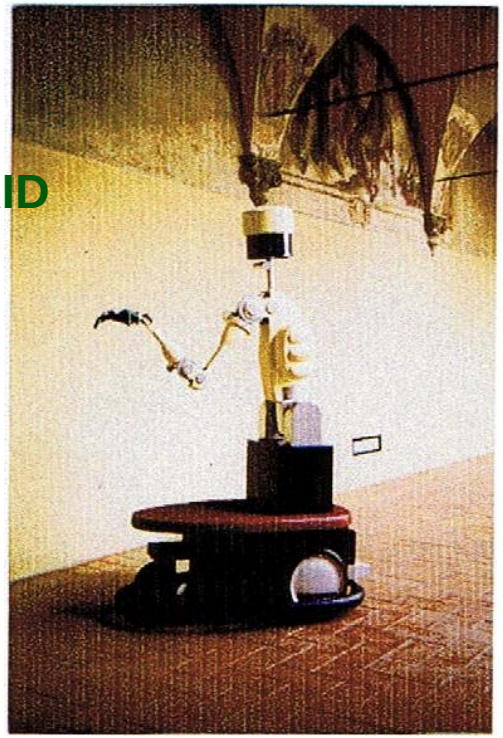
MOVAID



Intelligent autonomous robot

Where am I? ⇨ Localization problem

Where am I going? ⇨ Localization and/or place recognition problem

How do I get there? ⇨ Path planning problem

For the robot localization and/or navigation a map is required

measures association

path planning

A map of the environment (indoor environment) can be defined
- as a set of artificial (natural) markers
- a CAD model

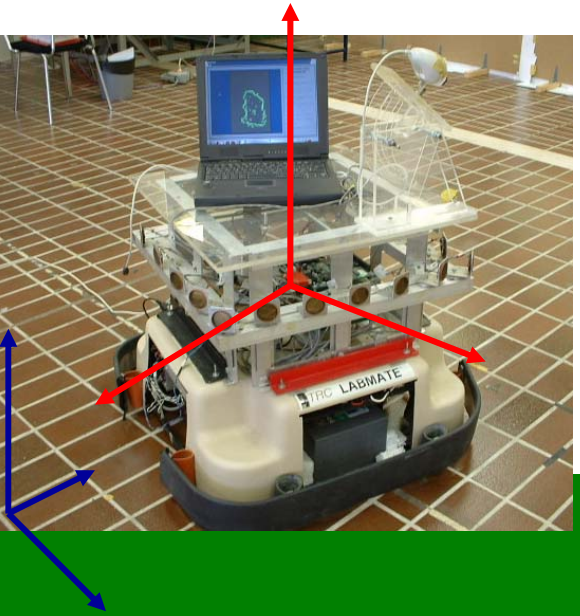
Automatic acquisition of environment knowledge (map building) := automatic acquisition of maps of the environment based on natural features (i.e. walls, doors, …)

Some definitions:

Pose tracking := estimation of the robot position and orientation using sensors readings, where the initial estimate of the robot pose (position and orientation) is known

A map is required and the measures association is simple to be performed

Global localization := estimation of the robot position and orientation using sensors readings, but where the initial estimate of the robot pose (position and orientation) is unknown (pose initialization)



A map is required and the measures association is more difficult to be performed!!!

It depends on the size of the environment, on the level of symmetry; a large set of sensors data must be integrated over time

Map building := online construction of a map of the environment by the integration of sensor data acquired by the robot; the position of the robot must be known!!!

SLAM := Simultaneous Localization And Mapping; pose estimation and mapping at the same time (at the same time to build a map and to estimate the pose of the robot);
it is a "chicken and egg" problem:
- for a pose estimation a map is required!!!
- for the map building the robot pose must be known!!!

It is an OPEN PROBLEM: there are different solutions for specific situations

Environment representations: there are 4 map representations (in-door):

- *Topological maps*
- *Feature maps*
- *Grid maps*
- *Appearance based methods*

geometric characteristics

Metric Maps: Features maps

The features maps are metric maps specified with elements (features) which characterize the environment: lines, corner, edges, … and they can parameterized of the function of colour, length, wide, …

map

$$M = \{ f_j \mid j=1, 2, \ldots m \}$$

elements

numbers of elements

These maps are generally used for the robot localization, in many cases lines are considered as features of the maps.

Drumheller 1987, Mobile robot localization using sonar, IEEE Trans. Pattern Analysis and Machine Intelligence, pp 325-332.

Sonar sensors used for detecting environment lines and for comparing them with primitive lines stored in the map.

Leonard and Durrant-Whyte, 1992, Direct sonar sensing for mobile robot navigation, Kluwerr Academic Publisher.

Natural geometric beacons that are easily observed by sonar readings and that are described by simple a geometric parameterization.

Thrum, 1998, Finding landmarks for mobile robot navigation, Proc. IEEE ICRA, pp 958-963.

Artificial landmarks that are simple to be detected, then the localization is simple and efficient; this solution requires to introduce some modification on the environment.

Castellanos and Trador 1999, Mobile robot localization and Map Building: A Multisensor Fusion Approach, Kluwer Academic Publishers.

Different features are used: lines, edges, corners, semi-planes

Cristensen, Kirkeby, Kristensen, Knudsen, 1994, Model-driven vision for in -door navigation, Robotics and Automation Systems, pp 199-207.

Stereo vision system and a CAD model of the environment.

Jetto, Longhi, Venturini, 1999, Development and experimental validation of an adaptive extended Kalman filter for the localization of mobile robots, *IEEE Transactions on Robotics & Automation*, pp. 219-229.

Sonar sensors and walls as environment features.

Matric maps: Grid maps

The environment (the work space) is decomposed into a grid of different accuracy, where each cell represents a part of the environment (path planning, obstacle avoidance, …)

This solution is generally used with sonar sensors; it represents a filtering tool for increasing the accuracy of sonar readings (at each cell is associated a probability to find an obstacle in that position)

Moravec and Elfes 1987, High resolution maps from wide angle sonar, Proc. IEEE ICRA, pp. 116-121

Fabrizi and Saffiotti, 2000, Extracting topological-based maps from gridmaps, Proc. IEEE ICRA, pp. 2555-2560.

In this case, the localization of the robot can be done by correlating the acquired local map with global map; different correlation procedure have been developed for increasing the efficiency of the procedure.

Borenstein and Koren, 1991, Histogram in-motion mapping for mobile robot obstacle avoidance, IEEE Trans. Pattern Analysis and Machine Intelligence, pp 535-539.

Many different simplifications are considered for improving the velocity of the map building.

Schiele and Crowley, 1994, A comparison of position estimation techniques using occupancy grids, Proc. IEEE ICRA, 1626-1634.

Many different solutions for correlating the local map with the global map:

i) the local map with the global map
ii) local line segments with the global map
iii) the local map with global line segments
iv) local line segments with global line segments

In the following our contributions to the on line construction of probabilistic grid map will be recalled and discussed, as a first example of sensor fusion in robotics

Real-time Map Building for Mobile Robots: Experiments with Sonar Sensors

Navigation System for Mobile Robots (general hybrid solution)

- ✓ Two main modules:

  motion planning module
  collision avoidance module

- ✓ Motion planning operates off-line to produce a collision-free path (a-priori knowledge about the environment)

- ✓ Collision-avoidance module exploits sensorial information in real-time to avoid unexpected obstacles along the pre-planned trajectory

- ✓ Sensor systems (to update the knowledge of the environment)

- ✓ To increase the autonomy of a mobile robot:

  real time operations on the sensor measures to update the knowledge of the environment

- ✓ A low cost solution to the problem of on-line acquiring environment data: a set of sonar sensors

- ✓ To improve the reliability and accuracy of the sonar measures:
  local map of the obstacles on the environment

To develop and to experimental evaluate three methods to fuse together the information carried by the sonar sensors in a mobile robot

A navigation system of a mobile robot:

the motion planning module

and

the collision avoidance module

hybrid navigation module

this module modifies the planned path in order to avoid unexpected obstacles

a simple a low cost solution for detecting obstacles on the environment is based on sonar sensors

The reliability and robustness of the collision avoidance algorithm

can be increased

with the use of an obstacle map of the environment

the choice of the avoidance direction can be produced on the basis of the local information stored in the environment map

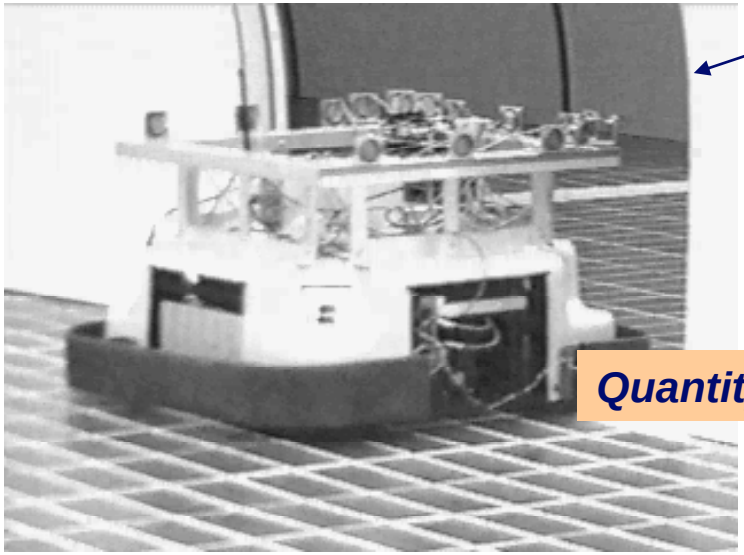
for simple obstacles the environment map could improve the efficiency of the algorithm

An hybrid navigation module with sonar sensors

the critical feature is

the on-line construction of the environment map

Cross-talk reduction

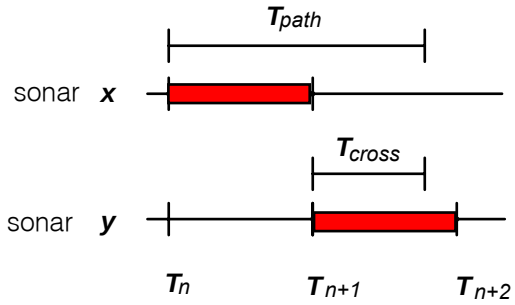


13 sonar sensors

Quantity & Quality of the sonar sensor measures

Quantity ↑ ***Sonar scanning times*** ↓ ***Quality*** ↓

$T_{scan} := T_n - T_{n+1}$



Cross-talk reduction by changing the time interval between two consecutive sonar measures (Borenstein and Koren, 1991)

$D_{cross} = D_{cross} \pm n\,\Delta TD$

This impulsive noise can be easily detected and filtered

Real-time map building

- ✓ Different approaches to the on-line map-building have been analyzed
  - *1* Probabilistic approach
  - *2* Evidential reasoning approach
  - *3* Fuzzy Logic approach
- ✓ A procedure for the reduction of the cross-talk interference has been used
- ✓ The above procedures have been analyzed by a set of experimental tests
- ✓ The same model of the sensor device and the same accuracy on the discretized map have been considered

Probabilistic approach

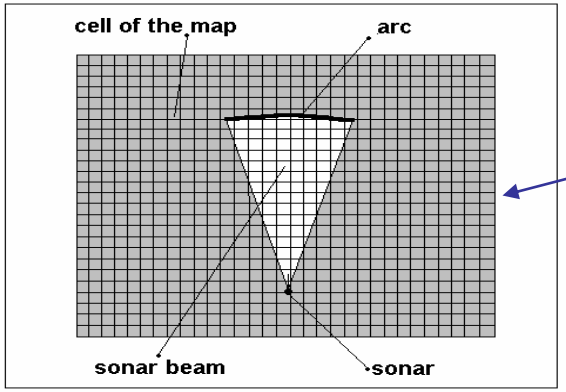
The on-line up-dating of the map requires a low computation cost at each sampling instant.

The solution proposed is able to find a trade-off between accuracy and computation cost.

The main features of the implemented procedure are the following ones:

- ✓ The map is composed by square cells (10 cm each side) containing an obstacle probability
- ✓ Each measure up-dates the obstacle probability of the cells in the measured zone by a obstacle probability
- ✓ The central part of the cone of the sonar beam has been considered
- ✓ An approximation of the Bayes theorem is introduced for reducing the computation efforts in the map up-dating

Obstacle probability of a cell after a sonar measure



grid-based model of sonar sensor

1) Sonar with a return signal: ("in range" measure)
high value of probability for the cells of the arc
low value of probability for the cells inside the sonar beam
0.5 elsewhere

2) Sonar without a return signal: ("empty" measure)
low value of probability for the cells of the beam
0.5 elsewhere

o_i= cell i occupied
S_j= sonar reading j
M = old information = sonar map

This probability has been deduced by consideration on how sonar sensors work

$$P(o_i / S_j, M) = \frac{P(o_i / S_j) \cdot P(o_j / M)}{P(o_i / S_j) \cdot P(o_j / M) + P(\overline{o}_i / S_j) \cdot P(\overline{o}_j / M)}$$

The new value to assign to the cell i

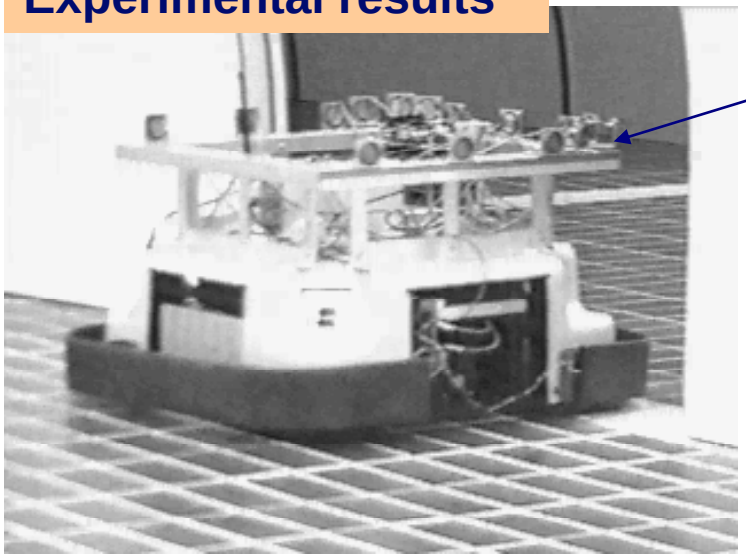
The following approximations have been introduced:

$P(S_j/o_i,M) \approx P(S_j/o_i)$ $\qquad$ $P(S_j/\overline{o}_i,M) \approx P(S_j/\overline{o}_i)$

$$P(o_i / S_j, M) = \frac{P(S_j / o_i, M) \cdot P(o_i / M)}{P(S_j / o_i, M) \cdot P(o_i / M) + P(S_j / \overline{o}_i, M) \cdot P(\overline{o}_i / M)}$$

Bayes theorem

Experimental results

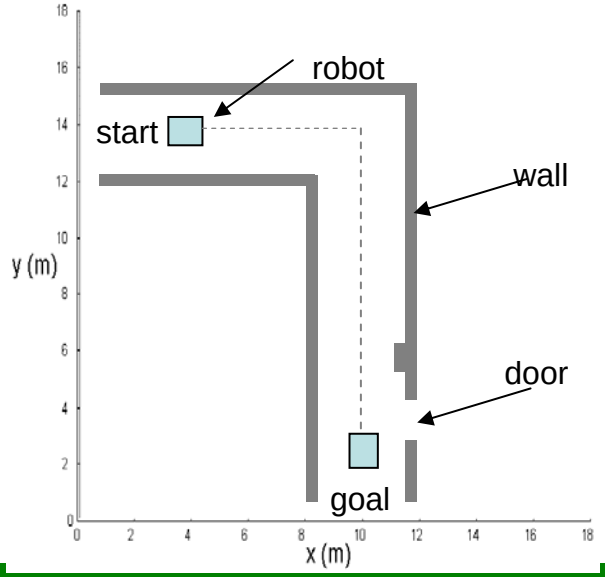


LabMate with 13 Polaroid sensors

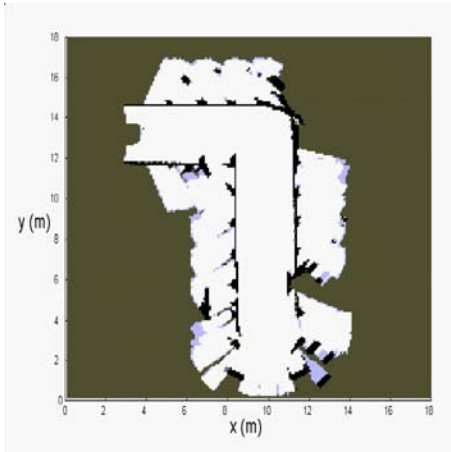
Tests:

in-door environments with a proper set of unknown obstacles

paths free of collisions *have been planned*

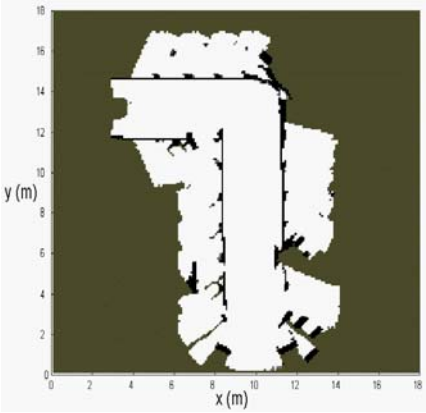


A corridor



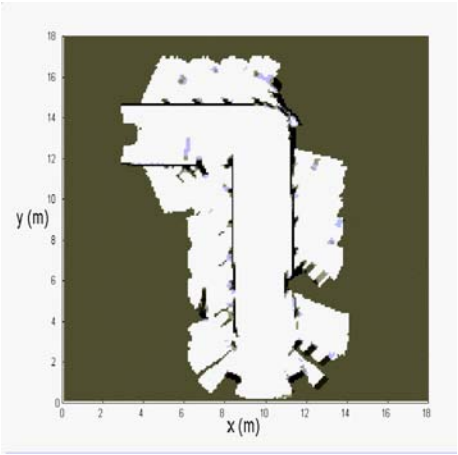
Probabilistic approach

Dark regions:= cells with an high probability of obstacle



Evidential reasoning approach

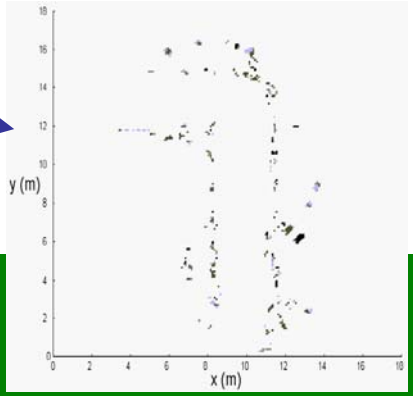
Dark regions:= cells with a lot of evidence supporting obstacle presence and few evidence supporting obstacle absence

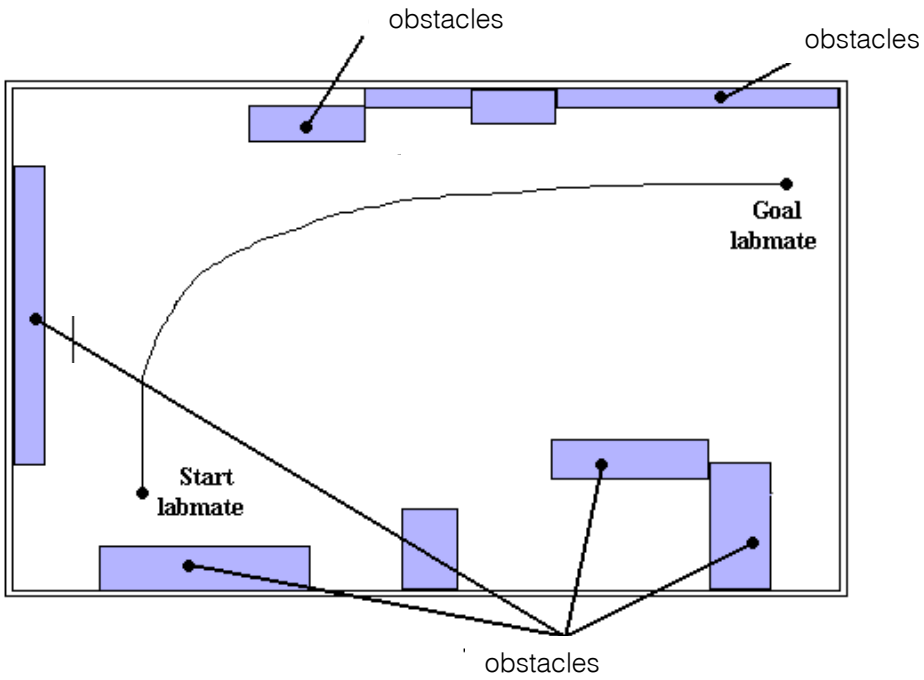


Fuzzy logic approach

Dark regions:= cells with an high risk for robot navigation

The map of conflict = cells where conflicting sonar readings are detected (dark regions correspond to cells with a high lack of consensus between sonar readings





Probabilistic approach

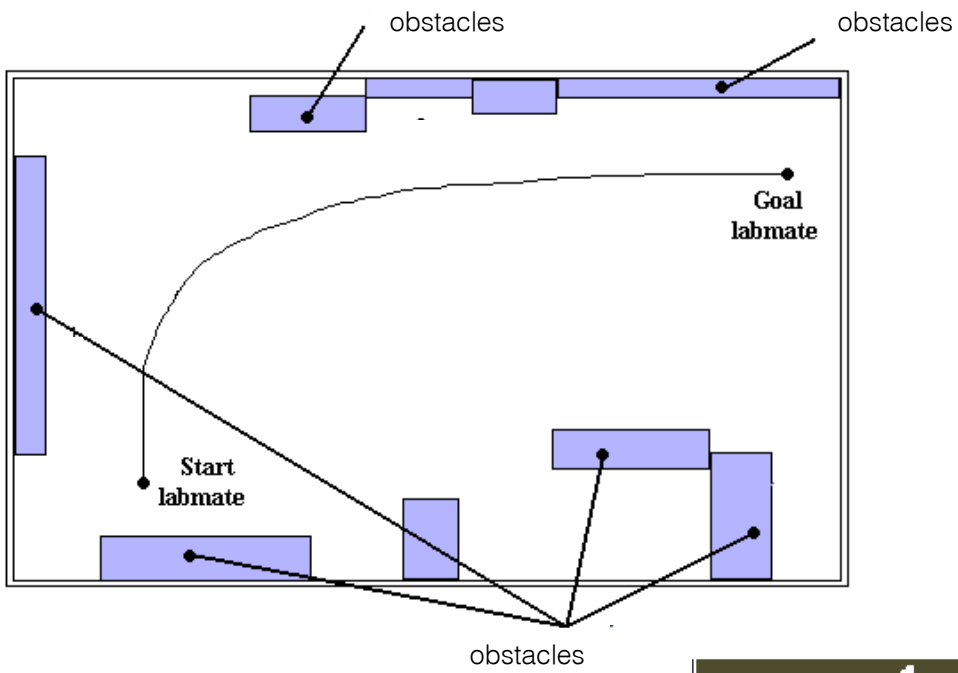
Unexplored area

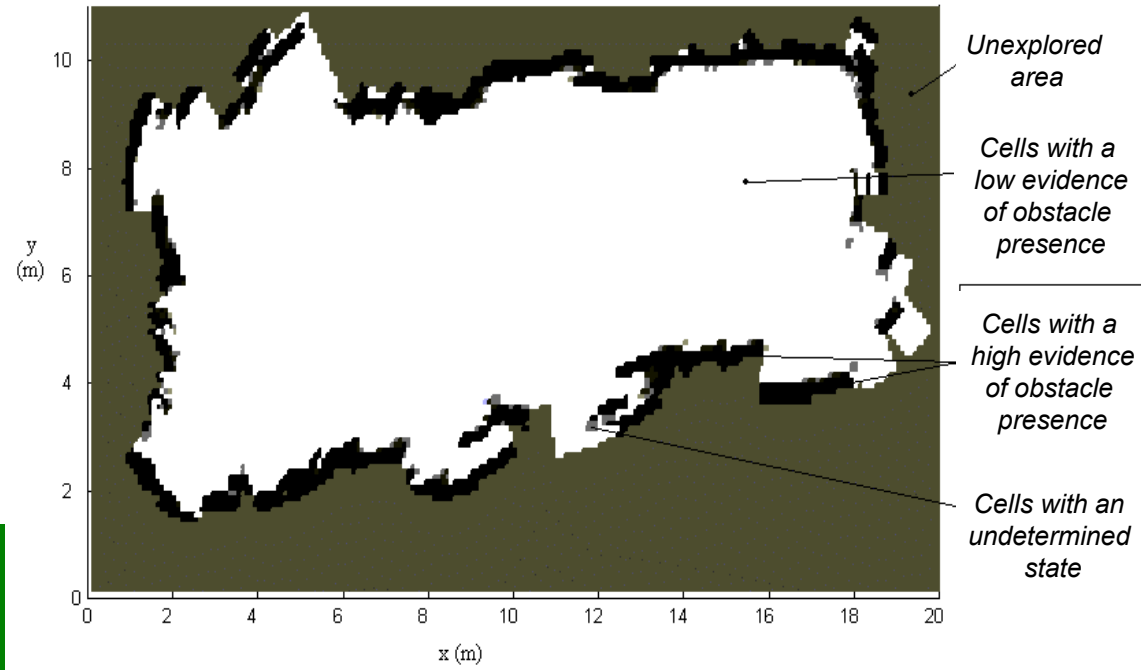
Cells with a low probability of obstacle presence

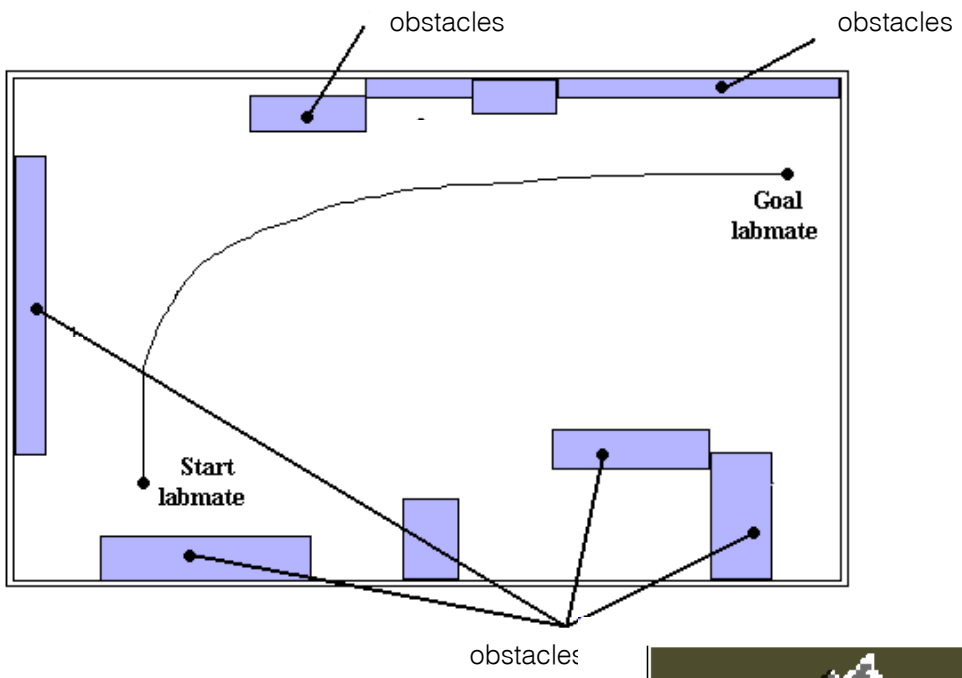
Cells with a high probability of obstacle presence

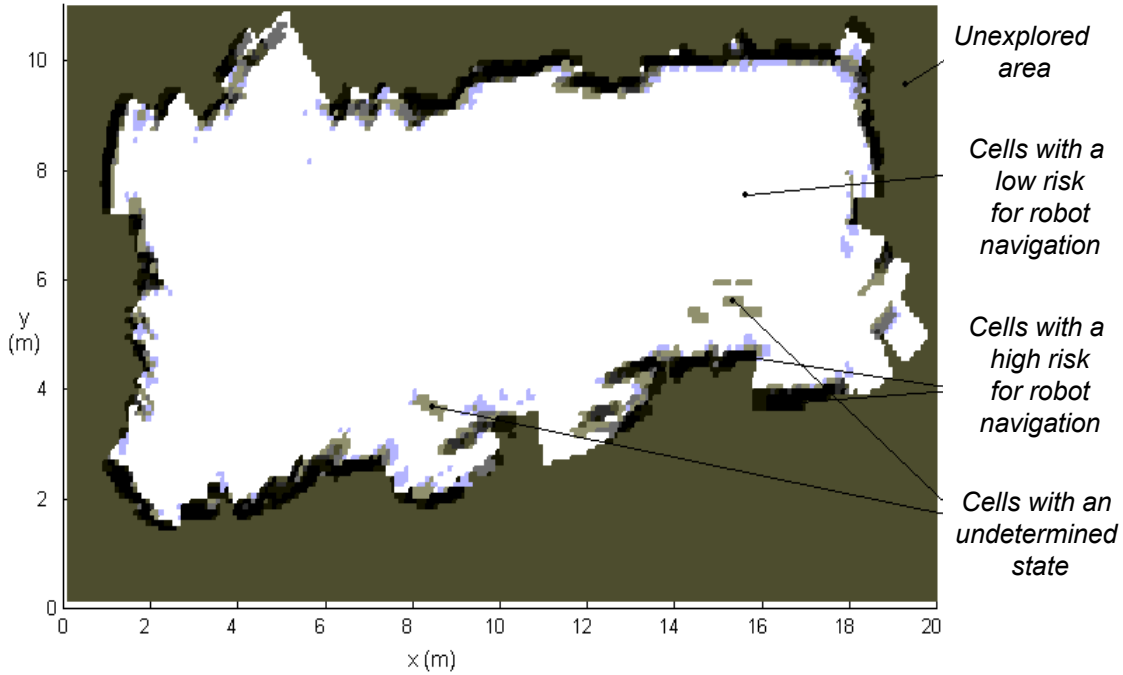
Cells with an undetermined state

Evidential reasoning approach






obstacles
obstacles
Goal
labmate
Start
labmate
obstacles


Unexplored area
Cells with a low risk for robot navigation
Cells with a high risk for robot navigation
Cells with an undetermined state
y (m)
x (m)
0
2
4
6
8
10
12
14
16
18
20

Results

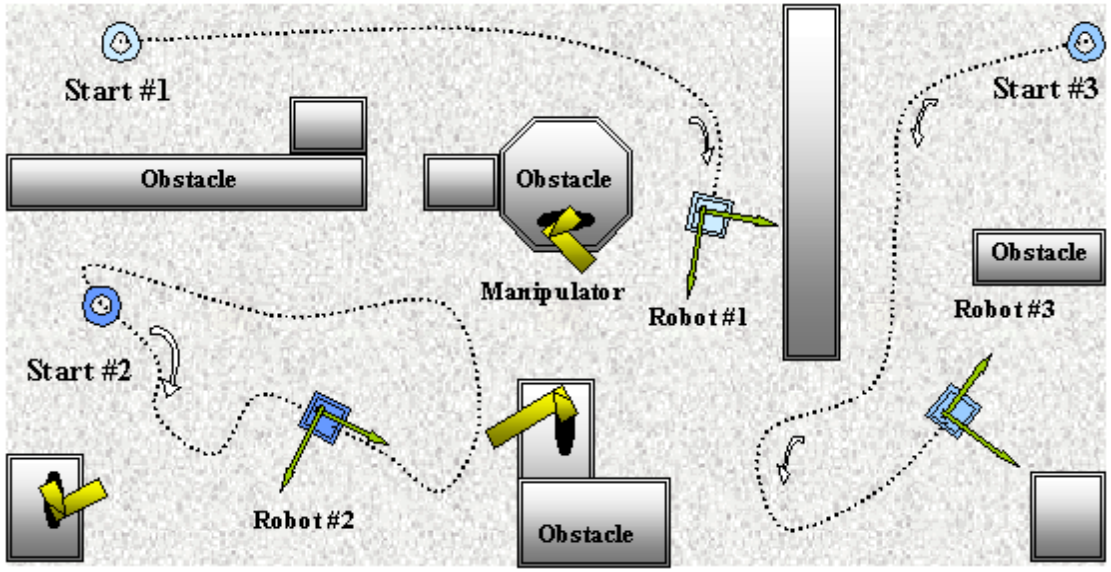
- ✓ In all the performed tests the second approach, based on the conditioned Dempster-Shafer theory, has produced the best results (the differences are "small")
- ✓ This method allows to detect and to analyze the conflict readings (by the map of weight of conflict).
- ✓ Moreover the map of weight of conflict can be used to decide on the reliability of a sonar sensor and if it is necessary to exclude this sonar temporarily or permanently

A Bonci, S. Longhi, F. Moscioni, "Real-time map building for mobile robots: experiments with sonar sensors", *Proc. of the 8th International Workshop on Robotics in Alpe-Adria-Danube Region (RAAD'99)*, Munich, Germany, June 1999, pp. 201-206 (ISBN 3-00-004482-5).

Other contributions:

- ✓ To fuse the environment data in a multirobot system.
- ✓ The map building of the environment by fusing sonar data with video data.

Multirobot systems



Problems:

the navigation in presence of the other robots

the perception of the other robots

the transmission of information among the robots

the fusion of the knowledge on the environment

The same hybrid structure for the navigation system of each robot:
path planner + obstacle avoidance module

The co-ordination problem in the path planning and in the obstacle avoidance can be solved by an hierarchical approach

The hierarchical approach requires:

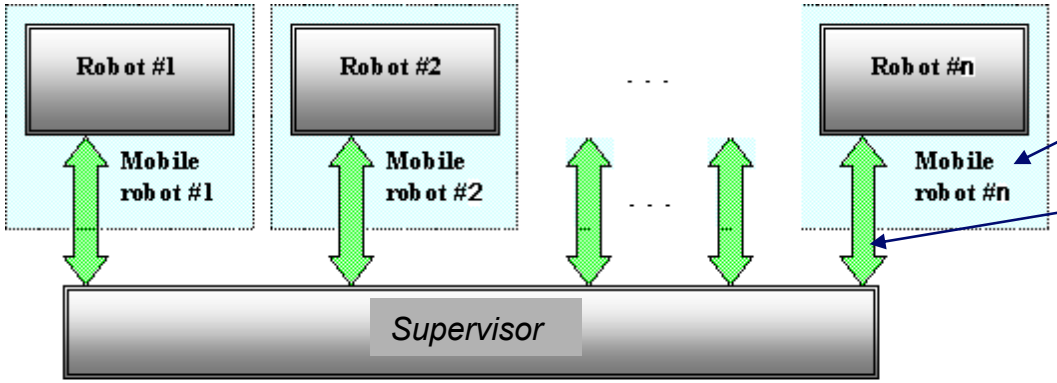
- data communication among the mobile robots
- co-ordination

a local area network

a protocol managed by the network supervisor

Reliability and robustness of this approach can be improved with a supervisor system which co-ordinates the activities and controls the status of different robots

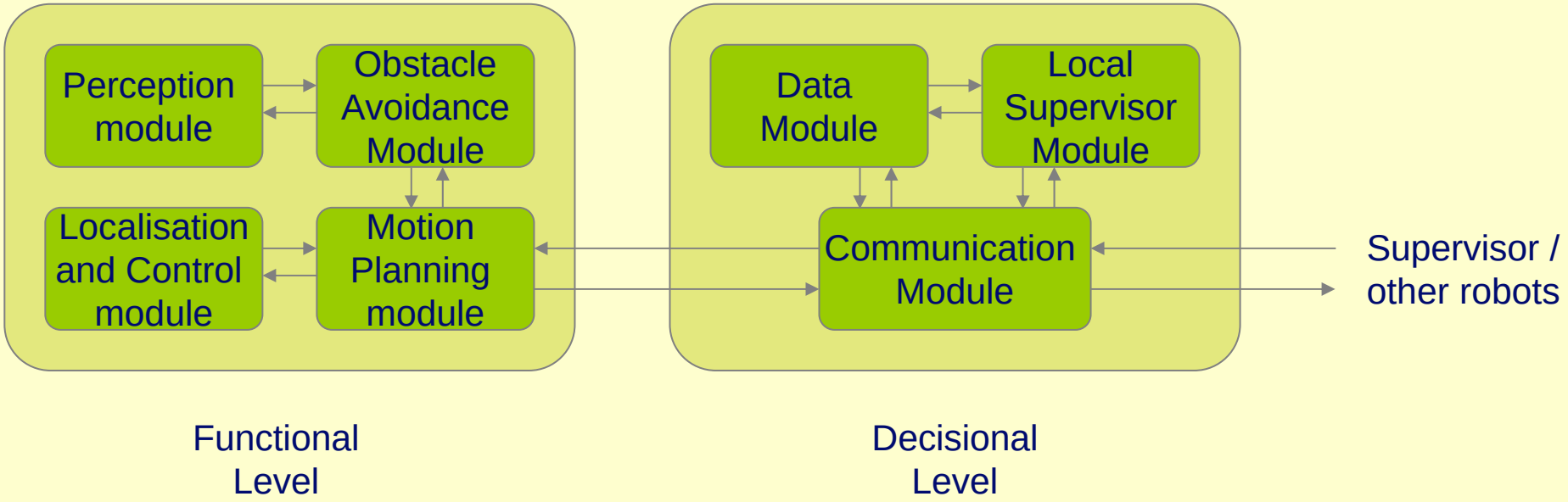
The supervisor system allows
to optimize the global task of the multirobot system
to integrate the environment information acquired by all the mobile robots



a hybrid navigation module

a local area network:
to impose the task and the related priority to acquire the environment information to communicate the integrated environment knowledge

Navigation system of each robot



Environment data fusion:

The global map of the environment can be updated with the sonar measures acquired by all the robots

The data fusion on the supervisor:

1. a unique map on the supervisor

2. the supervisor integrates the single maps

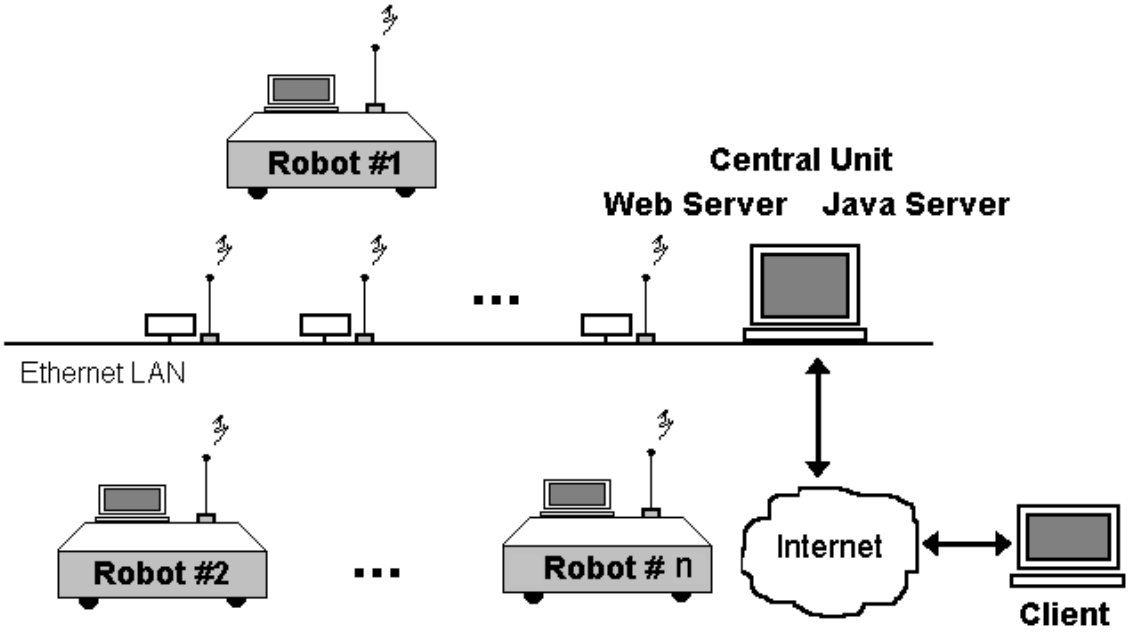
i. a simple average

ii. a weighted average

The sonar readings of each robot are used for the real-time up-dating of the local map of each robot and of the global map of the supervisor

This technique does not decrease the autonomy of each robot:

- each navigation module updates its own local map
- the supervisor integrates the single maps and communicates the global environment map to each robot



The Dempster-Shafer method is used for the global map and the local maps

The periodic data transmission is performed by radio link and a local area network (Ethernet LAN) with the User Datagram Protocol (UDP)

The Transmission Control Protocol (TCP) is used for the aperiodic data transmission

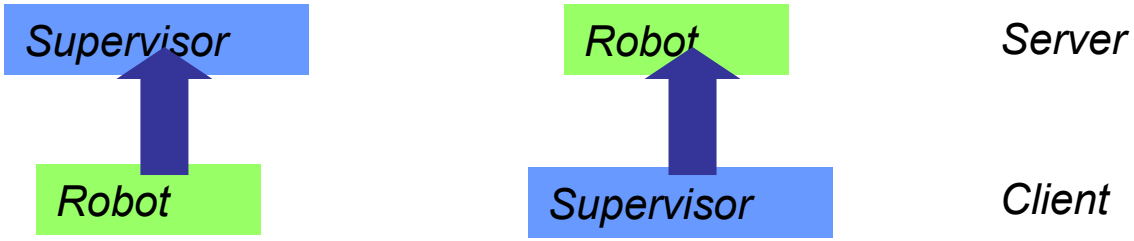
The main features:

TCP

The aperiodic data transmission: the global map, the planned task (high reliability is required)

*The low complexity of the **UDP*** → *real-time acquisition on the supervisor of all sonar readings*

A server/client solution is developed for the data communication:



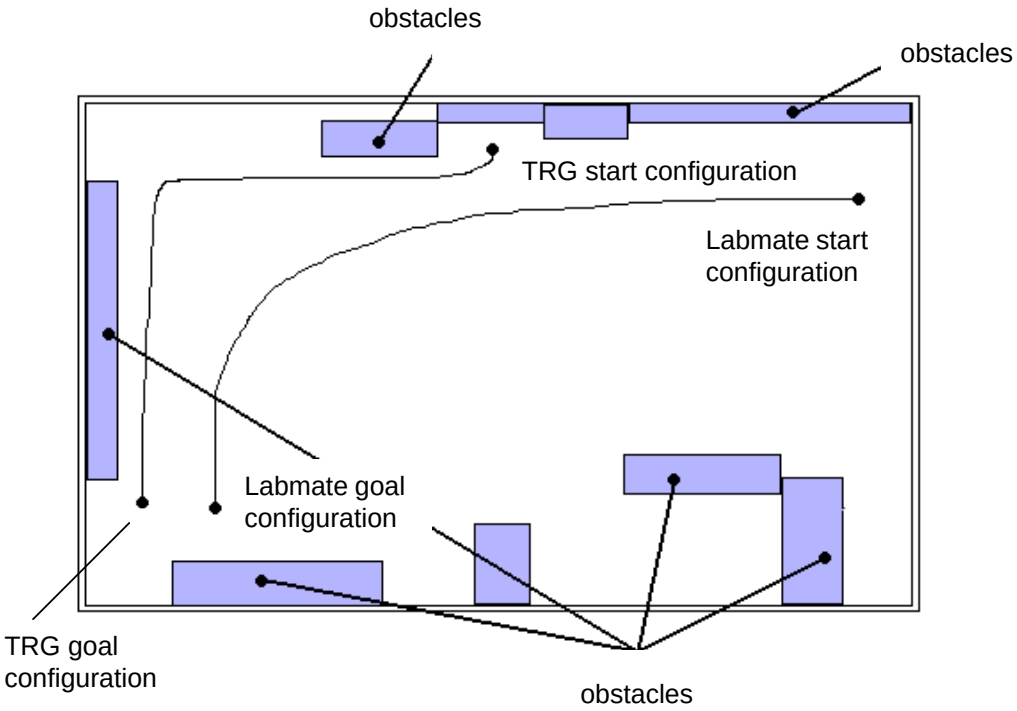
A remote Internet connection by a compatible Java browser → to analyze the global map to impose the tasks

Experimental results:

- ✓ 16 *Polaroid sensors on the Labmate base*
- ✓ 16 *Polaroid sensors on the TGR Explorer (powered wheelchair transformed in a autonomous vehicle)*
- ✓ *Crosstalk reduction: sensors distribution Borenstein- Koren procedure*
- ✓ *Navigation system of each vehicle in two PC:*
  - *Functional level: PC486 104-bus*
  - *Decisional level: desk PC Pentium*

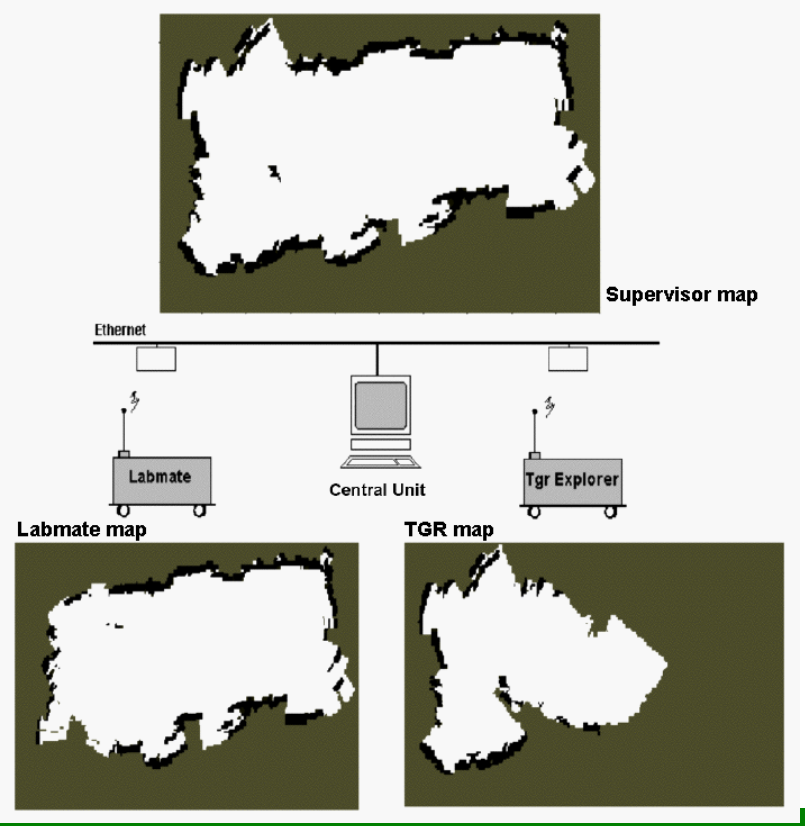
  connected to the Supervisor with the Ethernet Lan and to the Function level with a RS232 wirwless serial line

The communication module with three independent sub-modules:
Server sub-module manages the TCP and UDP protocols to the supervisor / other robots;
Client sub-module manages the TCP and UDP protocols from the other robots / supervisor;
Local module menages the serial communication functional level / decisional level.



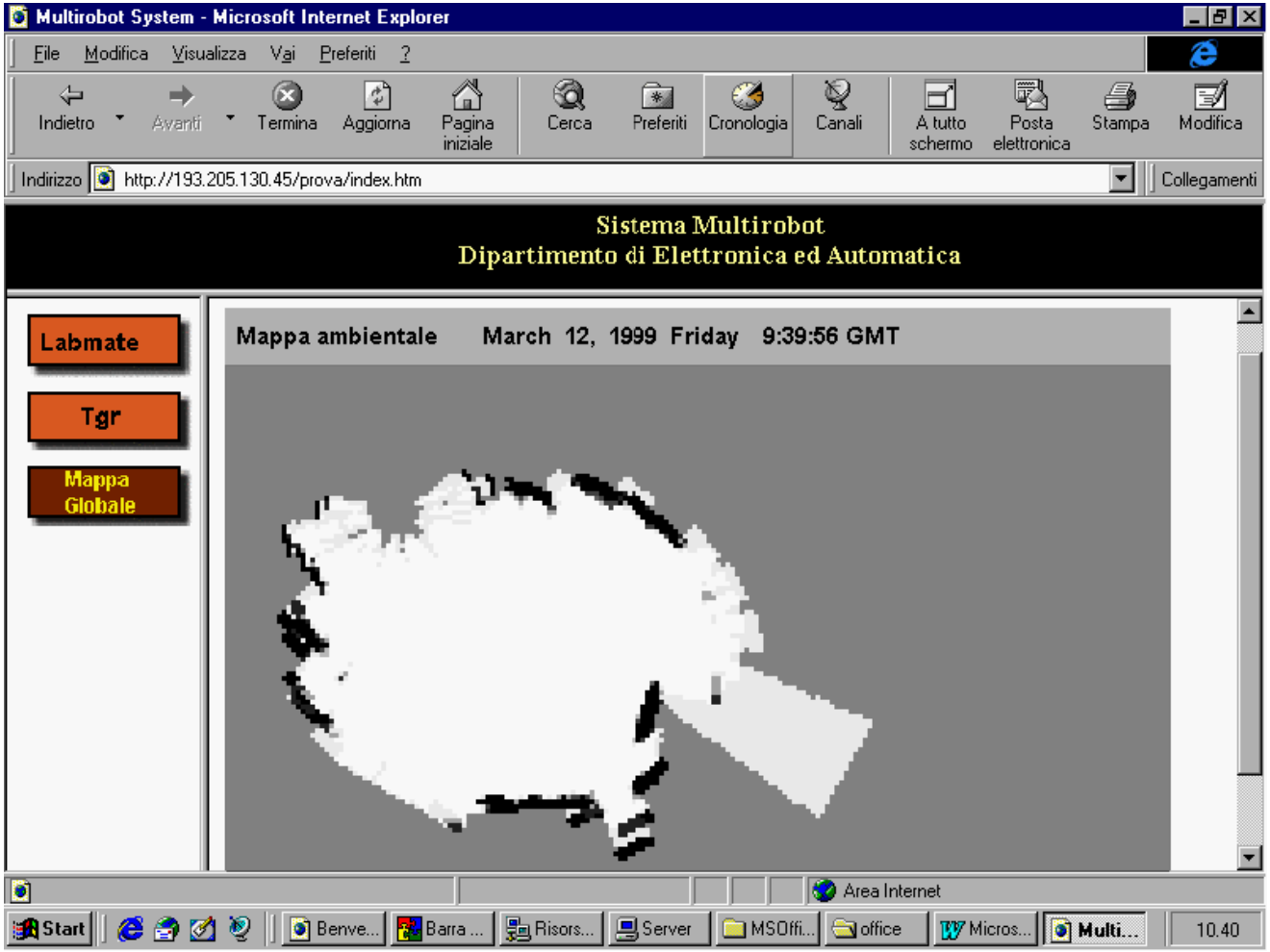
Two independent tasks free of collision

The proposed procedure improves the knowledge on the indoor environment



On the performed tests:
real-time acquisition of sonar readings by UDP

Internet connection: Java browser for acquiring the global map


Multirobot System - Microsoft Internet Explorer
File Modifica Visualizza Vai Preferiti ?
Indietro Avanti Termina Aggiorna Pagina iniziale Cerca Preferiti Cronologia Canali A tutto schermo Posta elettronica Stampa Modifica
Indirizzo http://193.205.130.45/prova/index.htm
Collegamenti
Sistema Multirobot
Dipartimento di Elettronica ed Automatica
Labmate
Tgr
Mappa Globale
Mappa ambientale March 12, 1999 Friday 9:39:56 GMT
Area Internet
Start
Benve...
Barra ...
Risors...
Server
MSOffi...
office
Micros...
Multi...
10.40

Results

- ✓ A developed method (architecture) is able to fuse together the information acquired by each single robot.
- ✓ The purpose is that of obtaining a global environment map increasing the reliability and accuracy of the sonar measures.
- ✓ Results: experimental tests (LABMATE + TGR).
- ✓ In all the performed tests the procedure has produced satisfactory results.
- ✓ The proposed procedures are quite general so they are directly applicable to multirobot systems composed of any number of robots and characterized by different kinds of sensor equipment.

S. Longhi, F. Moscioni, "Environment sonar maps for multirobot systems", *Proceedings of the 7th International Symposium on Intelligent Robotic Systems (SIRS'99),* Coimbra, Portugal, July 1999, pp. 339-348 (ISBN 972-96889-4-X).

The map building of the environment by fusing sonar data with video data.

Autonomous mobile robot navigation:

+ perception of local environment
  + obstacle avoidance in a unknown environment
+ vehicle pose estimation
  + auto-localization on a known environment
+ sensor readings

Local map environment:

+ grid base modelling

+ feature based modelling

Our contribution is to improve the feature based modelling by fusion of ultrasonic range readings and digital video images

Ultrasonic range readings

Digital video images

→ 2D modelling technique for indoor environments based on line features

For improving:
- accuracy on environment knowledge
- vehicle pose estimation

For reducing:
-the amount of computer memory in exploration of large environments
-the cost of the sensor system (by using data fusion techniques)

Sensor system

Sonar sensors: → aggregation of sonar measures in a probabilistic map of the environment:

- ✓ only information about existence of an obstacle;
- ✓ no information about shape of the obstacle's contour

Monocular Video sensor: → extraction of straight lines from video images:

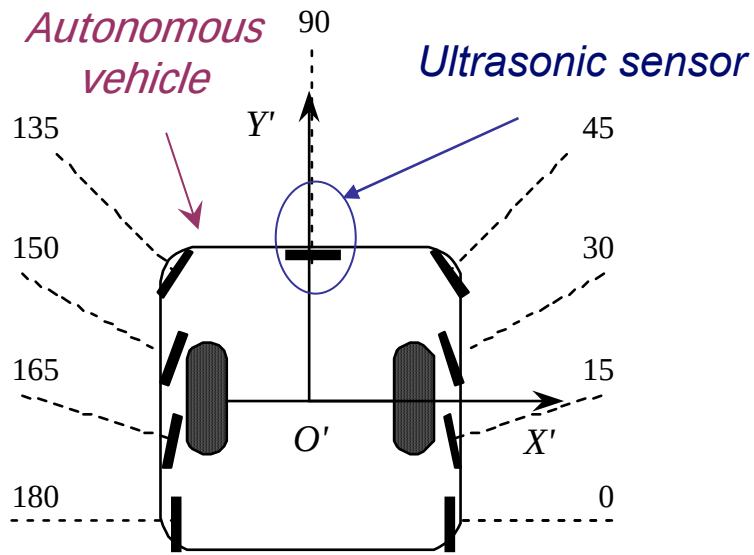
- ✓ accurate information about the contours of the objects in the image;
- ✓ it is not able to discern (by it self) obstacles from the contours of the objects

↓ *Accuracy improvement*

Data fusion → *gives to the system the capability to extract 2D obstacle's contour as straight lines features*

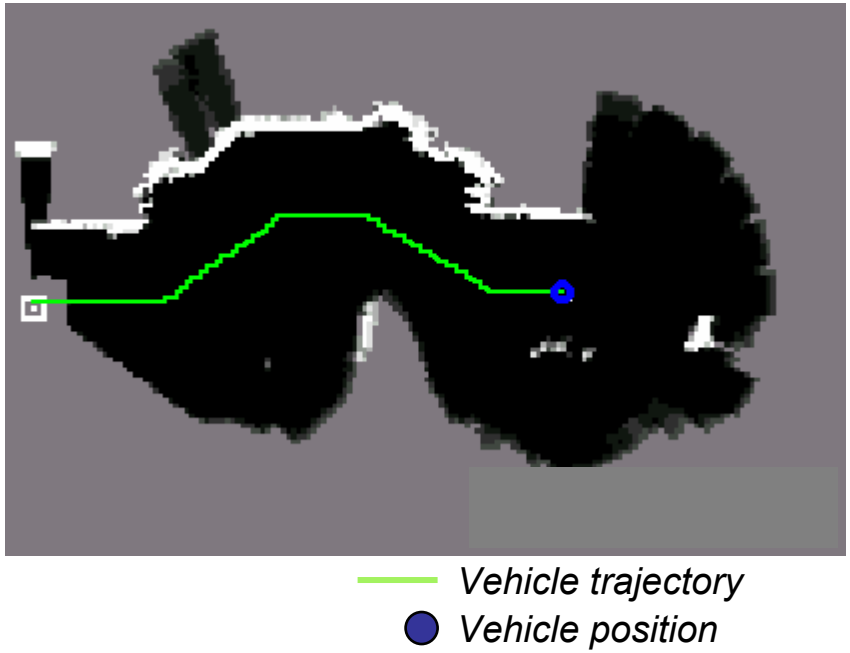
Proximity system: ultrasonic sensors

The ultrasonic sensors installed on the vehicle



Half ring of sonar sensors installed around the vehicle

The considered ***framework*** used for representing range information is the ***occupancy grid map***

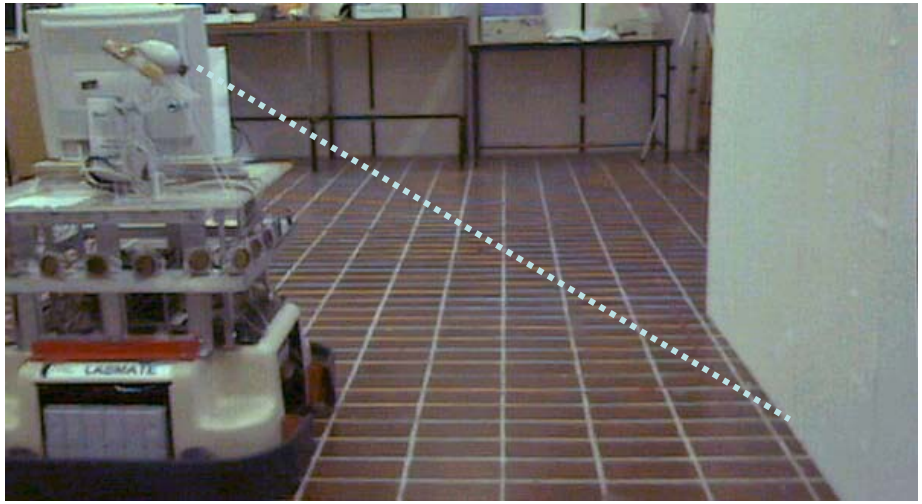


Occupancy grid map:

- it is a **2D** representation of the **whole environment**
- sensor readings are aggregated as occupancy probability values stored in the cells of a grid map

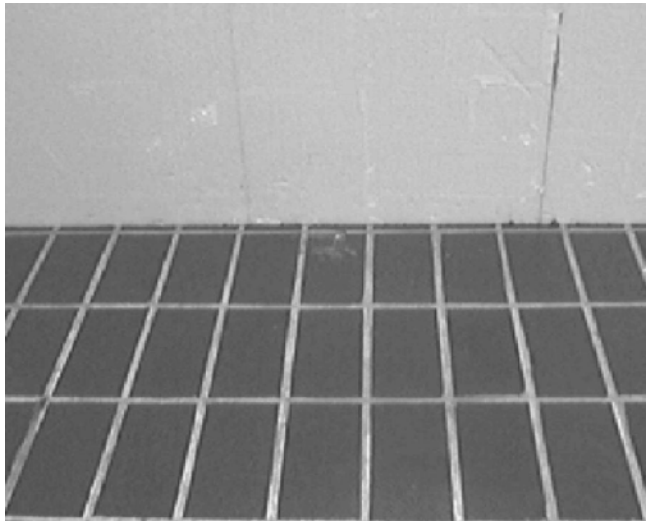
Video system: monocular CCD camera

The ***video sensor*** installed on the vehicle



it is a monocular CCD web-cam installed on the vehicle and pointed down toward the floor

The considered ***framework*** used for representing contour information of the obstacles is the ***digital image***



Digital image:

- it is a **2D** representation of a **part of the environment**
- sensor readings are not expressed in terms of probability values (probability measures must be computed)

Conditions for fusing ultrasonic and video data

1. To extract *common information* from both sets of sensor data:
   LINE FEATURES (Hough Transform)

2. To find a *common framework* for representing the common information:
   VISIBLE SPACE OF THE CAMERA

3. To find a *mathematical instrument* for relating line features of different framework:
   PIN-HOLE CAMERA MODEL

4. To match *line features* by using a
   FUSION TECHNIQUE

LINE FEATURES and the *HOUGH TRANSFORM (HT)*

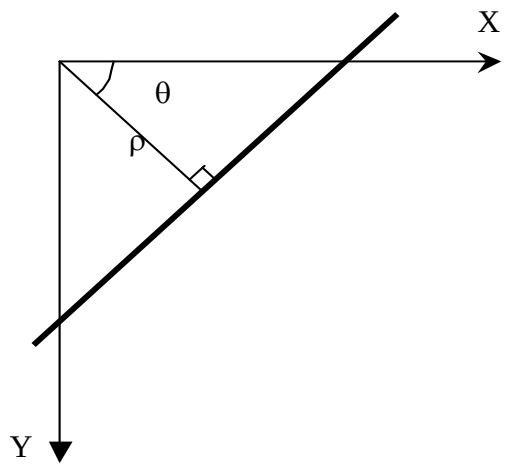
The HT is an image processing technique used for detecting line features

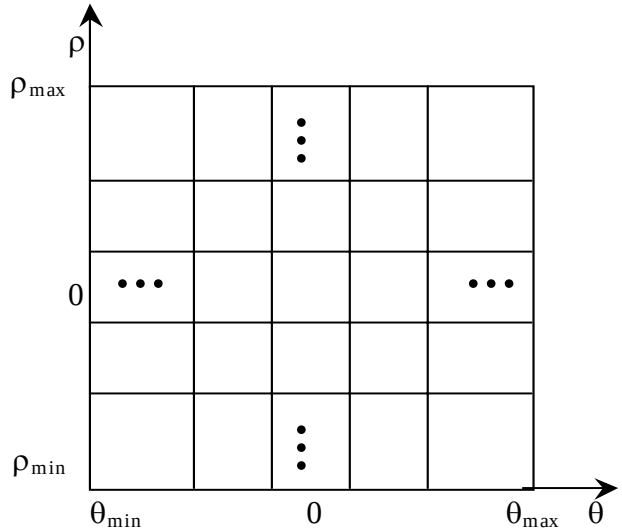
Extracted Information

- ✓ based on a polar representation of line features

$$\rho = x \cdot \cos\theta + y \cdot \sin\theta$$

- ✓ the Hough accumulator (Hough space) is a square array which rows and columns represent quantized values of line parameters ρ and θ; each cell of the array stores a value representing existence evidence for the corresponding line.





Probabilistic Hough Transform

It allows to associate a ***probability values to the line features*** detected ***from digital images*** by computing the probability contribution of each edge pixel to the Hough space $H_V(\theta,\rho)$

Denote:

- $\Theta_V=(\theta,\rho)$ a vector consisting of all possible *quantized values of line parameters θ and ρ* in the Hough space.
- $\hat{\Theta}_V = (\hat{\theta}, \hat{\rho})$ be a vector representing the *estimated line parameters from a pixel* *and assume* $\hat{\Theta}_V$ normal distributed as $\hat{\Theta}_V \approx N(\Theta_V, \Sigma_{\hat{\Theta}_V})$ where $\Sigma_{\hat{\Theta}_V}$ is the covariance matrix.

The *normal joint density distribution for* the estimation $\hat{\Theta}_V$ has the form

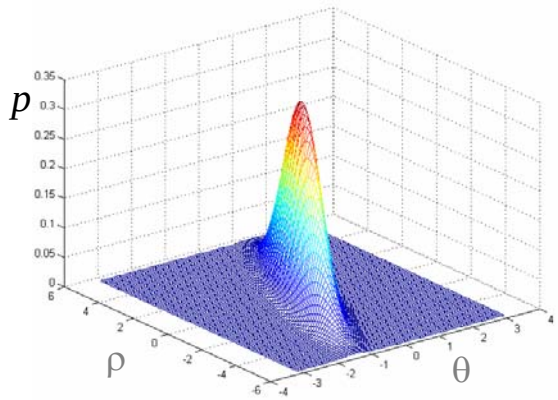
$$p(\hat{\Theta}_V \mid \Theta_V) = \frac{1}{2\pi}\left|\Sigma_{\hat{\Theta}}\right|^{-\frac{1}{2}} \exp\left(-\frac{1}{2}\left(\hat{\Theta}_V - \Theta_V\right)^T \cdot \Sigma_{\hat{\Theta}}^{-1} \cdot \left(\hat{\Theta}_V - \Theta_V\right)\right)$$

Considerations about the Normal joint density distribution $p(\hat{\Theta}_V \mid \Theta_V)$

General situation:

2 correlated normal r.v. $\hat{\theta}, \hat{\rho}$

$$\left|\Sigma_{\hat{\Theta}_V}\right| \neq 0$$



bivariate normal distribution

$p(\hat{\Theta}_V \mid \Theta_V)$

known

+

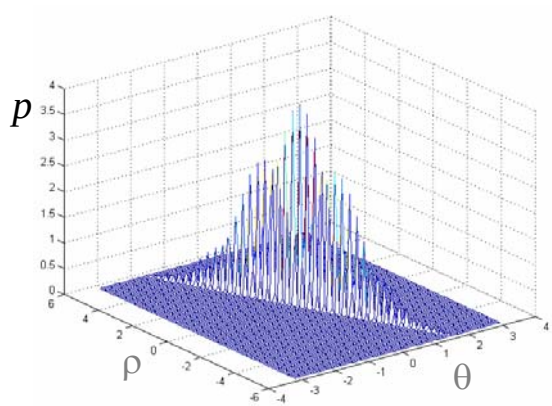
Probability:

$$P(\hat{\Theta}_V \mid \Theta_V) = \iint p \, d\theta \, d\rho$$

Singular situation:

2 linearly dependent normal r.v. $\hat{\theta}, \hat{\rho}$

$$\left|\Sigma_{\hat{\Theta}_V}\right| = 0$$



singular bivariate normal distribution

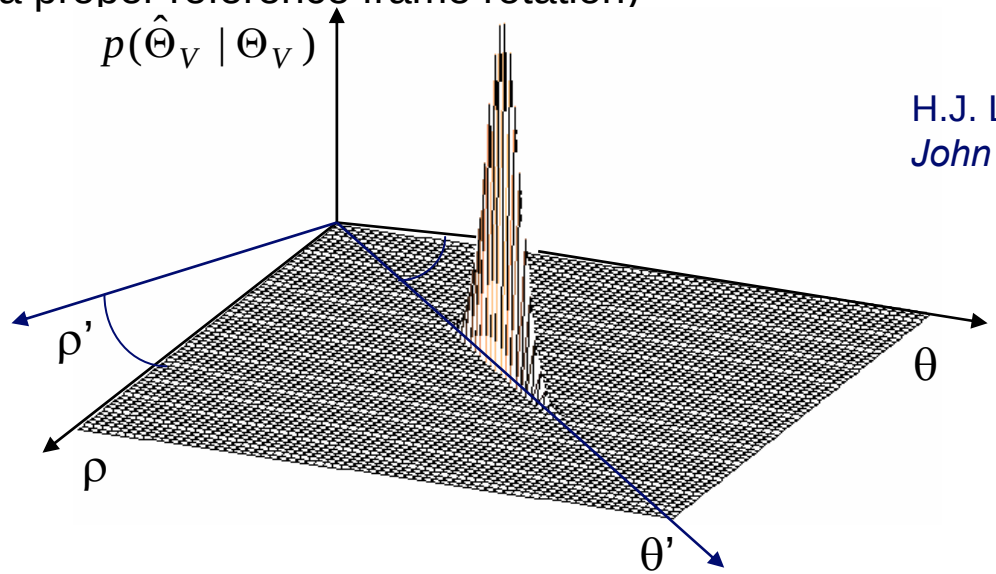
$p(\hat{\Theta}_V \mid \Theta_V)$

can't be computed in a simple way

Q. Ji &R.M. Haralik, *Int. Conf. SMS 1988*

It was shown that

1. for $\hat{\Theta}_V$ it results $\Sigma_{\hat{\Theta}_V}$ **singular** $\left|\Sigma_{\hat{\Theta}_V}\right| = 0$
2. $p(\hat{\Theta}_V \mid \Theta_V)$ **can be always computed** by applying a simple co-ordinate transformation which transform *p* in the **distribution of two independent r. v.** (by means of a proper reference frame rotation)

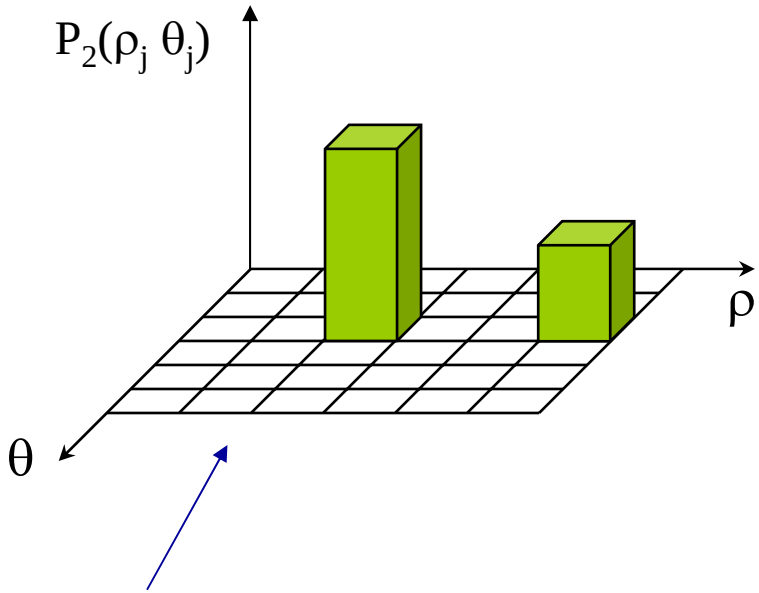


H.J. Larson & B.O. Shubert
John Wiley and Sons, 1979

3. by property 2 it can be showed that $p(\hat{\Theta}_V \mid \Theta_V)$ can be computed as a **function of only one r.v. (i.e. θ)** and then

$$p(\hat{\Theta}_V \mid \Theta_V) = p(\hat{\theta} \mid \theta) = \frac{1}{\sqrt{2\pi}\sigma_\theta} \exp\left(-\frac{1}{2}\frac{(\hat{\theta}-\theta)^2}{\sigma_\theta^2}\right) \Rightarrow P(\hat{\Theta}_V \mid \Theta_V) = \frac{1}{\sqrt{2\pi}\sigma_\theta} \int_{\hat{\theta}-\frac{\Delta\theta}{2}}^{\hat{\theta}+\frac{\Delta\theta}{2}} \exp\left(-\frac{1}{2}\frac{(\hat{\theta}-\theta)^2}{\sigma_\theta^2}\right) d\theta$$

Hough accumulator (Hough space) is a square array which rows and columns represent quantized values of line parameters ρ and θ; each cell of the array stores a value representing existence evidence for the corresponding line.



The contribution of each edge point to all the possible line is obtained by iterating the computation of the edge point probability $p(\hat{\Theta}_V \mid \Theta_V)$ for each possible set of $\Theta_v=(\theta,\rho)$ in the discrete array

The peaks identify the parameters of the most likely lines and the values of these peaks are the probability of these lines

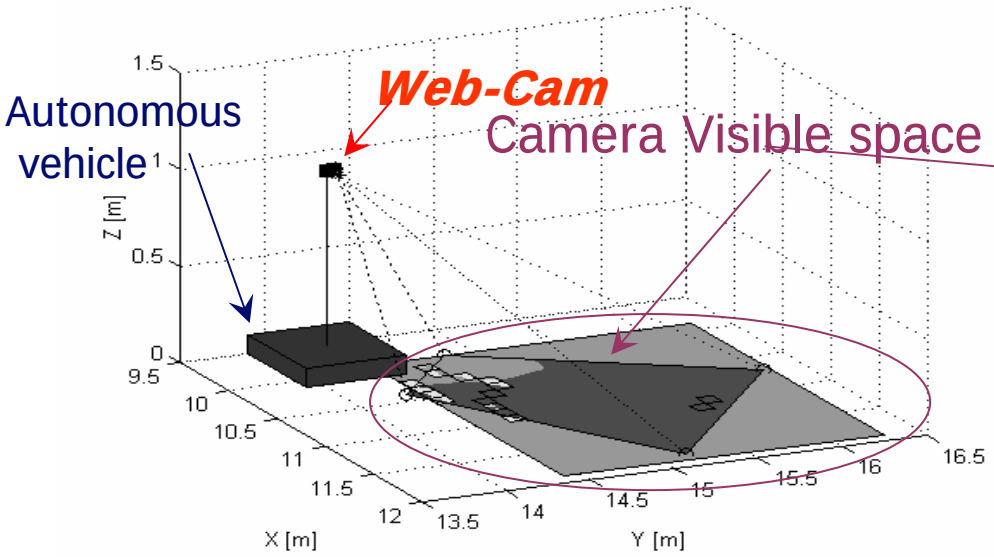
The common framework

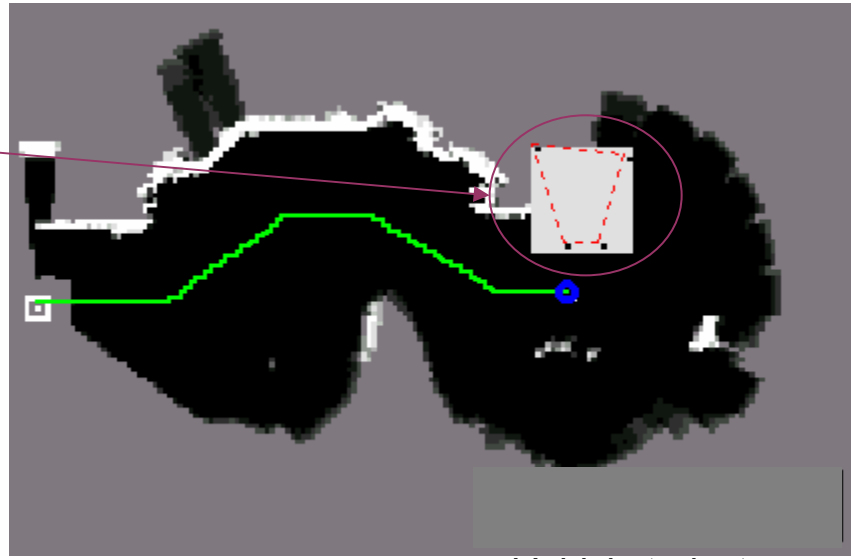
Occupancy grid map
a 2D representation of the considered environment

Digital image
a 2D representation of a part of the environment

Camera visible space (pin-hole camera model)

for defining *which part of the occupancy grid is framed from the camera*





Vehicle trajectory
Vehicle position

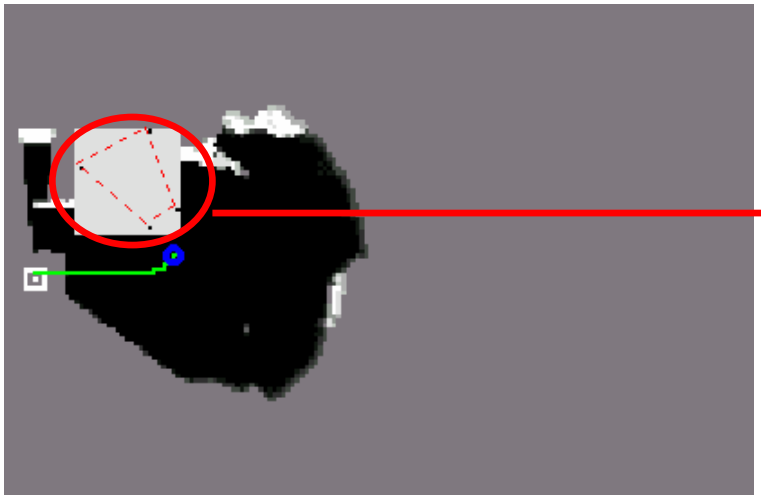
Features extraction from occupancy grid map

sonar image → *bitmap representation of* ***part of the occupancy grid in the visible space*** *of the camera at time interval t during the robot motion*

Occupancy probability values

0.0 *0.5* *0.9*

Occupancy grid map at time t



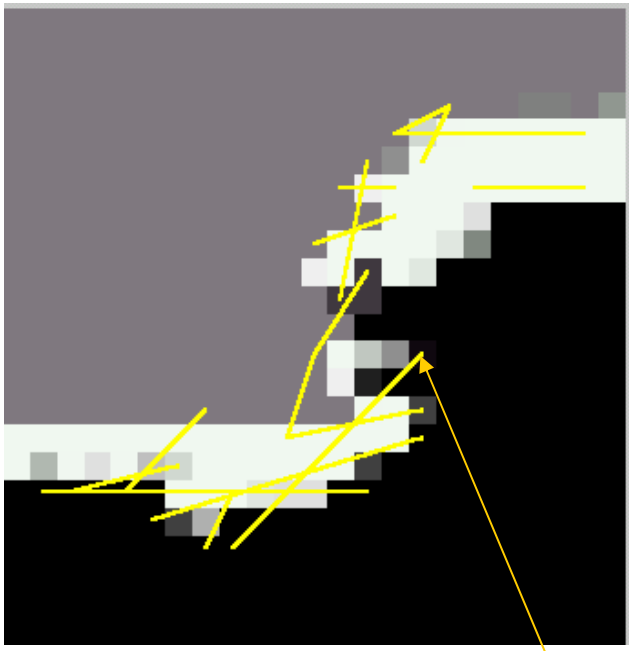
Sonar image at time t

Vehicle trajectory

Vehicle position

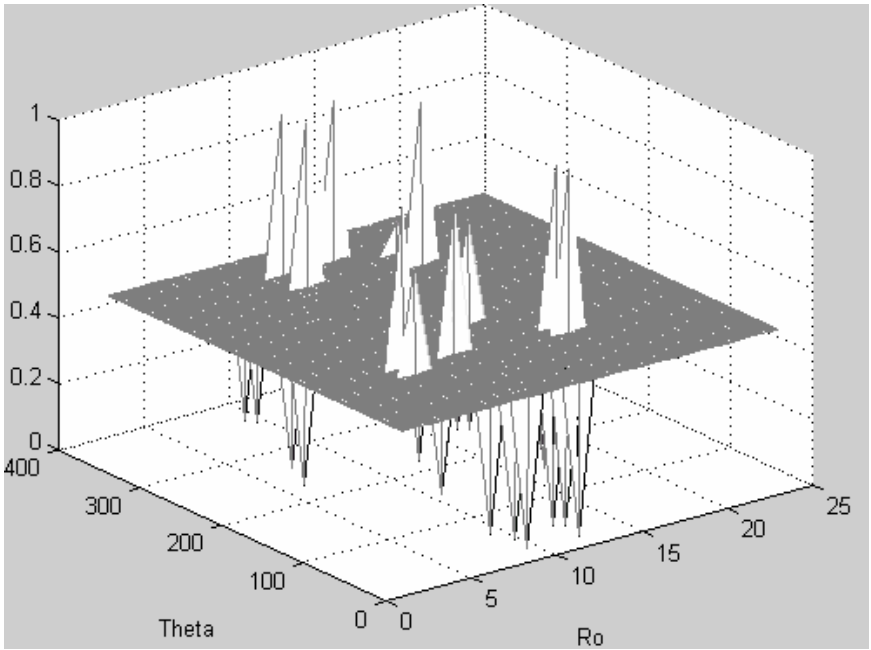
Feature lines extracted by applying the *Hough Transform to the Sonar Image*

Sonar image at time t



straight line extracted from S.I.

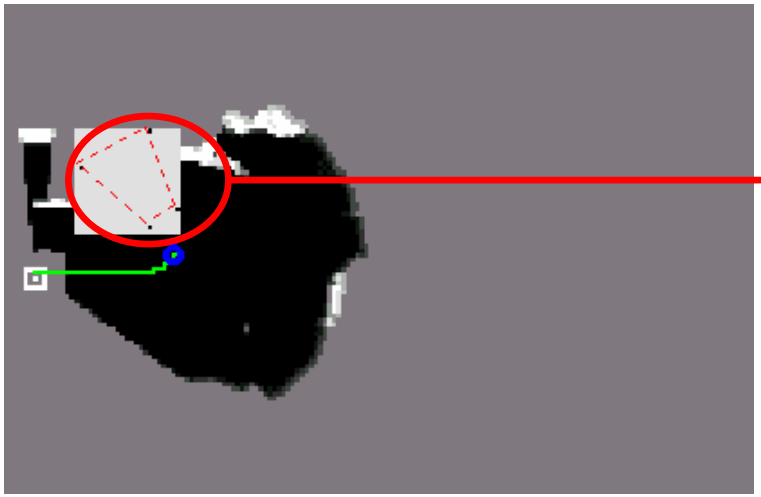
Hough accumulator of the sonar image



The peaks stored in the accumulator are the probability values of the extracted lines

Features extraction from digital images

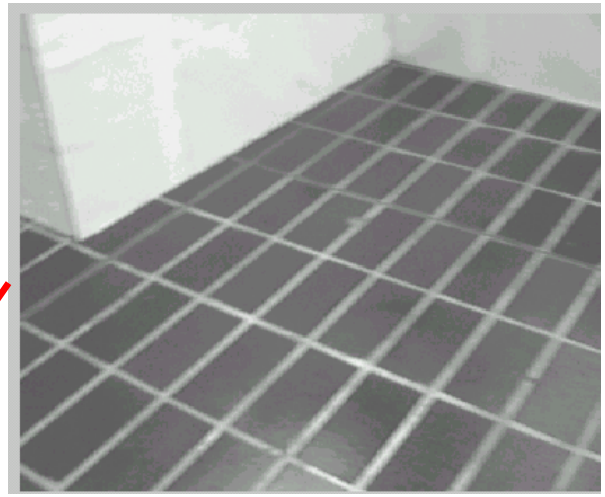
Occupancy grid map at time t



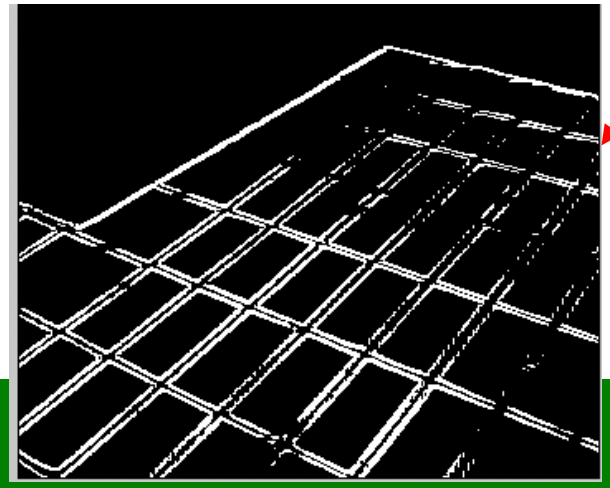
Vehicle trajectory

Vehicle position

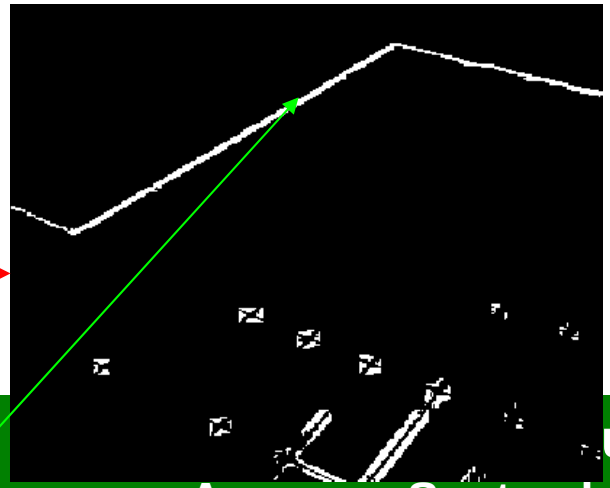
Digital image at time t



Edge detection of Digital image



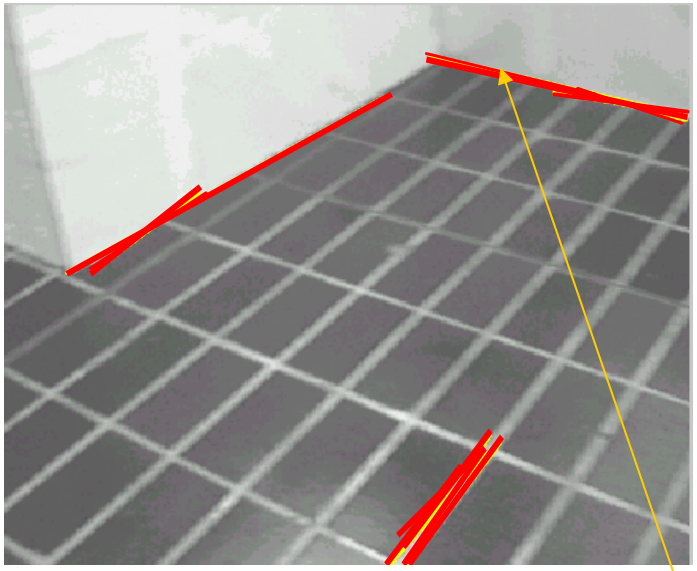
Digital filtering



straight lines
obstacle's contour

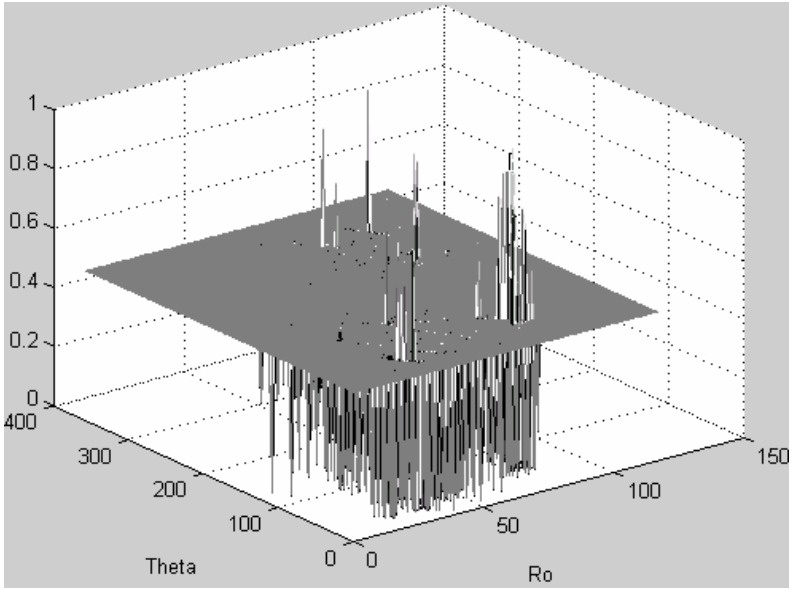
Feature lines extracted by applying the *probabilistic Hough Transform to the filtered digital image*

Digital image at time t



straight line extracted from D.I.

Hough accumulator of the digital image

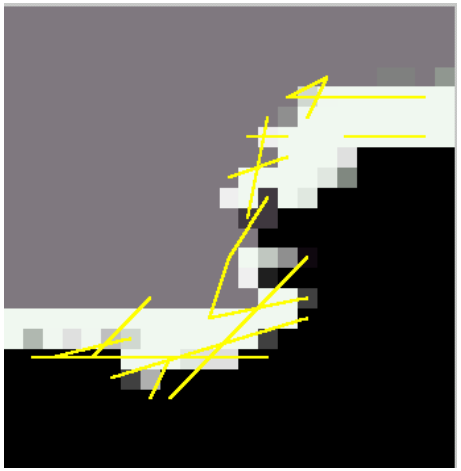


The peaks stored in the accumulator are probability values of the extracted lines

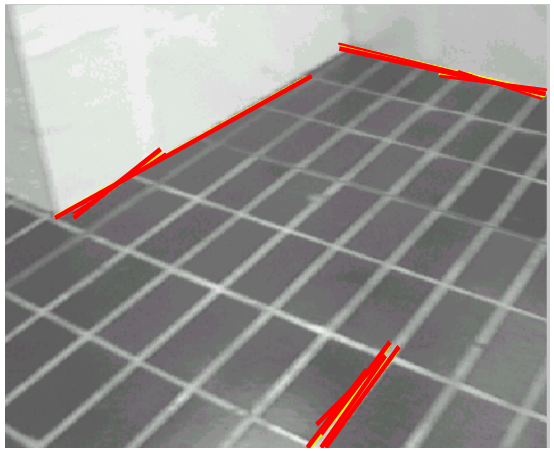
The common framework

Before fusing the lines they will be defined in a common framework (the sonar image)

Lines extracted from Sonar image



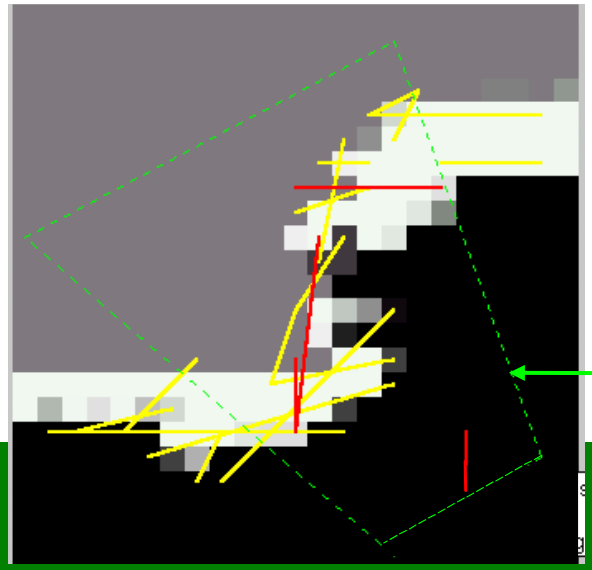
Lines extracted from Video Image



Lines equation:

$$x \cdot \cos\theta + y \cdot \sin\theta = \rho$$

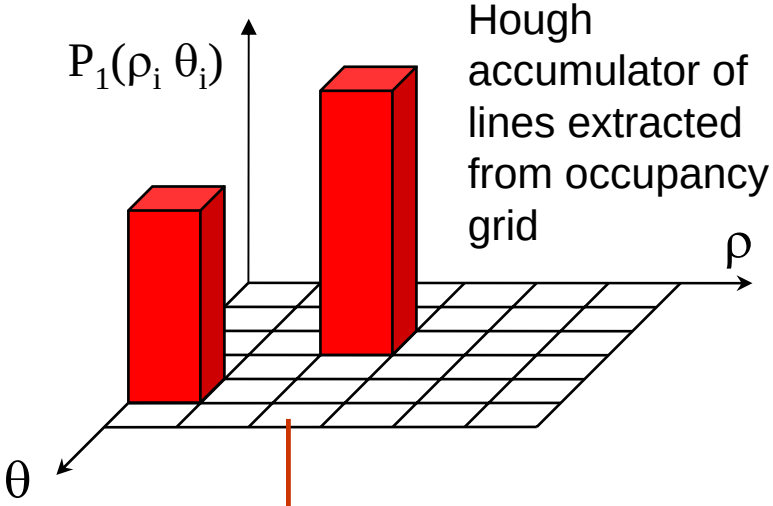
Perspective projection (pin-hole model) of video straight lines on the sonar image

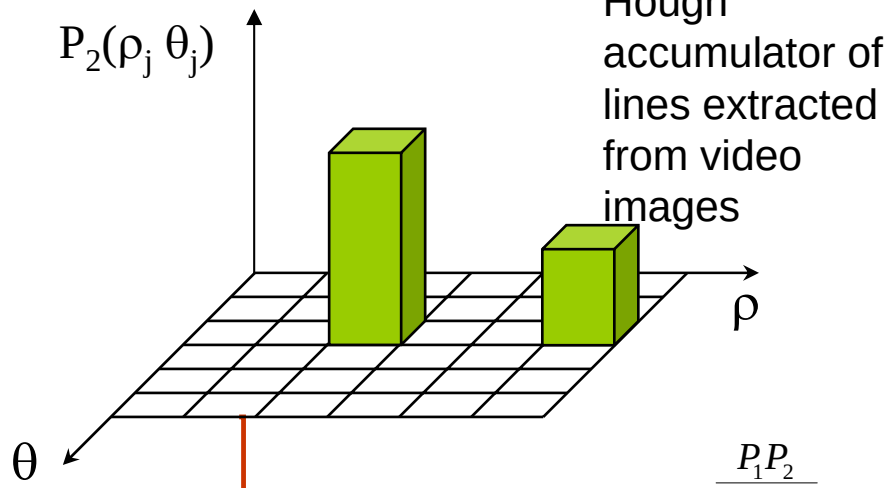


Visible space

Probabilistic Fusion technique

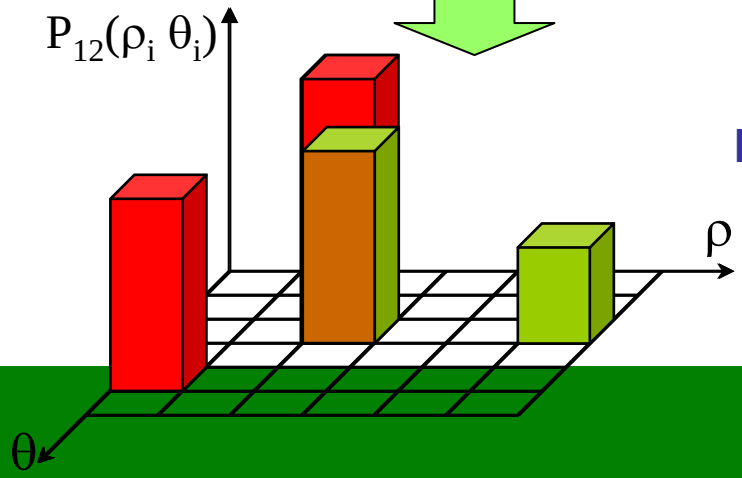
It is a probabilistic ***fusion of the Hough accumulators***



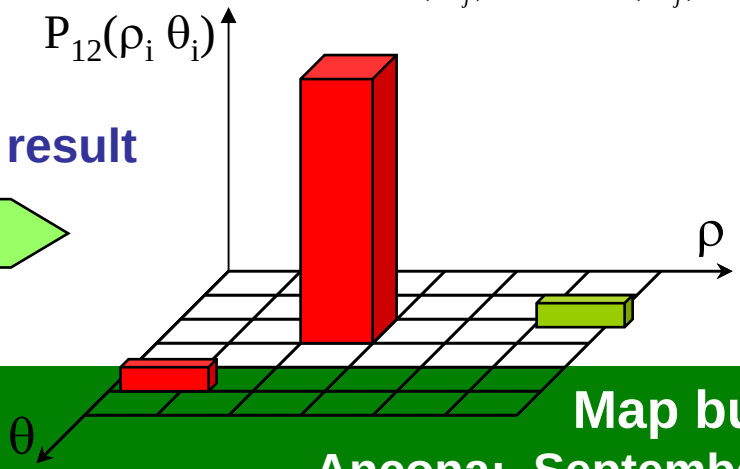


Beyes theorem

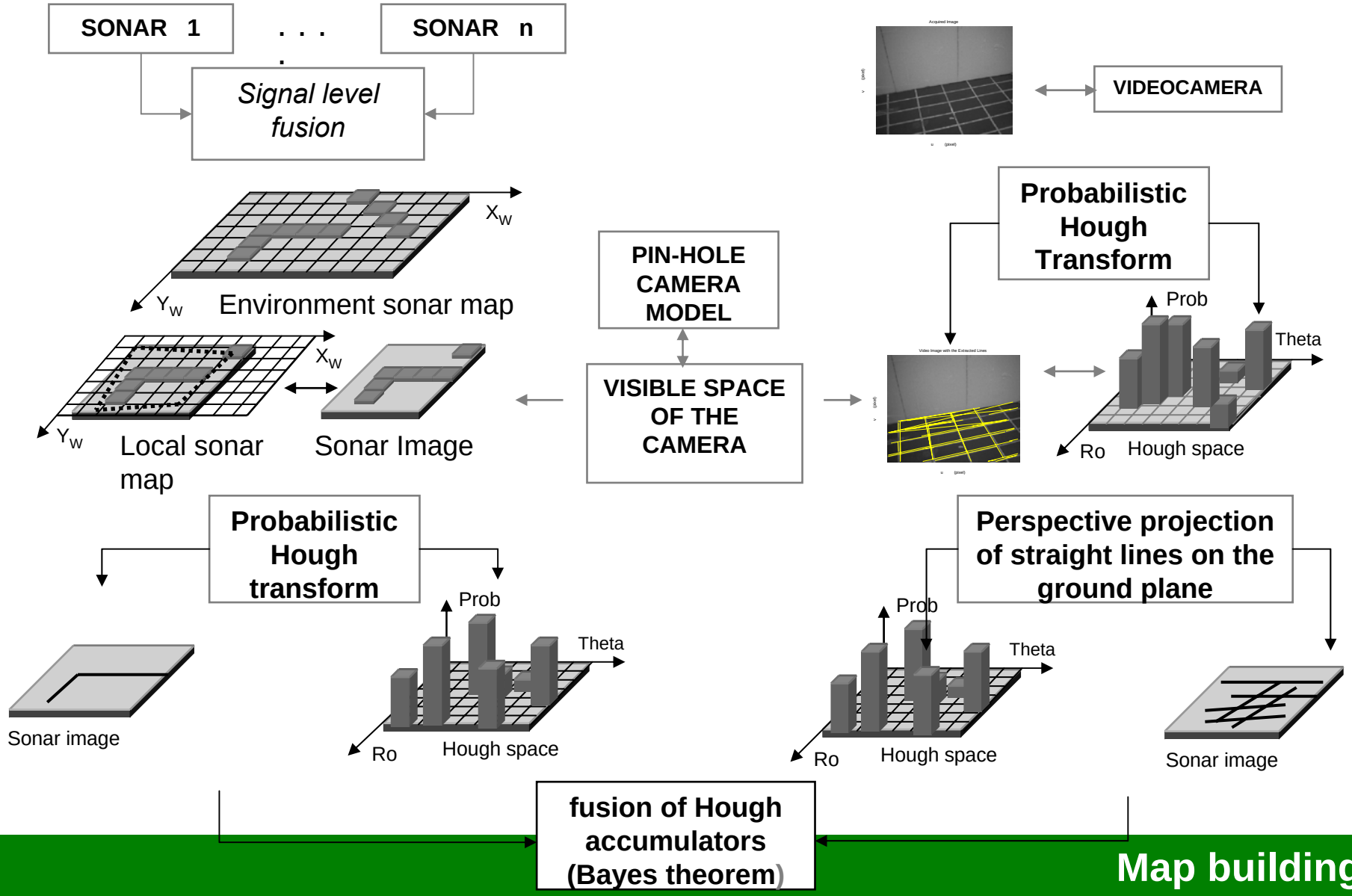
$$P(\Theta_j \mid \Theta_{1j} \cup \Theta_{2j}) = \frac{\dfrac{P_1 P_2}{P(\Theta_j)}}{\dfrac{P_1 P_2}{P(\Theta_j)} + \dfrac{(1-P_1)(1-P_2)}{1-P(\Theta_j)}}$$

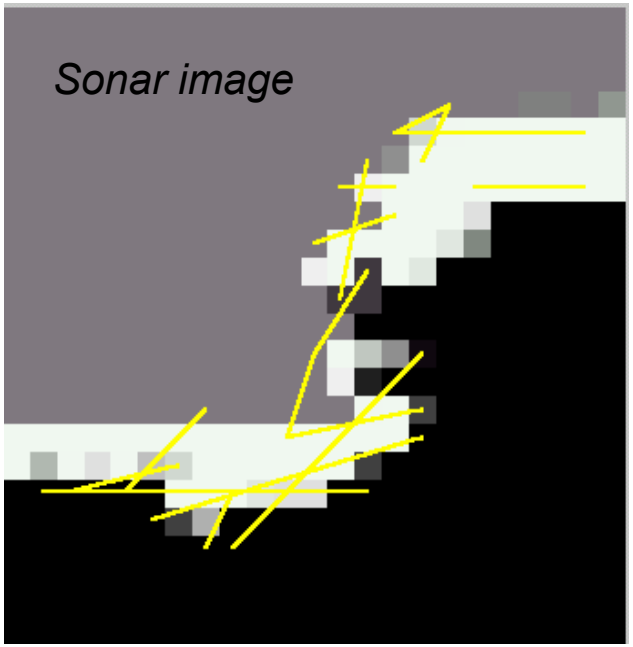


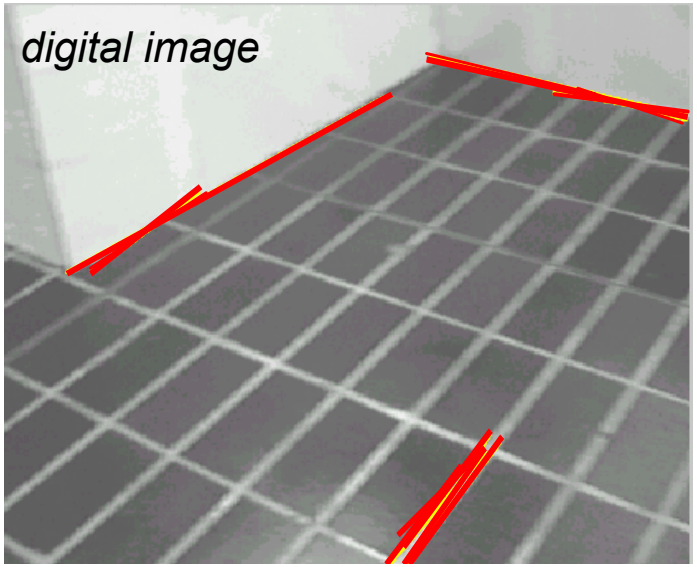
Fusion result

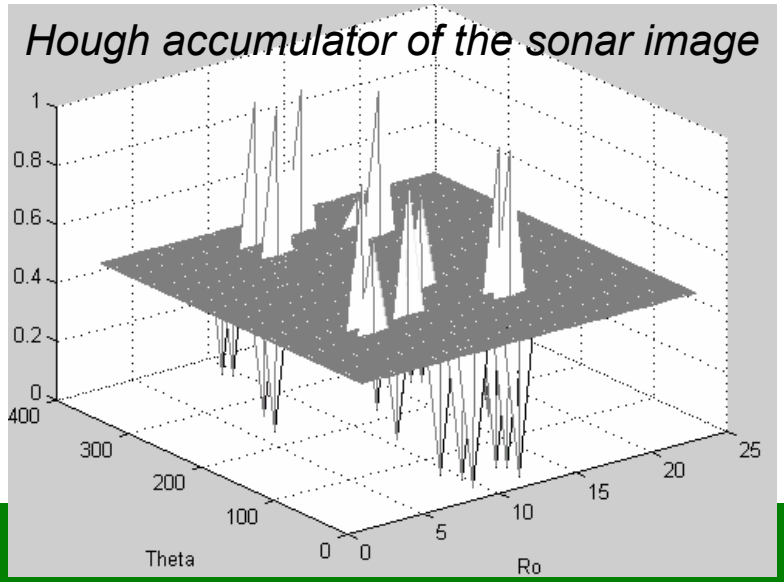


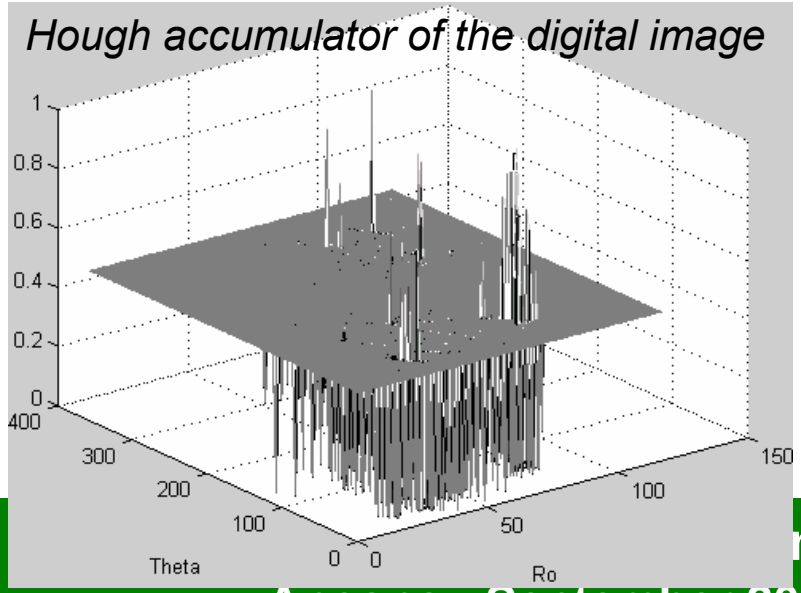
In summary


SONAR 1
. . .
SONAR n
Signal level fusion
VIDEOCAMERA
Probabilistic Hough Transform
Prob
Theta
Ro
Hough space
X_W
Y_W
Environment sonar map
PIN-HOLE CAMERA MODEL
VISIBLE SPACE OF THE CAMERA
X_W
Y_W
Local sonar map
Sonar Image
Probabilistic Hough transform
Sonar image
Prob
Theta
Ro
Hough space
Perspective projection of straight lines on the ground plane
Prob
Theta
Ro
Hough space
Sonar image
fusion of Hough accumulators (Bayes theorem)

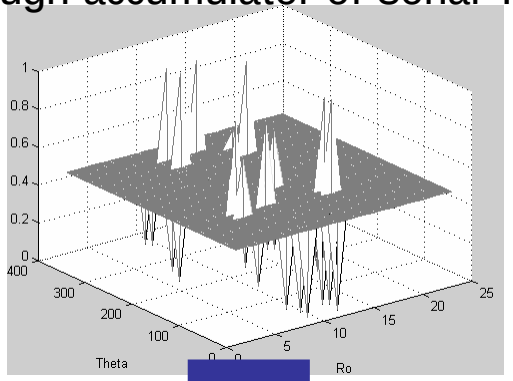

Sonar image


digital image

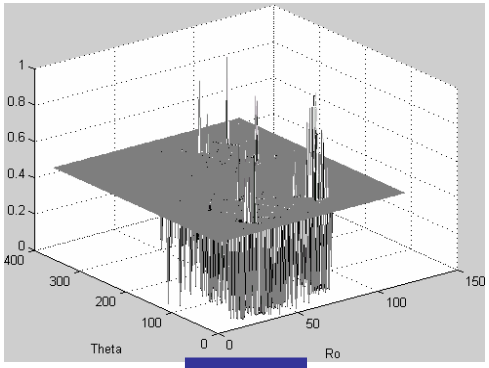

Hough accumulator of the sonar image
1
0.8
0.6
0.4
0.2
0
400
300
200
100
0
Theta
0
5
10
15
20
25
Ro

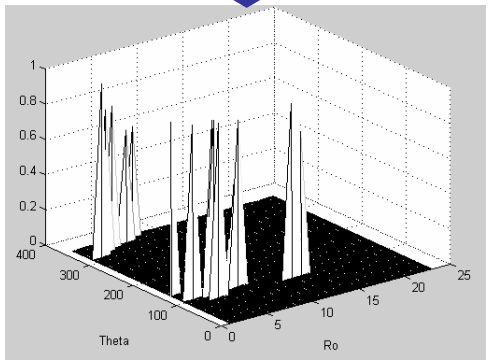

Hough accumulator of the digital image
1
0.8
0.6
0.4
0.2
0
400
300
200
100
0
Theta
0
50
100
150
Ro

Hough accumulator of Sonar Image

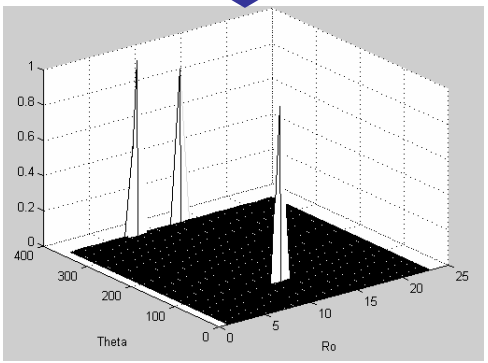


Hough accumulator of Video Image

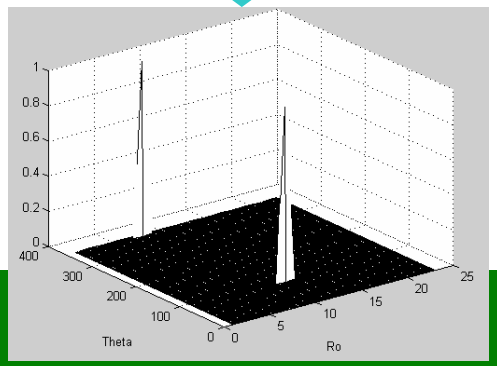


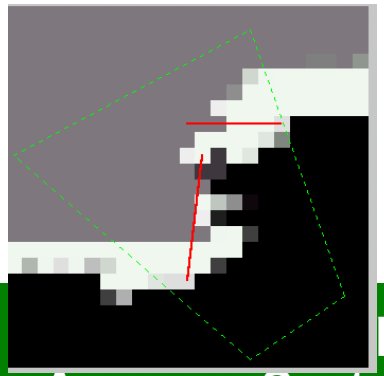


Probabilistic thresholding



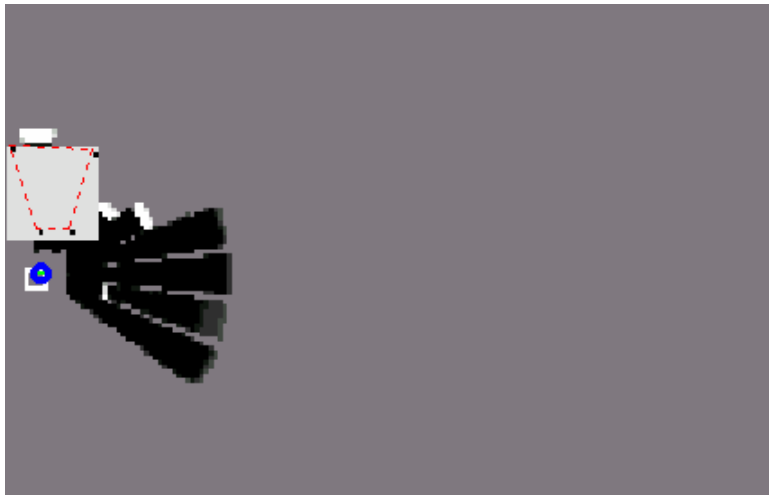
IOP Fusion

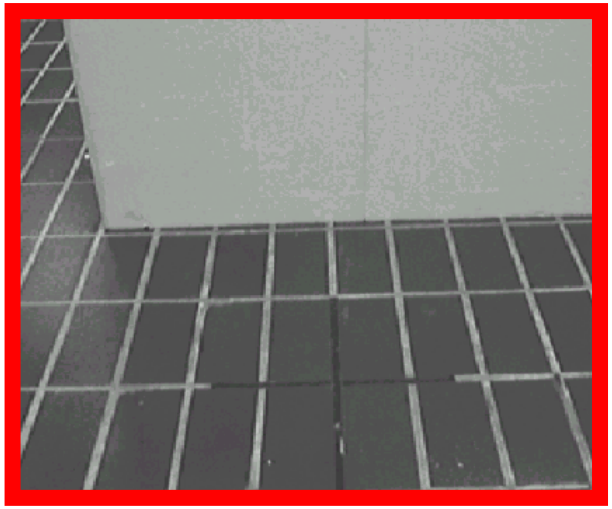




IOP := Independent Opinion Pool
E.A. Bender, Mathematical Methods in AI, IEEE CS Press, 1996

Experimental test

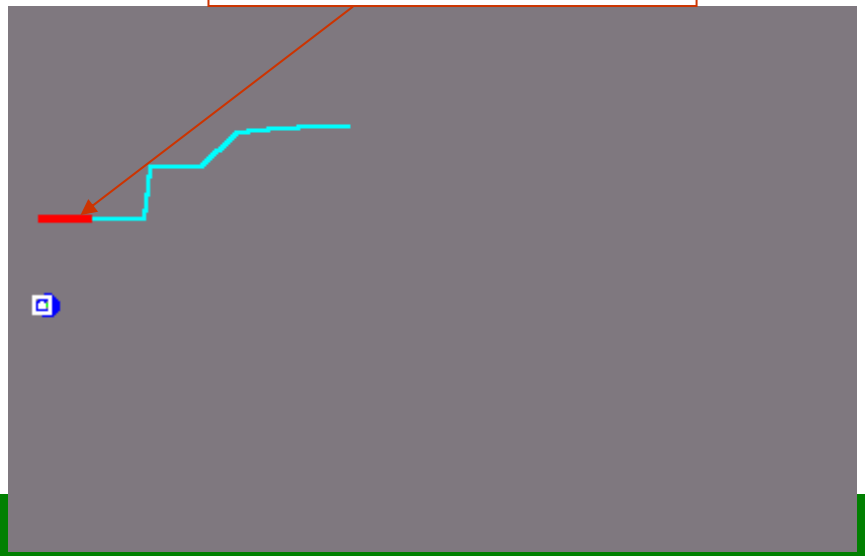




Vehicle's trajectory

Vehicle's position

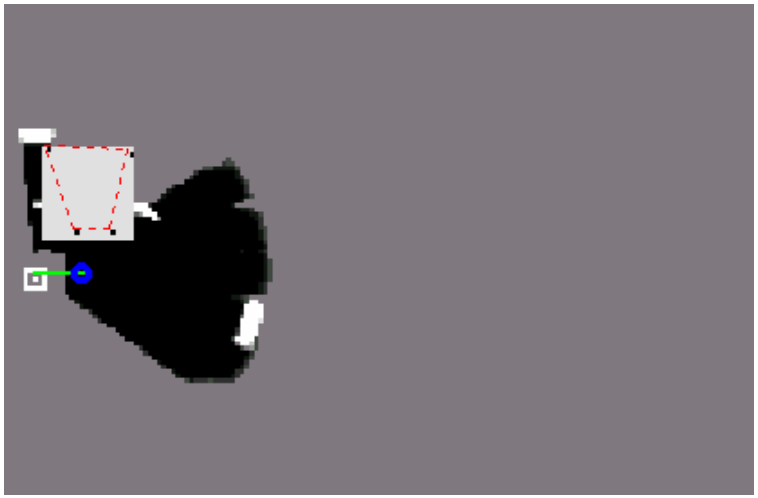
Detected obstacle

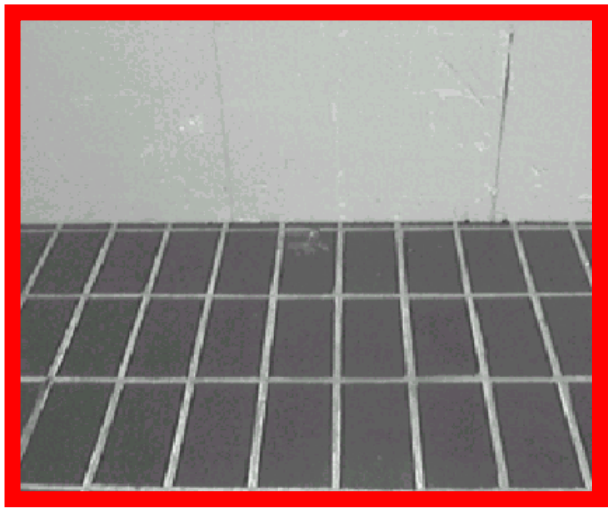


Vehicle's actual position

Real obstacles

detected obstacles

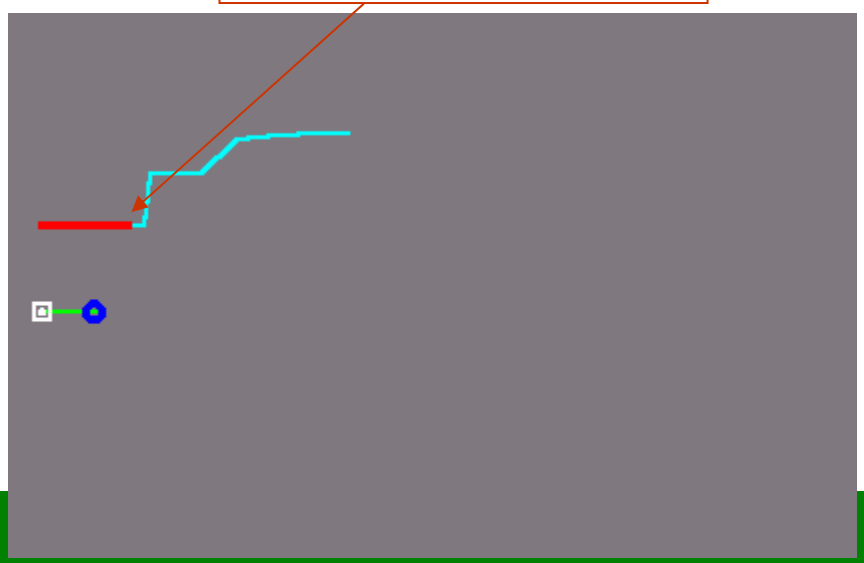




Vehicle's trajectory

Vehicle's position

Detected obstacle



Vehicle's actual position

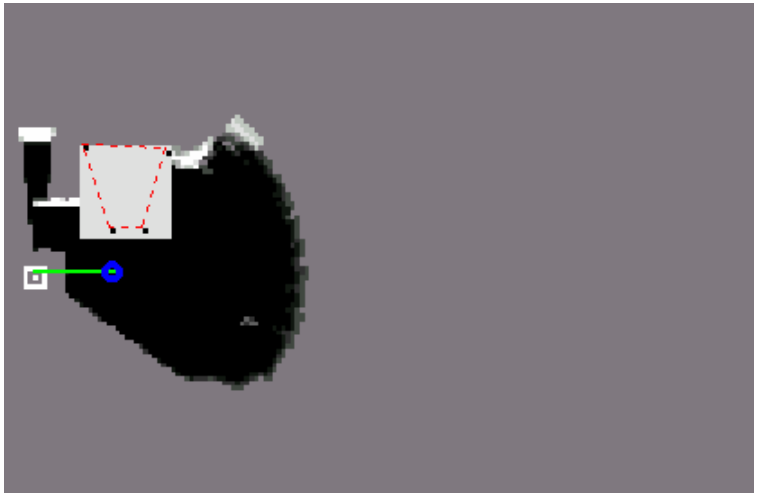
Real obstacles

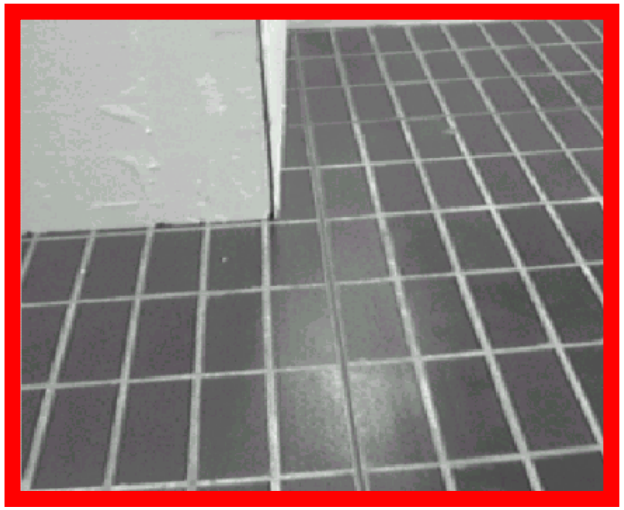
detected obstacles

Vehicle's trajectory

Map building

Ancona: September 2005

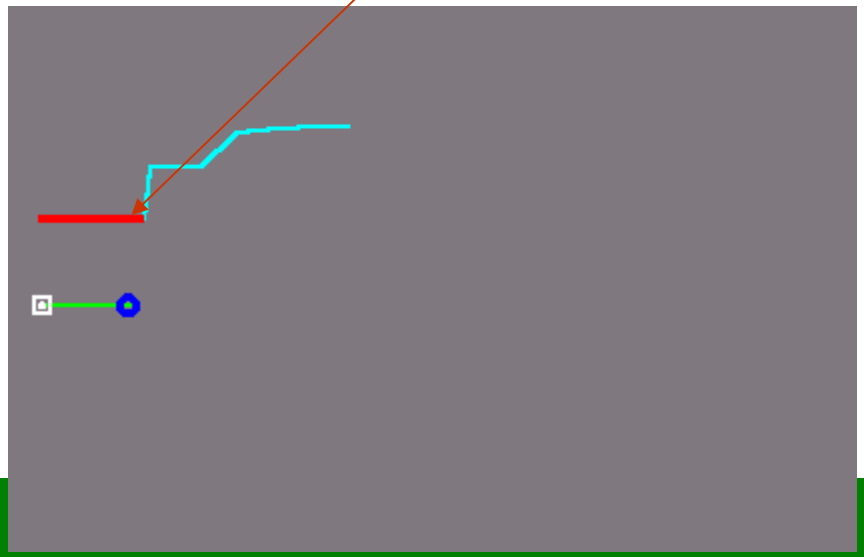




Vehicle's trajectory

Vehicle's position

Detected obstacle

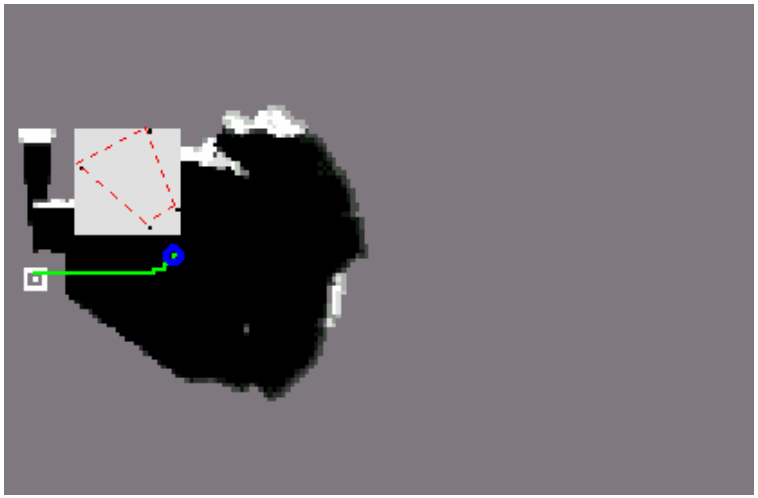


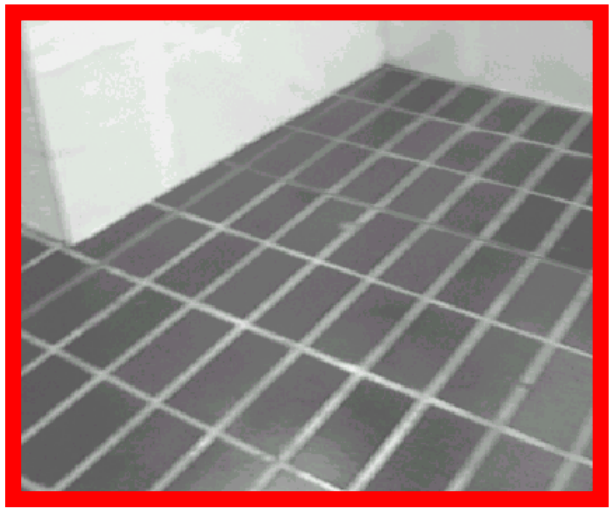
Vehicle's actual position

Real obstacles

detected obstacles

Vehicle's trajectory

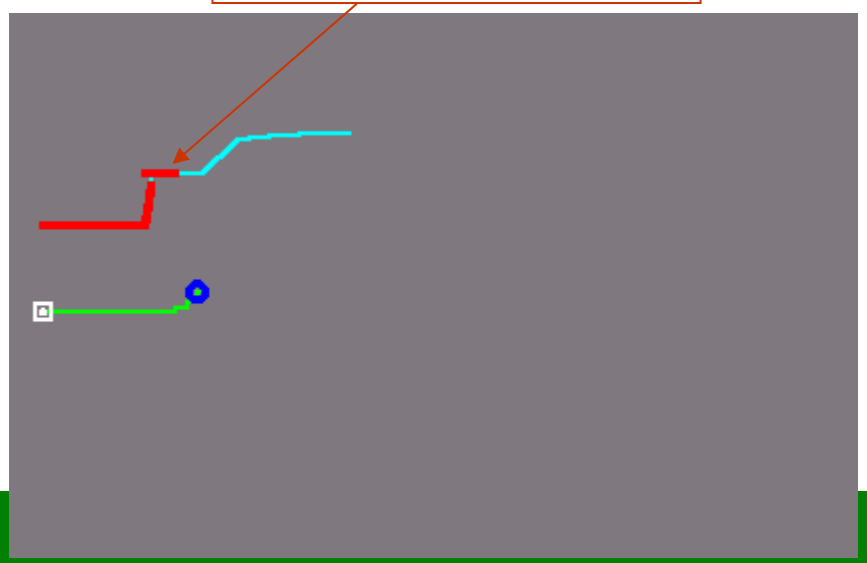




Vehicle's trajectory

Vehicle's position

Detected obstacle

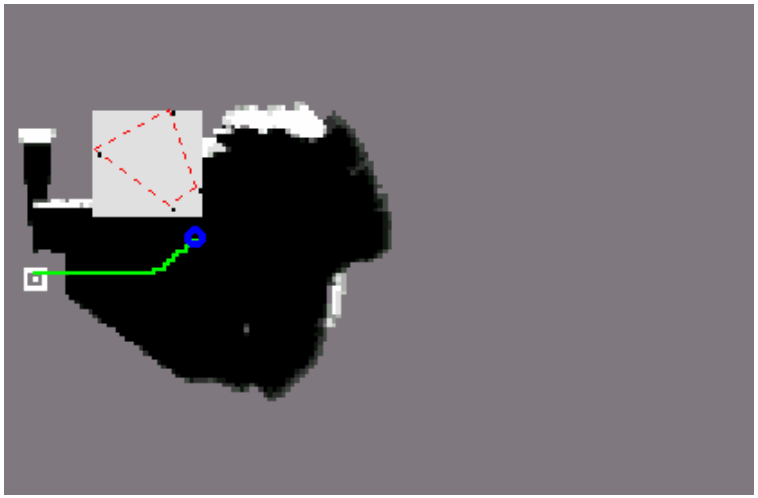


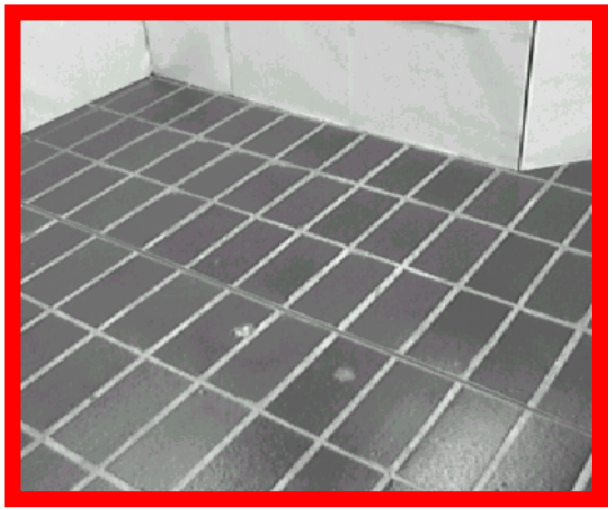
Vehicle's actual position

Real obstacles

detected obstacles

Vehicle's trajectory

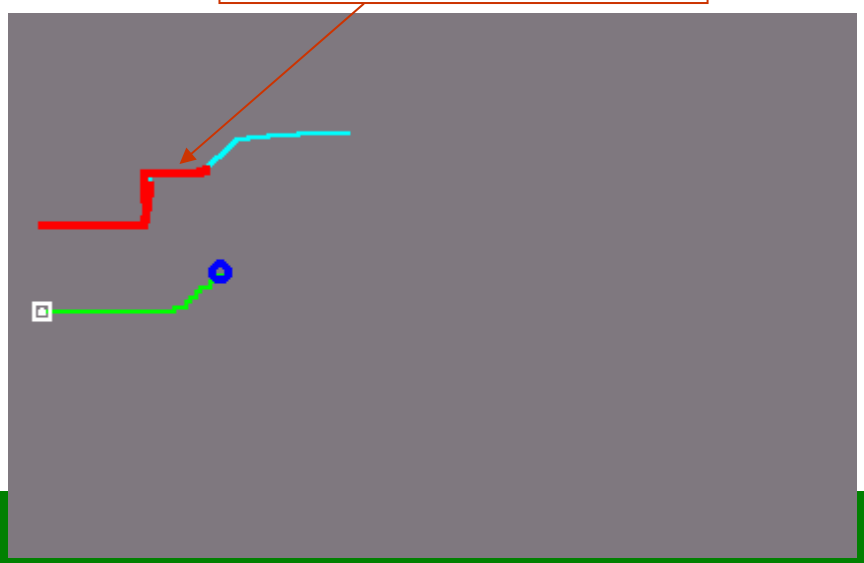




Vehicle's trajectory

Vehicle's position

Detected obstacle

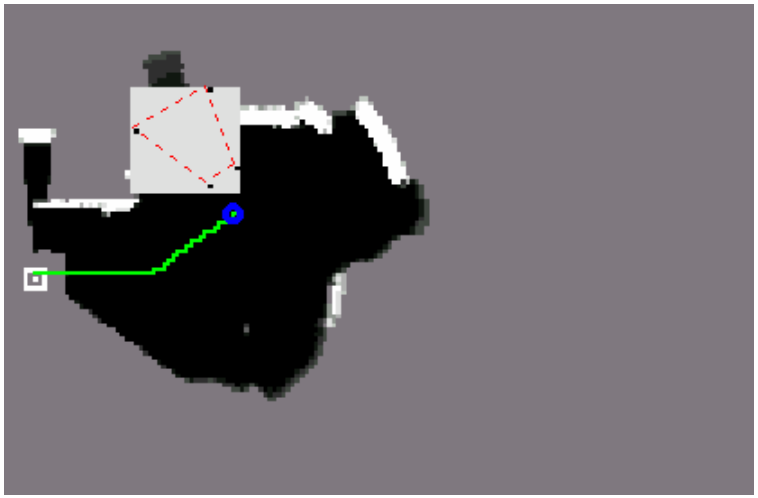


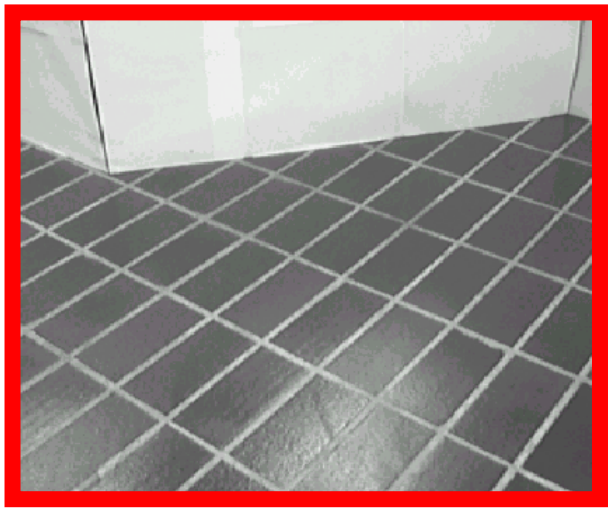
Vehicle's actual position

Real obstacles

detected obstacles

Vehicle's trajectory

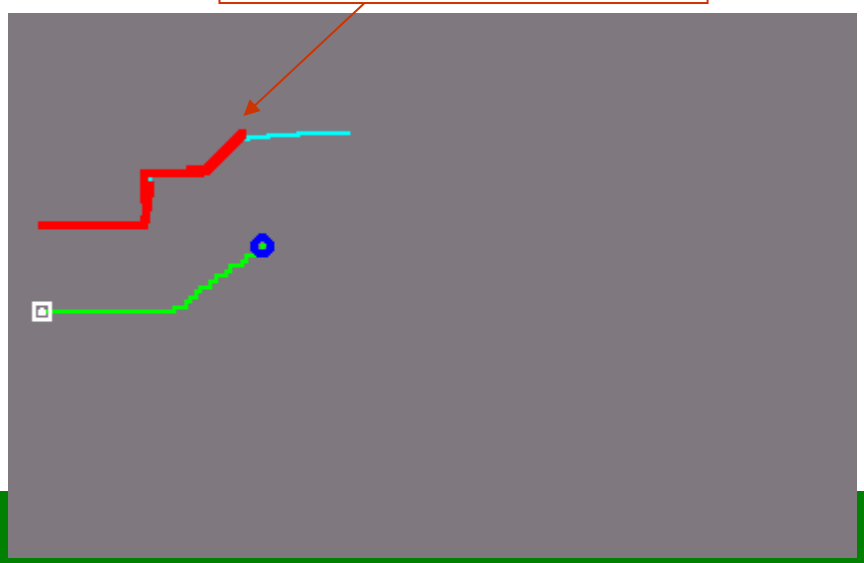




Vehicle's trajectory

Vehicle's position

Detected obstacle

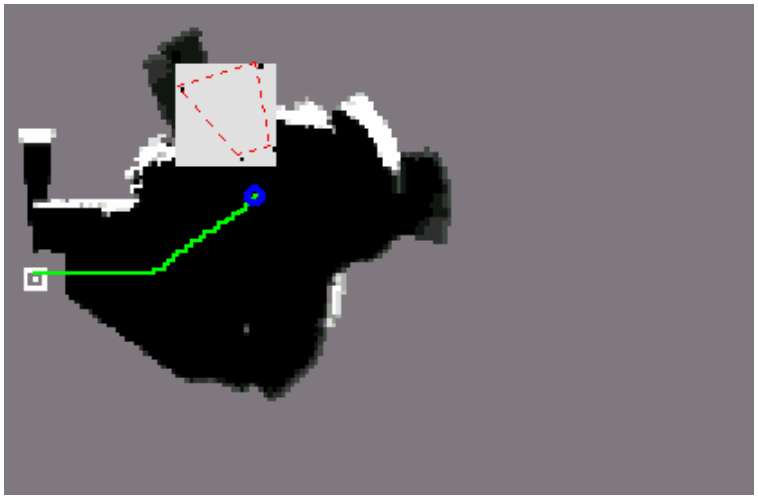


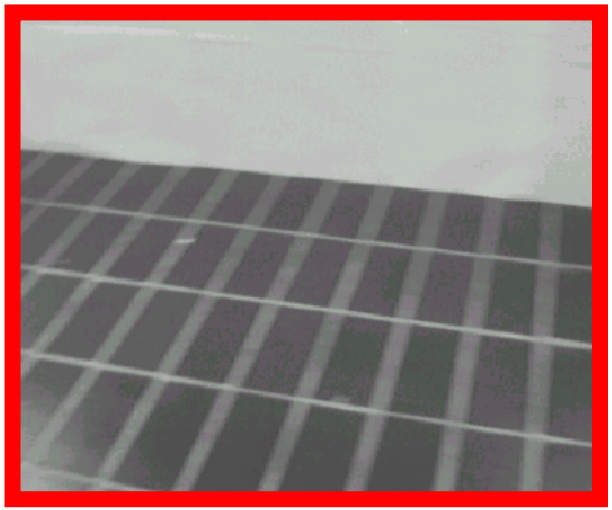
Vehicle's actual position

Real obstacles

detected obstacles

Vehicle's trajectory

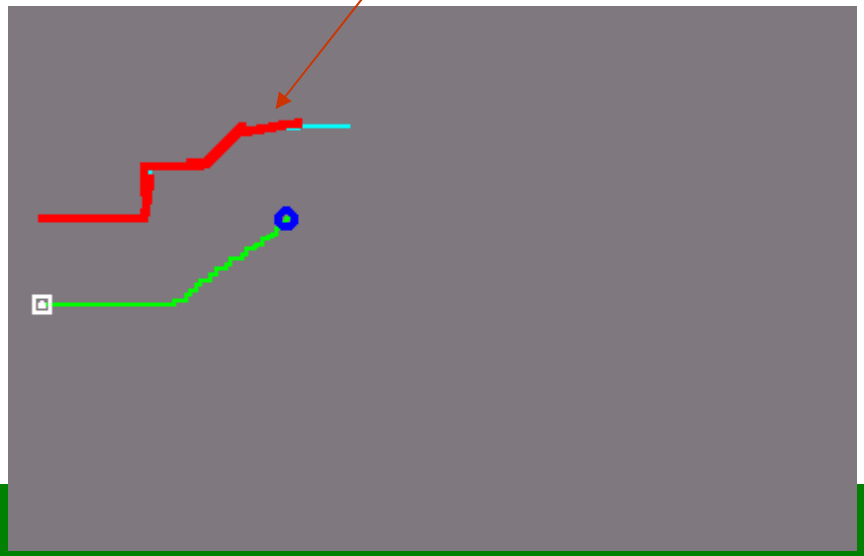




Vehicle's trajectory

Vehicle's position

Detected obstacle

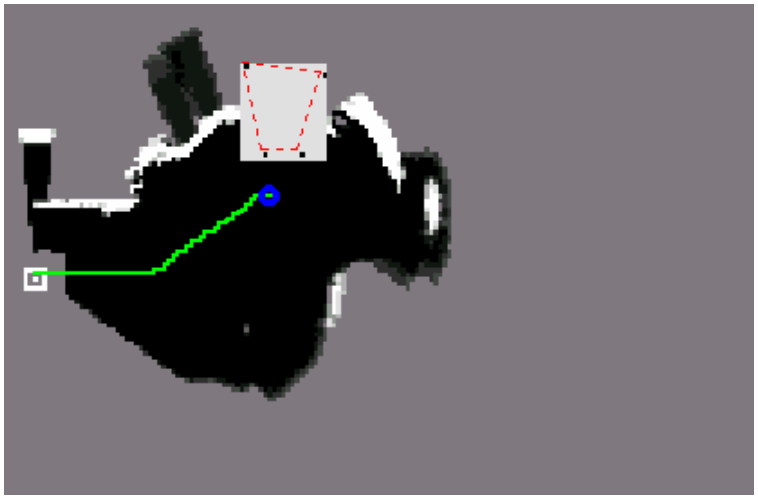


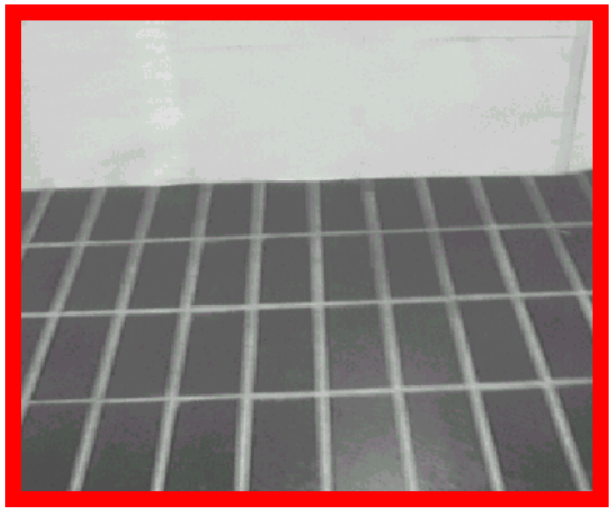
Vehicle's actual position

Real obstacles

detected obstacles

Vehicle's trajectory

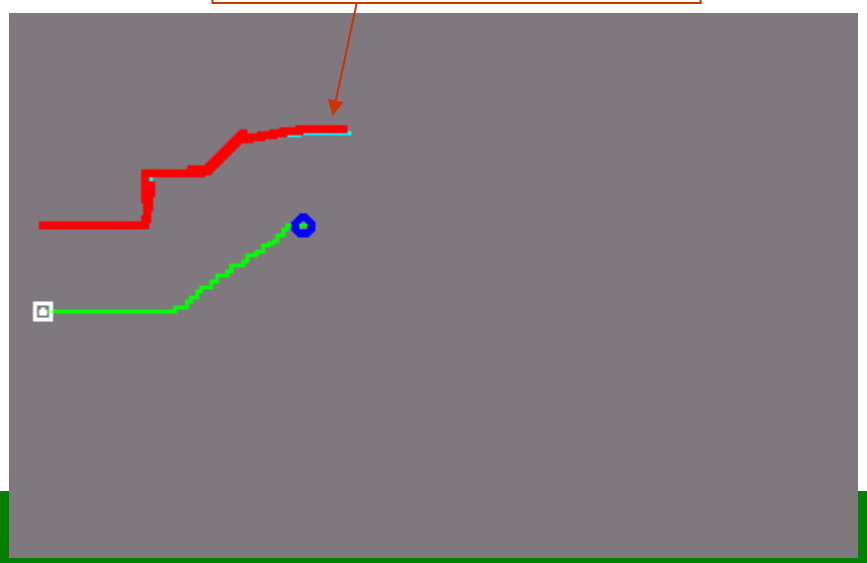




Vehicle's trajectory

Vehicle's position

Detected obstacle



Vehicle's actual position

Real obstacles

detected obstacles

Vehicle's trajectory

Results:

- ✓ The sensor fusion increases the reliability of the acquired environment model
- ✓ The feature based modelling here described can be used for local path planning and reactive navigation of mobile robot
- ✓ Reduction of the memory demand for environment model
- ✓ Experimental results encourage further research
- ✓ Further developments of this work include the application of the proposed techniques for probabilistic localization problems

A. Bonci, G. Di Francesco, S. Longhi, "A Bayesian approach to the Hough Transform for Video and Ultrasonic Data Fusion in Mobile Robot Navigation", *Proceedings of the 2002 IEEE international Conference on Systems, Man and Cybernetics*, Hammamet, Tunisia, October 2002, paper n. TA1H1.

A. Bonci, T. Leo, S. Longhi, "A Bayesian Approach to the Hough Transform for Line Detection", IEEE Transaction in Systems, Man and Cybernetics, part A, (to be published).

Obstacle avoidance

The on-line map building is the main tool also for obstacle avoidance: the map is used for detecting with the necessary reliability the obstacle on the environment

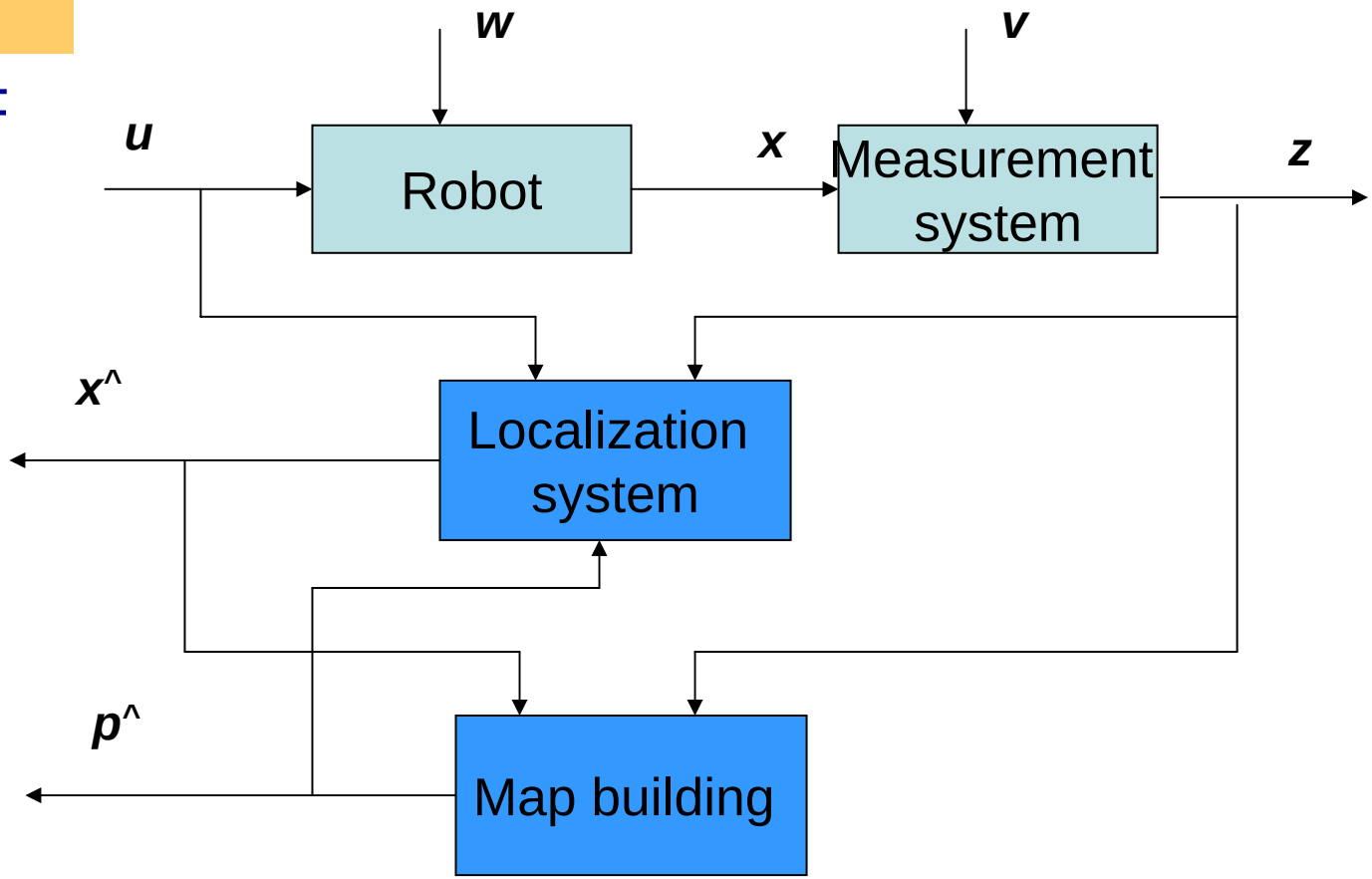
Angeloni et al, "Real time collision avoidance for mobile robots", Proc. SMCR, 1996

*An algorithm has been developed on a proper extension of the **Bug2** algorithm (introduced by Lumenlsky for the motion planning problem) with the introduction*

- ✓ *of visual capabilities by sonar sensors*
- ✓ *of a predefined trajectory*
- ✓ *of an avoidance strategy (the choice of the avoidance direction is produced on the basis of the available local information)*

SLAM

EKF



Anausaki and Kyriakopoulos, 1999, Simultaneous localization and map building for mobile robot navigation, IEEE Robotics & Automation Magazine, pp.42-53.

Data fusion between sonar readings and video data for improving the construction of a feature map to be used for the localization.

Part 3: “Kalman Filter”

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In mobile robotics sensor fusion is used for base localization and map building

Different sets of sensors are used (internal, external) proprioceptive and exteroceptive sensors

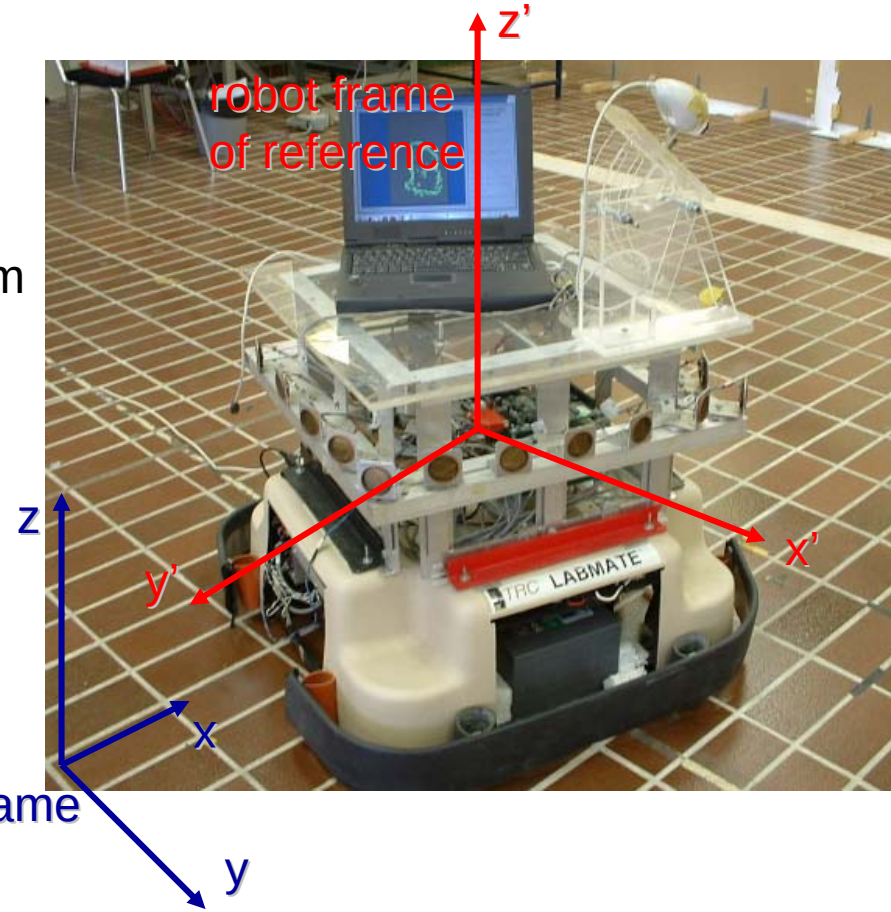
Problem to be solve is the integration of the different sensors readings

A simple and efficient solution is based on a proper designed Kalman filter

Main hypothesis: linearity and Gaussian distributions for modelling the uncertainties of the sensor readings

Intelligent autonomous robot

Where am I? ⇨ Localization problem



environment frame
of reference

There are many different techniques for estimating the pose of a mobile robot
$\mathbf{x} := [\, x \;\; y \;\; \theta \,]^T$

pose := robot position over the plane xy + orientation

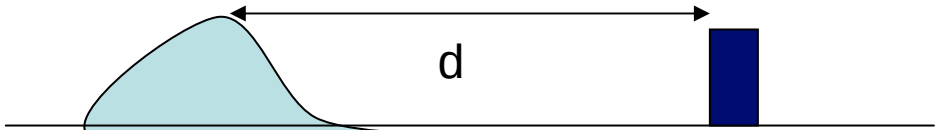
(Pose tracking if the initial robot pose is known)

For example in a **Bayesian approach**:
to find $p(\mathbf{x}_k | \mathbf{z}_1, \mathbf{z}_2, \ldots, \mathbf{z}_k)$ where $\mathbf{x}_k$ is a time varying signal and $\{\mathbf{z}_i\}$ are measurements acquired by sensors.

A more complete description of the state of the robot is not possible.

When $p(\mathbf{x}_k | \mathbf{z}_1, \mathbf{z}_2, \ldots, \mathbf{z}_k)$ can be represented by a Gaussian, the mean and the covariance give a full description of the state.

Most of Localization procedures are based on different method for approximating the distribution $p(\mathbf{x}_k | \mathbf{z}_1, \mathbf{z}_2, \ldots, \mathbf{z}_k)$

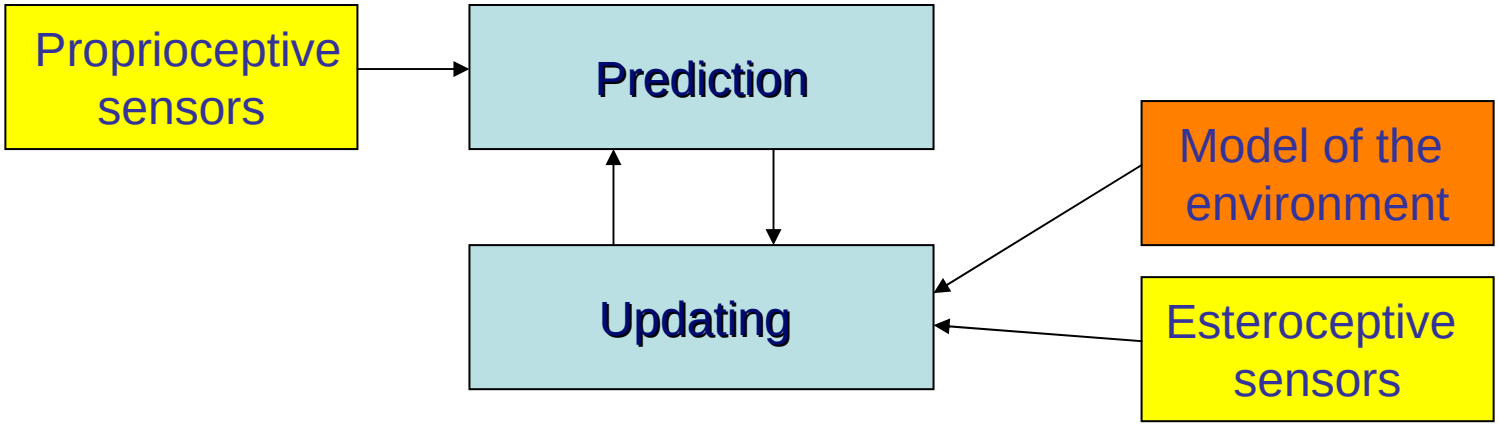


In the robot localization, the main problem is the right association between sensor data and environment model

If the data association can be performed, then the localization problem is a classical estimation problem, where the sources of all measures are known

Then the pose estimation can be decomposed in two main steps: prediction + updating

For example:



The prediction step is introduced for avoiding "ambiguity" on the sensor data (video, sonar, laser… exteroceptive sensors), it is always necessary!!!

Data Association

It is necessary for determining the measurement "source", the "object" of the measurement

Some measurements must be neglected, because they are related to objects of the environment that are not modelled in the map, and therefore they cannot be used for the localization (unknown obstacles…)

$M = \{ f_j \mid j=1, 2, \ldots m \}$ is the environment model (Feature map)

In the data association there are two possibilities for **z**:

i) it is a measurement of an element f_j of M
ii) it is a measurement of an object not included in the map (to be neglected?)

Pose estimation (a possible classification)

- ✓ *Dead-Reckoning*
- ✓ *Topological*
- ✓ *Gaussian*
- ✓ *Position Probability Grids*
- ✓ *Monte Carlo Methods*

This possible classification is based on the considered representations for modelling the uncertainty on the robot pose

Gaussian

The Gaussian distributions are the most considered tools to represent the uncertainty of the robot (there are many different independent sources of uncertainty)

The Kalman Filter is generally used in this context together with a metric map as a model of the environment (the model is generally based on edges, lines, planes…)

The Kalman Filter is a simple and optimal recursive data processing algorithm. For the considered problem the key point is the "recursive" aspect: the measures are processed as they are acquired

The Kalman Filter provides an optimal estimation of **x** given the measurements **z** if:
- the system is linear
- the model noise is white and Gaussian
- the measurement noise is white and Gaussian

This solution (Kalman Filter for pose tracking) will be deeply analyzed in the following

There are many contributions based on this approach:

Crowley, 1985, navigation for an intelligent mobile robot, IEEE J. of Robotics and Automation, pp 31-41

Durrant-Whyte, 1994, "Where am I", Industrial robot, pp. 11-16

Jetto el al., 1999, Development and experimental validation of an adaptive extended Kalman filter for the localization of mobile robots, IEEE Trans. Robotics and Automation, pp. 219-229

Fabrizi et al., An integrated sensing guidance system for robotized wheelchair, Proc. Of the 14th IFAC World Congress, pp. 457-462

…

A simple classification:

	Accuracy	Complexity
Topological	low	low
Gaussian	high	low
Pose grid	medium	high
MCM	high	medium

Kalman Filter for the pose tracking of mobile robot

- ✓ Different set of sensors
- ✓ Feature model of the environment (the metric map it is assumed to be known)
- ✓ Different hypotheses of the measurement errors
- ✓ Experimental validation

Kalman filter

Linear system with state noise $\mathbf{w}_k \sim N(0, Q_k)$ and measurement noise $\mathbf{v}_k \sim N(0, R_k)$ (independent)

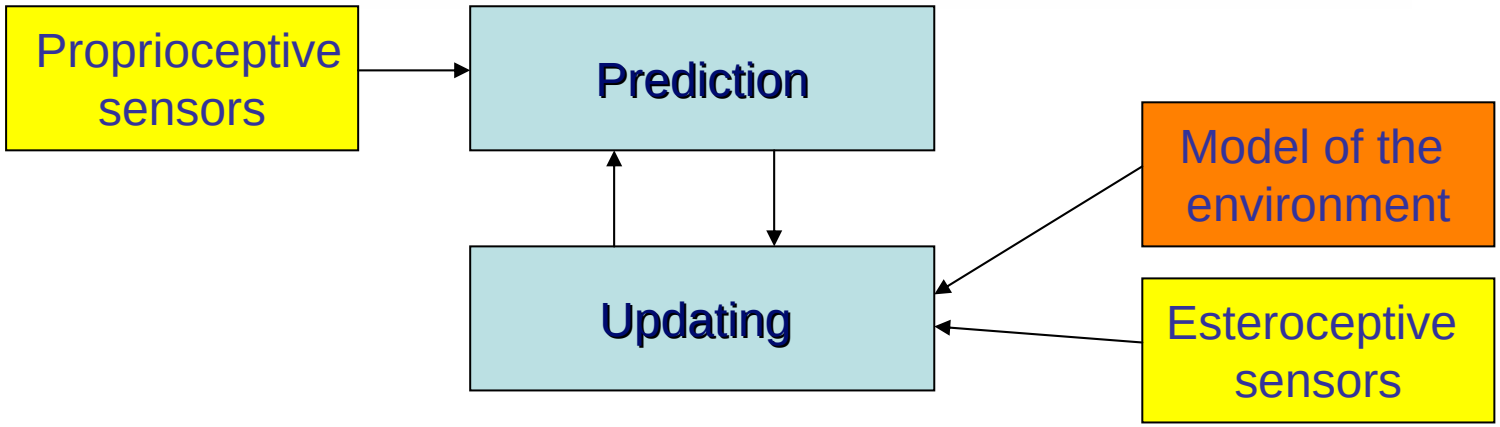
$$\mathbf{x}_k = F\mathbf{x}_{k-1} + G\mathbf{u}_{k-1} + \mathbf{w}_{k-1}$$

$$\mathbf{z}_k = H\mathbf{x}_k + \mathbf{v}_k$$

Prediction: a priori estimation of the state and of the error covariance

$$\hat{\mathbf{x}}_{k|k-1} = F\hat{\mathbf{x}}_{k-1|k-1} + G\mathbf{u}_{k-1}$$

$$P_{k|k-1} = FP_{k-1|k-1}F^T + Q_{k-1}$$



Updating: the measure $\mathbf{z}_k$ is used to correct the estimate

$$S_k = H P_{k|k-1} H^T + R_k$$ covariance of the innovation process

$$K_k = P_{k|k-1} H^T S_k^{-1}$$ filter gain

$$\nu_k = \mathbf{z}_k - H \hat{\mathbf{x}}_{k|k-1}$$ innovation process

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + K_k \nu_k$$

$$P_{k|k} = (I - K_k H) P_{k|k-1}$$

Cox, 1964, On the estimation of state variables and parameters for noisy dynamic systems, IEEE Trans. Autom. Control, pp. 5, 12..

Jazwinski, 1970, Stochastic processes and filtering theory, vol. 64, Math. in Science and Engin., Accademic Press.

Bar-Shalom and Fortman, 1988, Tracking and Data Association, Accademic Press.

Initialization: the initial state and initial value of the error covariance matrix $P_{0|0}$

These choices depend on the available a priori knowledge on the considered estimation problem

On the Kalman filter it is assumed known a priori the time-invariant system dynamics, the measurement equations, the model of the noise

The Kalman filter it one of the most important results of the use of state space methods in modern control theory.

The Kalman filter it one of the most important results of the use of state space methods in modern control theory.

Under the assumptions introduced in the Kalman filter (linearity and Gaussian distributions) the Kalman filter is equivalent to the maximum likelihood, Bayesian, least square, and minimum mean-square error estimations

Brown, Durrant-Whyte, Leonard, Rao and Steer, 1992, Distributed data fusion using Kalman filtering: a robotics applications, in *Data Fusion in Robotics and Machine Intelligence*, Abidi and Gonzales Eds, Academic Press.

This solution can be also extended to the non-linear case (Extended Kalman Filter) by a simple linearization technique

In this case no results exist on the filter convergence

The performance depends on the accuracy and significance of the linear model used

For the problems here considered: the robot model is not linear (for example the kinematic model), in this case a linearization technique can be introduced and this case the solution of the estimation problem is based on a Extended Kalman Filter

Non linear model:

$$\mathbf{x}_k = \mathbf{f}(\mathbf{x}_{k-1}, \mathbf{u}_{k-1}, \mathbf{w}_{k-1})$$
$$\mathbf{z}_k = \mathbf{h}(\mathbf{x}_k, \mathbf{v}_k).$$

defining:

$$F_k = \left.\frac{\partial \mathbf{f}}{\partial \mathbf{x}_k}\right|_{\hat{\mathbf{x}}_{k-1|k-1}, \mathbf{u}_{k-1}, 0}$$
$$W_k = \left.\frac{\partial \mathbf{f}}{\partial \mathbf{w}_k}\right|_{\hat{\mathbf{x}}_{k-1|k-1}, \mathbf{u}_{k-1}, 0},$$

Prediction: a priori estimation of the state and of the error covariance

$$\hat{\mathbf{x}}_{k|k-1} = \mathbf{f}(\hat{\mathbf{x}}_{k-1|k-1}, \mathbf{u}_{k-1}, 0)$$
$$P_{k|k-1} = F_k P_{k-1|k-1} F_k^T + W_k Q_{k-1} W_k^T$$

Updating: the measure $\mathbf{z}_k$ is used to correct the estimate

$$H_k = \left.\frac{\partial \mathbf{h}}{\partial \mathbf{x}_k}\right|_{\hat{\mathbf{x}}_{k|k-1},0}$$

$$V_k = \left.\frac{\partial \mathbf{h}}{\partial \mathbf{v}_k}\right|_{\hat{\mathbf{x}}_{k|k-1},0}$$

$$S_k = H_k P_{k|k-1} H_k^T + V_k R_k V_k^T$$

$$K_k = P_{k|k-1} H_k^T S_k^{-1}$$

$$\nu_k = \mathbf{z}_k - \mathbf{h}(\hat{\mathbf{x}}_{k|k-1}, 0)$$

innovation process

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + K_k \nu_k$$

$$P_{k|k} = (I - K_k H_k) P_{k|k-1}$$

A note:

in this algorithm the linear model is time-varying along the state trajectory and therefore also the filter equations have time-varying matrices!!!

Data association:

For determining the origin of the measurement, the object of the measurement

Some sensor readings must be rejected; when the measurements are referred to objects of the environment that are not modelled in the map and therefore such measurements can not used for the localization (unknown obstacles, furniture,

$$\rho_k = \nu_k S_k^{-1} \nu_k^T$$

(Mahalanobis distance) the difference between the measure $\mathbf{z}_k$ and its expected value $h(x_{k|k+1},0)$

$$\rho_k \leq \gamma$$

Bar-Shalom and Fortmann, 1988, Tracking and Data Association, Academic Press

Approaches to localization using the Kalman filter

- ✓ Adaptive estimation of robot location through an Adaptive Extended Kalman Filter integrating odometric and sonar measures

  Jetto el al., 1999, Development and experimental validation of an adaptive extended Kalman filter for the localization of mobile robots, IEEE Trans. Robotics and Automation, pp. 219-229

- ✓ An alternative adaptive approach, where the adaptation algorithm is based on fuzzy logic

  Jetto el al., 1999, Localization of a wheeled mobile robot by sensor data fusion based on a fuzzy logic adapted Kalman filter, Control Engineering Practice, pp. 763-771

- ✓ Integration of odometric, FOG and laser scanner measures; the high accuracy of gyroscope measures gives rise to a singular filtering problem

  Ippoliti et al., A properly designed extended Kalman filtering approach for robor localization by sensors with different degree of accuracy, Proc. of the fourth International Symposium on Robotics an Automation (ISRA 2004), Queretaro, Mexico, 2004

Adaptive Extended Kalman Filter

The performance of the filter is improved by an on line adjustment of the input and measurement noise covariances obtained by a suitably defined estimation algorithm

Data fusion algorithms can provide a reliable estimate of the robot location exploiting the advantages offered by different and complementary sensors (in this case, incremental encoders for relative localization and sonar sensors for absolute localization)

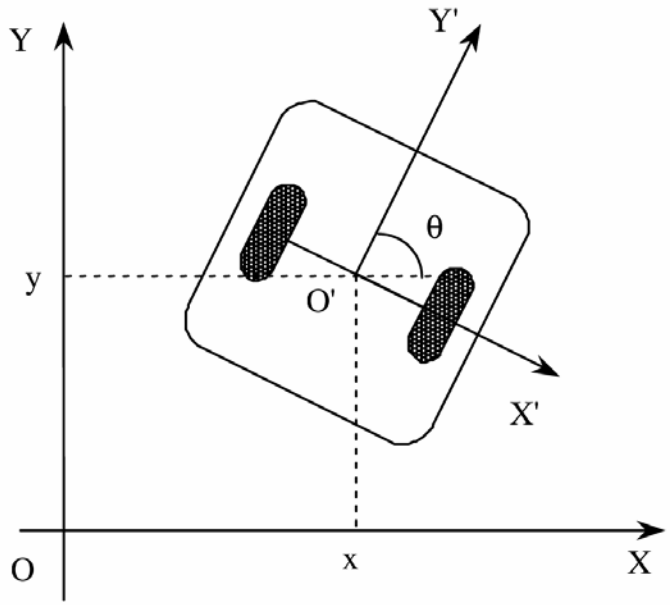
A data fusion of odometric and sonar measures is performed through an Adaptive Extended Kalman Filter (AEKF)

A sonar reading selection is introduced

Unicycle-like Mobile Robot

Localization requires knowledge of:

- ✓ coordinates *x* and *y* of the midpoint between the two driving wheels
- ✓ angle θ between the main axis of the robot and the *X*-direction



The kinematic model of the unicycle vehicle is described by the equations:

$$\begin{aligned} \dot{x}(t) &= \nu(t) cos\theta(t) \\ \dot{y}(t) &= \nu(t) sin\theta(t) \\ \dot{\theta}(t) &= \omega(t) \end{aligned}$$

$\nu(t)$: displacement velocity of the robot
$\omega(t)$: angular velocity of the robot

Odometric measures

Position and orientation of the robot:

$$
\begin{aligned}
x(t_{k+1}) &= x(t_k) + \bar{\nu}(t_k)\Delta t_k \frac{sin\frac{\bar{\omega}(t_k)\Delta t_k}{2}}{\frac{\bar{\omega}(t_k)\Delta t_k}{2}} cos(\theta(t_k) + \frac{\bar{\omega}(t_k)\Delta t_k}{2}), \\
y(t_{k+1}) &= y(t_k) + \bar{\nu}(t_k)\Delta t_k \frac{sin\frac{\bar{\omega}(t_k)\Delta t_k}{2}}{\frac{\bar{\omega}(t_k)\Delta t_k}{2}} sin(\theta(t_k) + \frac{\bar{\omega}(t_k)\Delta t_k}{2}), \\
\theta(t_{k+1}) &= \theta(t_k) + \bar{\omega}(t_k)\Delta t_k.
\end{aligned}
$$

$\bar{\nu}(t_k)\Delta t_k$ and $\bar{\omega}(t_k)\Delta t_k$ depend on the incremental distances, measured by the encoders, covered by the right and left wheels of the robot

Really available values:

$$
\begin{aligned}
y_\nu(t_k) &= \bar{\nu}(t_k)\Delta t_k + n_\nu(t_k) \\
y_\omega(t_k) &= \bar{\omega}(t_k)\Delta t_k + n_\omega(t_k)
\end{aligned}
$$

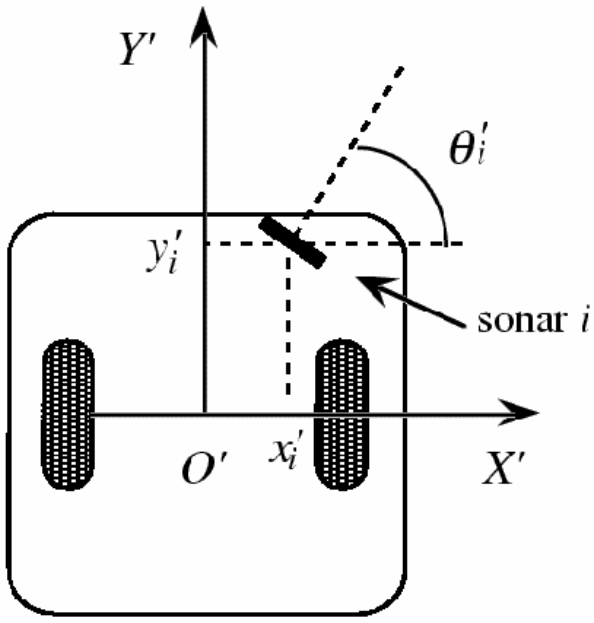
Measurement errors

$$n_\nu(\cdot) \sim N(0, \sigma_\nu^2)$$

$$n_\omega(\cdot) \sim N(0, \sigma_\omega^2)$$

Sonar Measures

The distance readings by sonar sensors are related to the indoor environment model and to the configuration of the mobile robot

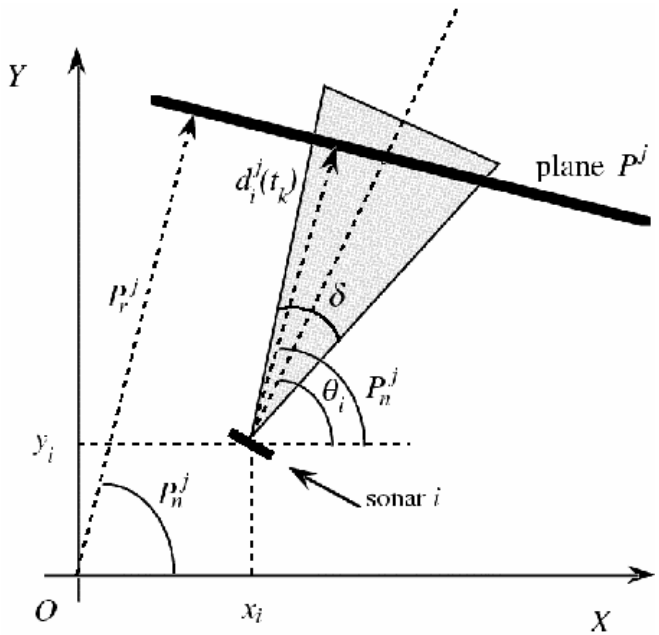


Position of the *i*-th sonar referred to the inertial coordinate system:

$$
\begin{aligned}
x_i(t_k) &= x(t_k) + x_i' sin\theta(t_k) + y_i' cos\theta(t_k) \\
y_i(t_k) &= y(t_k) - x_i' cos\theta(t_k) + y_i' sin\theta(t_k) \\
\theta_i(t_k) &= \theta(t_k) + \theta_i
\end{aligned}
$$

Sonar Measures

The walls and the obstacles in an indoor environment are represented by a proper set of planes orthogonal to the plane *X*-*Y* of the inertial system



Each plane is represented by the triplet:

- ✓ P_r^j : normal distance of the plane from the origin
- ✓ P_n^j : angle between the normal line to the plane and the *X*-direction
- ✓ $P_\nu^j \in \{-1,\ 1\}$ defines the face of the plane reflecting the sonar beam

Expected distance of the sonar from the plane:

$$d_i^j(t_k) = P_\nu^j(P_r^j - x_i(t_k)cosP_n^j - y_i(t_k)sinP_n^j)$$
$$P_n^j \in [\theta_i(t_k) - \delta/2,\ \theta_i(t_k) + \delta/2]$$

Adaptive estimation of robot location

Denote with:

- ✓ $X(t) := [x(t) \quad y(t) \quad \theta(t)]^T$ the robot state
- ✓ $U(t) := [\nu(t) \quad \omega(t)]^T$ the robot control input

The kinematic model of the robot can be written in the following compact form:

$$dX(t) = F(X(t),\, U(t))\, dt + d\eta(t)$$
$$Z((k+1)T) = G(X((k+1)T),\, \Pi) + v(kT)$$

$d\eta(t)/dt$ is a white noise process $\sim N(0,\, Q(t))$

$v(kT)$ is a white sequence $\sim N(0,\, R(kT))$

The dimension p_k of $Z(kT)$ is not constant

Adaptive estimation of robot location

Linearization and discretization result in the following EKF:

$$
\begin{aligned}
\hat{X}(k+1,k) &= \hat{X}(k,k) \\
&+ B_d(k)B(k)F(\hat{X}(k,k),U(k-1)) \\
&+ B_d(k)(U(k)-U(k-1)),
\end{aligned}
$$

$$
P(k+1,k) = A_d(k)P(k,k)A_d^T(k) + Q_d(k),
$$

$$
K(k+1) = P(k+1,k)C^T(k+1)S(k+1)^{-1},
$$

$$
\begin{aligned}
S(k+1) &= [C(k+1)P(k+1)C^T(k+1) \\
&\quad +R(k+1)],
\end{aligned}
$$

$$
\hat{X}(k+1,k+1) = \hat{X}(k+1,k) + K(k+1)\Gamma(k+1),
$$

$$
\Gamma(k+1) = [Z(k+1) - G(\hat{X}(k+1,k))],
$$

$$
P(k+1,k+1) = [I - K(k+1)C(k+1)]P(k+1,k),
$$

Adaptive estimation of robot location

… where

$$A_d(k) = e^{A(k)T},$$

$$A(k) =: \left[\frac{\partial F(X(t),U(t))}{\partial X(t)}\right]_{\substack{X(t)=\hat{X}(k,k)\\ U(t)=U(k-1)}},$$

$$B(k) =: \left[\frac{\partial F(X(t),U(t))}{\partial U(t)}\right]_{\substack{X(t)=\hat{X}(k,k)\\ U(t)=U(k-1)}},$$

$$C(k) =: \left[\frac{\partial G(X(k))}{\partial X(k)}\right]_{X(k)=\hat{X}(k,k-1)},$$

$$B_d(k) = \int_{kT}^{(k+1)T} e^{A(k)((k+1)T-\tau)} d\tau,$$

$$Q_d(k) = \int_{kT}^{(k+1)T} e^{A(k)((k+1)T-\tau)} Q(\tau) e^{A^T(k)((k+1)T)} d\tau.$$

Adaptive estimation of robot location

The covariance matrices $Q(\tau)$, $\tau \in [kT, (k+1)T]$ and $R(k)$ are assumed to have the following form:

$$Q(\tau) = \sigma_\eta^2(k) I_3, \tau \in [kT, (k+1)T]$$
$$R(k) = diag[\sigma_{v,1}^2(k), \cdots, \sigma_{v,p_k}^2(k)]$$

From which

$$Q_d(k) = \sigma_\eta^2(k) \bar{Q}(k),$$

$$\bar{Q}(k) = \int_{kT}^{(k+1)T} e^{(A(k)((k+1)T-\tau)} e^{(A^T(k)((k+1)T-\tau)} d\tau.$$

so that $Q_d(k)$ is completely known save that for the multiplicative scalar $\sigma_\eta^2(k)$

Adaptive estimation of robot location

Processing each measure one at a time results in

$$\hat{X}(k+1,k+1) = \hat{X}(k+1,k) + K_i\gamma_i(k+1),$$
$$\gamma_i(k+1) = z_i(k+1) - G_i(k+1)(\hat{X}(k+1,k))$$

The final state estimate is given by

$$\begin{aligned}\hat{X}(k+1,k+1) &= \hat{X}(k,k) \\ &+ B_d(k)B(k)F(\hat{X}(k,k),U(k-1)) \\ &+ B_d(k)(U(k)-U(k-1)) \\ &+ \sum_{i=1}^{i=p_k} K_i(k+1)\gamma_i(k+1).\end{aligned}$$

Adaptive estimation of $Q_d(k)$ and $R(k)$

The following assumptions are made:

1. The parameters $\sigma^2_{v,i}(k)$, $i = 1, \cdots, p_k$ and $\sigma^2_\eta(k)$ are nearly constant over $n_v \geq 2$ and $n_\eta \geq 2$ samples respectively
2. Residuals $\gamma_i(k+1)$, $i = 1, \cdots, p_k$ are called the innovation process samples and are assumed to be well described by a white sequence $\sim N(0, s_i(k+1))$,

$$s_i(k+1) = C_i(k+1)[A_d(k)P(k,k)A_d^T(k) + \sigma^2_\eta(k)\bar{Q}(k)]C_i^T(k+1) + \sigma^2_{v,i}(k)$$

The parameters $\sigma^2_\eta(k)$ and $\sigma^2_{v,i}$, $i = 1, \cdots, p_k$ are estimated imposing the condition of consistency between the innovation process samples and their predicted statistics

Adaptive estimation of $Q_d(k)$ and $R(k)$

As the p_k measures are processed one at a time, at each step, p_k estimates $\hat{\sigma}^2_{\eta,i}(k)$ of the same parameter $\sigma^2_\eta(k)$ are obtained

They are determined by the operation $\max \text{prob}_{\sigma^2_{\eta,i}(k+1)\geq 0}\gamma_i(k+1)$

One has

$$\begin{aligned}\hat{\sigma}^2_{\eta,i}(k) &= \max\Big\{\epsilon_i(k+1)\times\big[\gamma_i(k+1)^2 \\ &- C_i(k+1)A_d(k)P(k,k)A_d^T(k)C_i^T(k+1) \\ &- \bar{\hat{\sigma}}^2_{v,i}(k+1)\big],0\Big\}\end{aligned}$$

where

$$\epsilon_i(k+1) =: \frac{1}{C_i(k+1)\bar{Q}_d(k)C_i^T(k+1)}$$

Adaptive estimation of $Q_d(k)$ and $R(k)$

The following recursive smoothed estimate is obtained:

$$\bar{\hat{\sigma}}^2_\eta(k) = \bar{\hat{\sigma}}^2_\eta(k-1) + \frac{1}{(l_\eta+1)p_k} \times \left[\sum_{i=1}^{p_k}\left(\hat{\sigma}^2_{\eta,i}(k) - \hat{\sigma}^2_{\eta,i}(k-(l_\eta+1))\right)\right]$$

Analogously, $\max \text{prob}_{\sigma^2_{v,i}(k+1)\geq 0}\gamma_i(k+1)$

The following recursive smoothed estimate is obtained:

$$\bar{\hat{\sigma}}^2_{v,i}(k+1) = \bar{\hat{\sigma}}^2_{v,i}(k) + \frac{1}{l_v+1}(\hat{\sigma}^2(k+1) - \hat{\sigma}^2(k-l_v))$$

where

$$\begin{aligned}\hat{\sigma}^2_{v,i}(k+1) = \max\Big\{&\gamma_i^2(k+1) \\ &-(C_i(k+1)A_d(k)P(k,k)A_d^T(k)C_i^T(k+1) \\ &+\bar{\hat{\sigma}}^2_{\eta,i}(k)\bar{Q}(k)), 0\Big\},\end{aligned}$$

Sonar Reading Selection

Reduce the probability of an inadequate interpretation of erroneous sensor data

- ✓ Interferences produced by
  - ✓ presence of unknown obstacles in the environment
  - ✓ uncertainty on the sensor readings

Compare the actual sensor readings with their expected values

$$\gamma_i(k) = z_{\not{2}+i}(k) - \hat{d}_i^j \qquad \gamma_i(k) \sim N(0, s_i(k))$$

3

The current value $z_{\not{2}+i}(k)$ is accepted if $|\gamma_i(k)| \leq 2\sqrt{s_i(k)}$

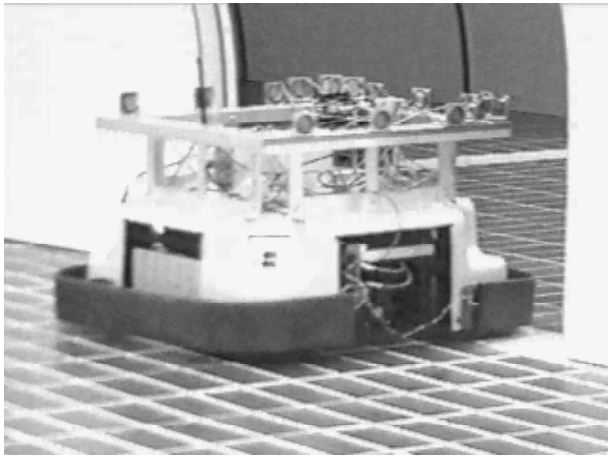
3

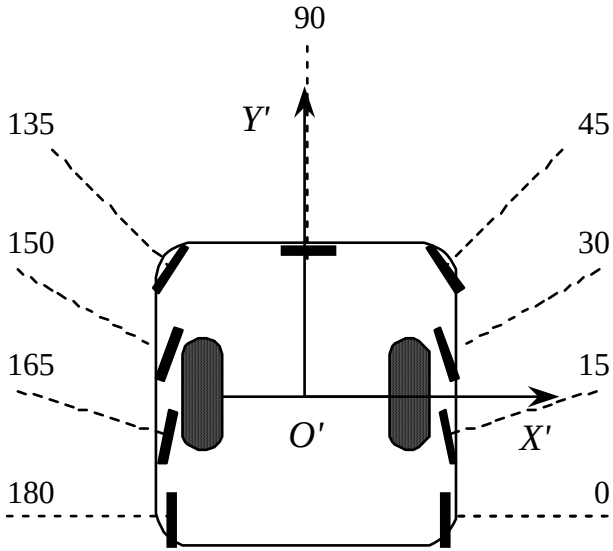
- ✓ Variable threshold chosen as twice the standard deviation of the innovation process

Experimental Results

The experimental tests have been performed on the LabMate mobile base in an indoor environment with different geometries

This mobile robot has two driving wheels





Control algorithm

The control algorithm is based on a proper discrete-time implementation of the control algorithm based on the kinematic inversion approach

$$\begin{aligned}\nu(t) &= K_\nu(\dot{y}_d(t)cos\theta(t) - \dot{x}_d(t)sin\theta(t)) + C\nu e_t(t),\\ \omega(t) &= K_\omega(\theta_d(t) - \theta(t)) + C\omega e_n(t),\end{aligned}$$

where

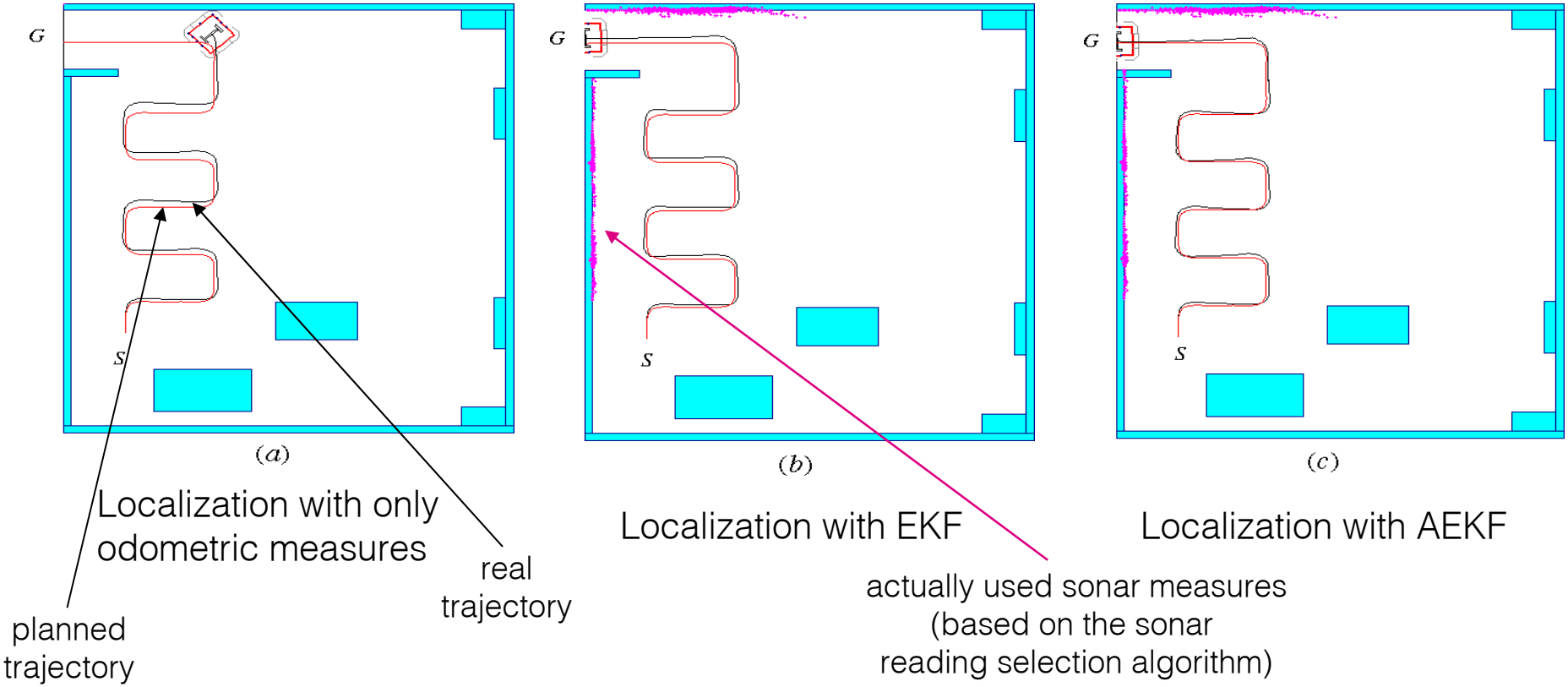
$$\begin{aligned}e_t(t) &= (y_d(t) - y(t))cos\theta(t) - (x_d(t) - x(t))sin\theta(t)),\\ e_n(t) &= (y_d(t) - y(t))sin\theta(t) + (x_d(t) - x(t))cos\theta(t)).\end{aligned}$$

The system is connected directly with the robot low level controller and the proximity system by a standard serial port RS232

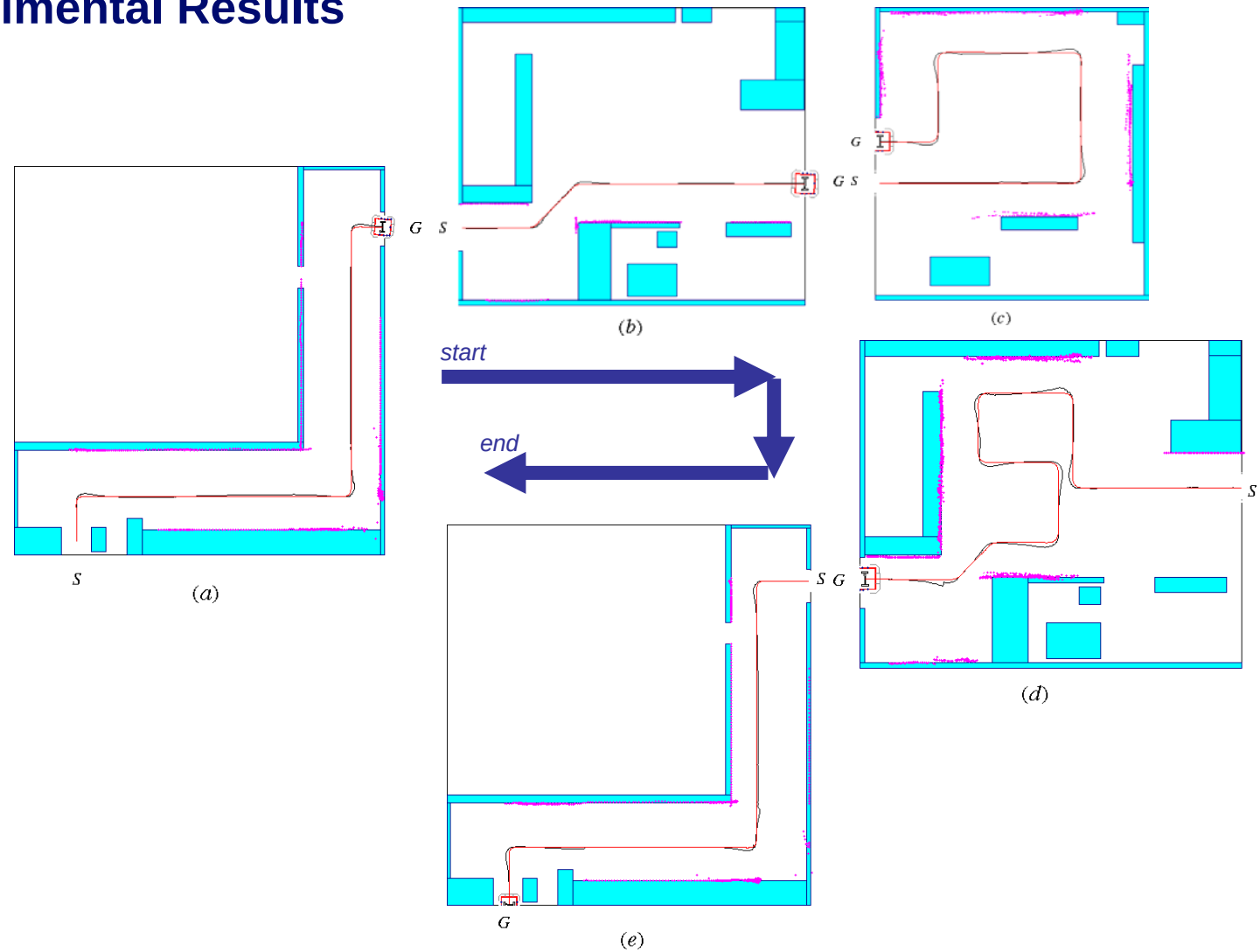
The proposed localization algorithm has been tested with relatively long trajectories in an indoor environment completely represented by a suitable set of planes orthogonal to the plane *XY* of the inertial system

Experimental Results

In order to test the limitations of odometric measures, the planned trajectory is composed of a large set of orientation changes

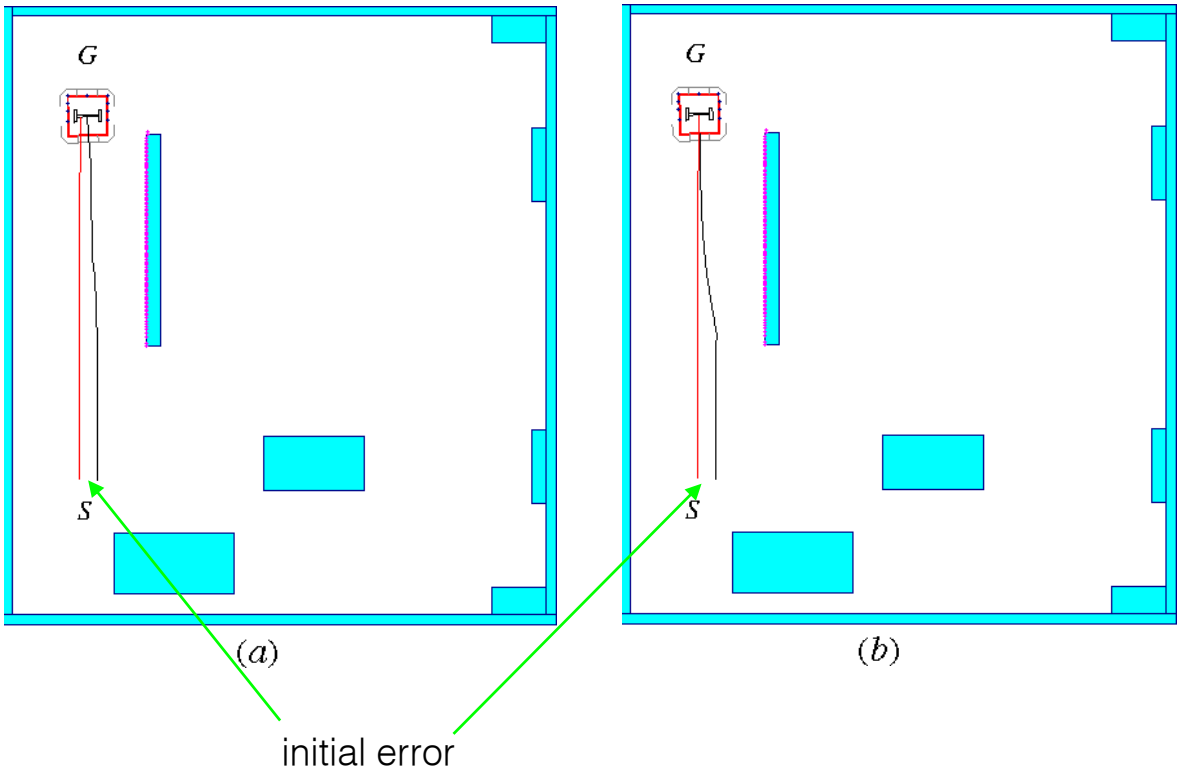


Experimental Results



Experimental Results

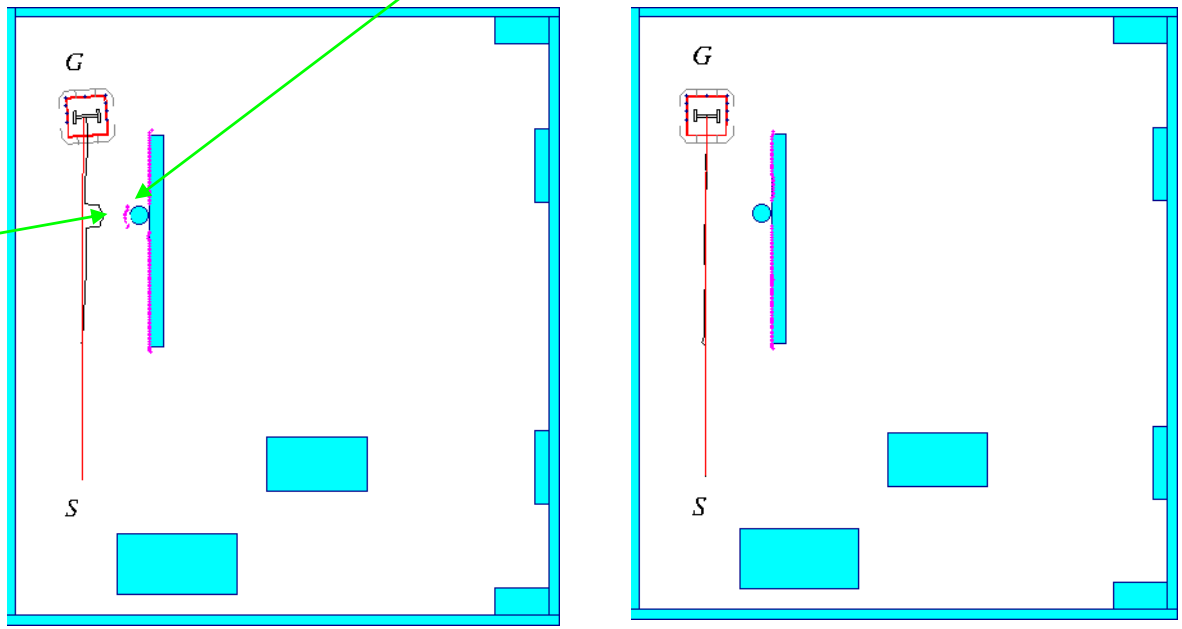
The adaptation algorithm is able to reduce the initial position error to zero by better exploiting the information carried by sonar readings in correspondence of an obstacle



Experimental Results

If an unknown obstacle which is not introduced in the environment map is placed at the side of a wall, the corresponding readings are seen as undesired interferences, and are eliminated by the proposed procedure

unknown obstacle



Fuzzy Adaptive Extended Kalman Filter

In this case the adaptive estimation of noise statistics is based on a fuzzy logic approach

The principles of fuzzy expert systems lead to a valid on-line adaptive algorithm which improves the performance of the Extended Kalman Filter

Adaptive estimation of $Q_d(k)$

Warning: poor estimates of $Q_d(k)$ may lead to filter divergence

The heuristic adaptation algorithm is based on rules:

IF <antecedent> THEN <consequent>

A fuzzy implication between the parameter $\sigma_\eta^2(k)$ and a parameter relative to the expected value of the sample:

$$r(k+1) = y(k+1) - C(k+1)\hat{X}(k+1,k)$$

In the linear case $r(k+1)$ is called the "innovation process" and is a white discrete sequence $\sim \mathcal{N}(0, \tilde{S}(k+1))$, where

$$\tilde{S}(k+1) = C(k+1)[A_d(k)P(k,k)A_d(k)^T + \sigma_\eta^2(k)\bar{Q}(k)]C^T(k+1) + R(k+1)$$

Adaptive estimation of $Q_d(k)$

An heuristic extension of these properties to the linearized model:

a good estimate $\hat{Q}_d(k)$ of $Q_d(k)$ produces innovation process samples consistent with their statistics

In other words:

If the innovation process sample $r(k+1)$ is observed and its absolute value $|r(k+1)|$ is within the range predicted from the theory, this means that the current value of $\hat{Q}_d(k)$ is large enough

On the contrary, if $|r(k+1)|$ is so large to exceed the predicted range, then $\hat{Q}_d(k)$ should be increased (as a consequence, also $P(k,k)$ and $K(k)$ are increased and filter divergence is prevented)

Adaptive estimation of $Q_d(k)$

This suggests the following adaptation mechanism:

If $|r(k+1)|$ is neither too small nor too large, then leave $\hat{Q}_d(k)$ nearly unchanged

If it is very small, then reduce $\hat{Q}_d(k)$

If it is large, then increase $\hat{Q}_d(k)$

A Fuzzy Logic Approach

Compute: $\beta(k+1) := \dfrac{\bar{r}(k+1)}{\bar{s}(k+1)}$

$$\bar{r}(k+1) := \frac{1}{p_k}\sum_{i=1}^{p_k}|r_i(k+1)| \qquad \bar{s}(k+1) := \frac{1}{p_k}\sum_{i=1}^{p_k}\tilde{s}_{i,i}(k+1)^{1/2}$$

At each step, parameter $\sigma_\eta^2(k+1)$ is estimated from $\beta(k+1)$ by:

1. If $\beta(k+1)$ is very small, then $\sigma_\eta^2(k+1)$ is small enough
2. If $\beta(k+1)$ is small, then $\sigma_\eta^2(k+1)$ is near to 1
3. If $\beta(k+1)$ is neither small nor large, then $\sigma_\eta^2(k+1)$ is a bit larger than 1
4. If $\beta(k+1)$ is large enough, then $\sigma_\eta^2(k+1)$ is somewhat larger than 1
5. If $\beta(k+1)$ is very large, then $\sigma_\eta^2(k+1)$ is very large

A Fuzzy Logic Approach

The universes of the discourse relative to $\beta(k+1)$ and $\sigma_\eta^2(k+1)$ are U_β and $U_{\sigma_\eta^2}$

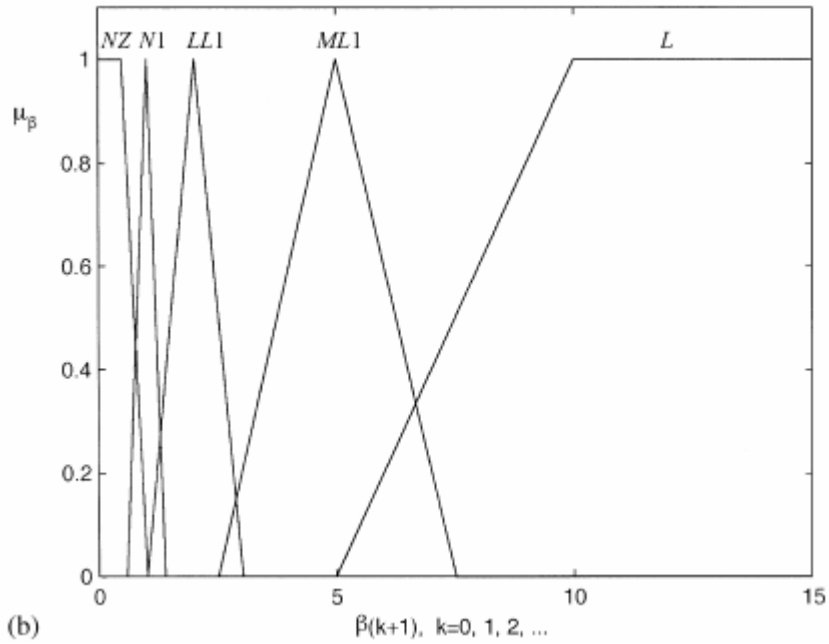
The characteristic functions of $\beta(k+1)$ and $\sigma_\eta^2(k+1)$ are μ_β and $\mu_{\sigma_\eta^2}$

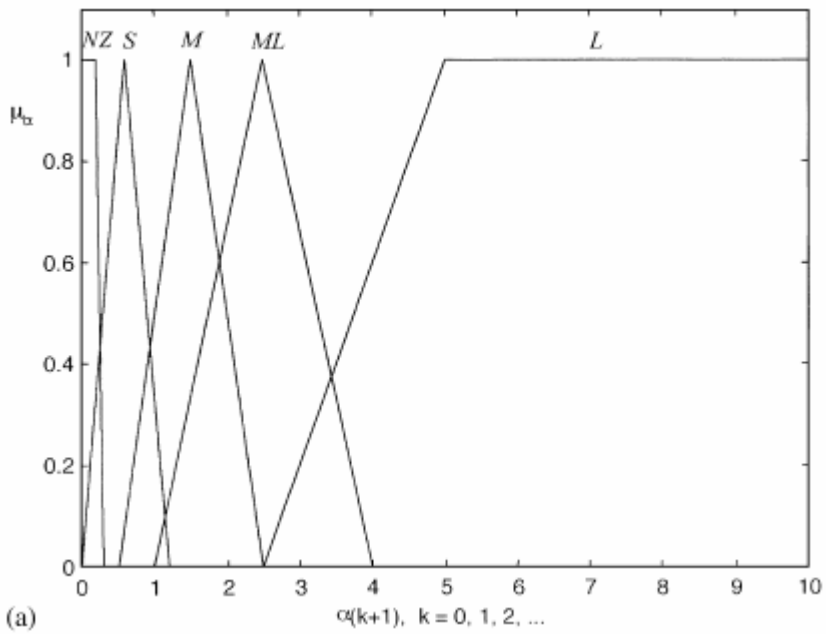
The discretization of the universes and the shape of the characteristic functions have been fixed:

- ✓ on the basis of the above mentioned heuristic knowledge that the probability density function of $r(k+1)$ can be well approximated by a normal density
- ✓ and on the basis of a wide working expertise on understanding the phenomenon of filter divergence

A Fuzzy Logic Approach

Representation of fuzzy sets:





A Fuzzy Logic Approach

To simplify the defuzzification procedure

- ✓ The characteristic function $\mu_{\sigma_\eta^2}$ of $\sigma_\eta^2(k+1)$ has been considered piecewise constant over intervals Δ = 0.01
- ✓ The numerical value $\sigma_\eta^2(k+1)$ has been computed according to the center of area method:

$$\sigma_\eta^2(k+1) = \frac{\frac{1}{2}\sum_{i=1}^{n} \mu_{\sigma_{\eta,i}^2}(x_i^2 - x_{i-1}^2)}{\sum_{i=1}^{n} \mu_{\sigma_{\eta,i}^2}(x_i - x_{i-1})}$$

x_{i-1} and x_i are the extreme points of the *i*-th interval of amplitude Δ

$\mu_{\sigma_{\eta,i}^2}$ is the constant value of the characteristic function $\mu_{\sigma_\eta^2}$ on the interval

n is the number of intervals

A Fuzzy Logic Approach

To avoid excessive oscillations of the numerical value of $\sigma_\eta^2(k+1)$, the smoothed estimate is computed:

$$\bar{\sigma}_\eta^2(k+1) = \bar{\sigma}_\eta^2(k) + \frac{1}{l+1}(\sigma_\eta^2(k+1) - \sigma_\eta^2(k-l))$$

where l is a positive integer

The final estimate is $\hat{Q}_d(k+1) = \bar{\sigma}_\eta^2(k+1)\bar{Q}(k)$

Sonar Reading Selection (same solution …)

Reduce the probability of an inadequate interpretation of erroneous sensor data

- ✓ Interferences produced by
  - ✓ presence of unknown obstacles in the environment
  - ✓ uncertainty on the sensor readings

Compare the actual sensor readings with their expected values

$$\gamma_i(k) = z_{\not{2}+i}(k) - \hat{d}_i^j \qquad \gamma_i(k) \sim N(0, s_i(k))$$

3

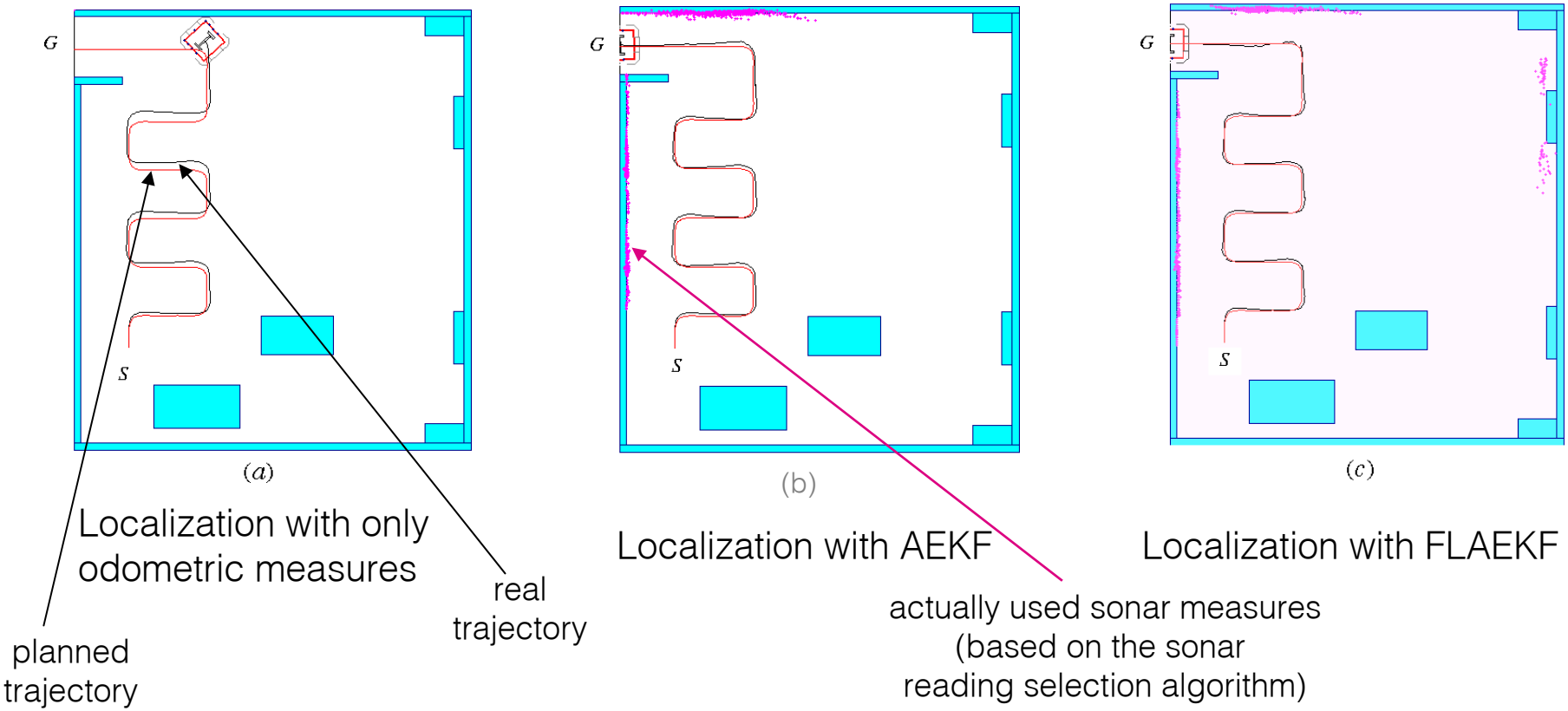
The current value $z_{\not{2}+i}(k)$ is accepted if $|\gamma_i(k)| \leq 2\sqrt{s_i(k)}$

3

- ✓ Variable threshold chosen as twice the standard deviation of the innovation process

Experimental Results

In order to test the limitations of odometric measures, the planned trajectory is composed of a large set of orientation changes



Nearly Singular Filtering

Different sensors are characterized by different accuracies

Some measures could be more reliable than others

When fusing the measures in the Kalman filter these aspects must be considered: the measure with an high reliability could introduce problems of singularity in the Kalman filter

For example if we combine (fuse) in the Kalman filter odometric measures with FOG measures (characterized by an high reliability), the matrix *R* is singular and in this case a lower order non singular EKF can be derived

Nearly Singular Filtering

The algorithm operates in a stochastic framework, and is based on the ascertainment that the angular measure $\theta_g(t_k)$ provided by the FOG is much more reliable than the angular measure $y_\omega(t_k)$ obtainable by encoders

The estimation algorithm is an EKF defined on the basis of:

- ✓ a stochastic state-space model derived from:
  - ✓ the kinematic model of the unicycle vehicle
- ✓ a measure equation containing:
  - ✓ the incremental measure of the encoders $y_\nu(t_k)$
  - ✓ the angular measure of the gyroscope $\theta_g(t_k)$
  - ✓ distance measures provided by the set of sonar sensors from environment planes

FOG Measures

The Fiber Optic Gyroscope (FOG) installed on the robot produces an accurate estimation of robot orientation

The FOG readings are denoted by:

$$\theta_g(\cdot) = \theta_g^r(\cdot) + n_\theta(\cdot)$$

true value

$$n_\theta(\cdot) \sim N(0, \sigma_\theta^2)$$

Stochastic State-Space Model

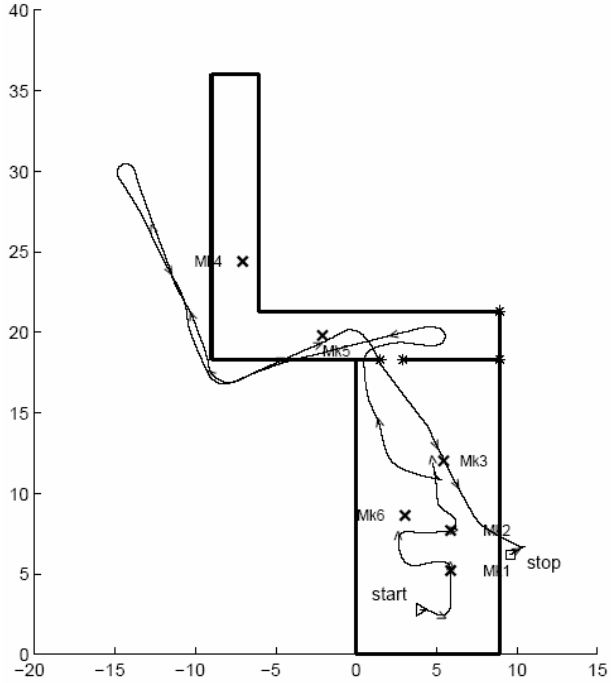
State vector: $X(t) = [X_1(t)^T, \theta(t)]^T$ where $X_1(t) = [x(t), y(t)]^T$

Measurement vector: $Z(k) := [Z_1(k)^T, Z_2(k)^T]^T$

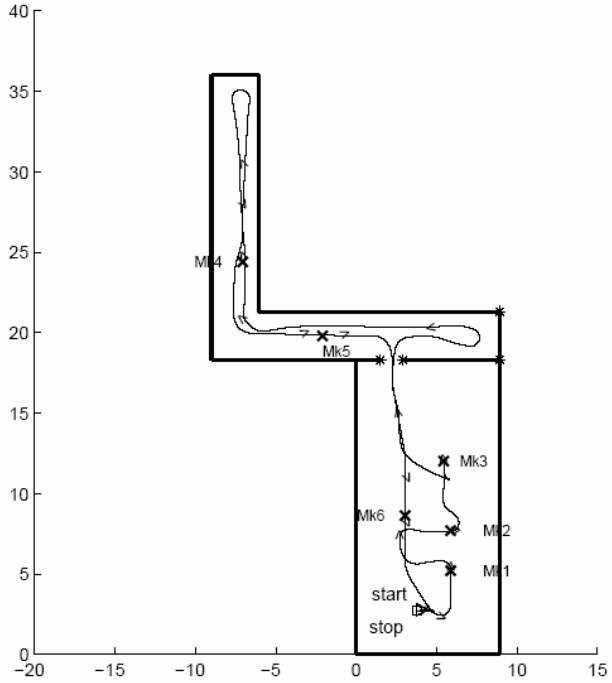
- ✓ $Z_1(k) = [z_1(k), z_2(k)]^T$
  - ✓ Measure provided by the encoders: $z_1 = \bar{\nu}(t_k)\Delta t_k + n_\nu(t_k)$
  - ✓ Measure provided by the FOG: $z_2 = \theta_g^r(\cdot) + n_\theta(\cdot)$

Odometric-inertial localization vs mere odometry

A localization algorithm which integrates odometric and inertial measures instead of using odometry only performs much better when the robot trajectory is long and winding, which is shown by the comparison of these figures:



Odometric localization



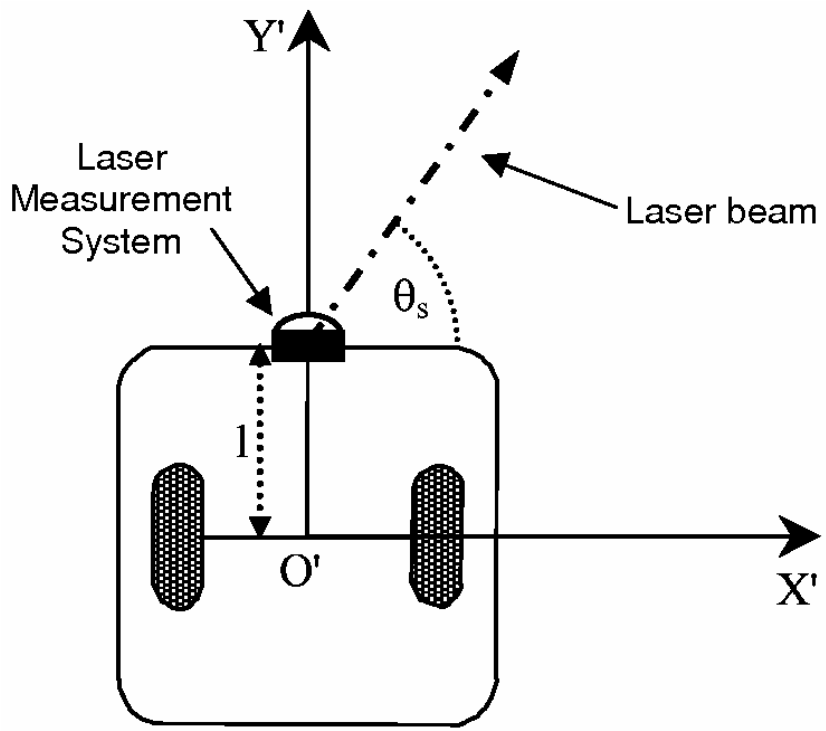
Odometric-inertial localization

Laser Measures

The distance readings by laser scanner are related to the indoor environment model and to the configuration of the mobile robot

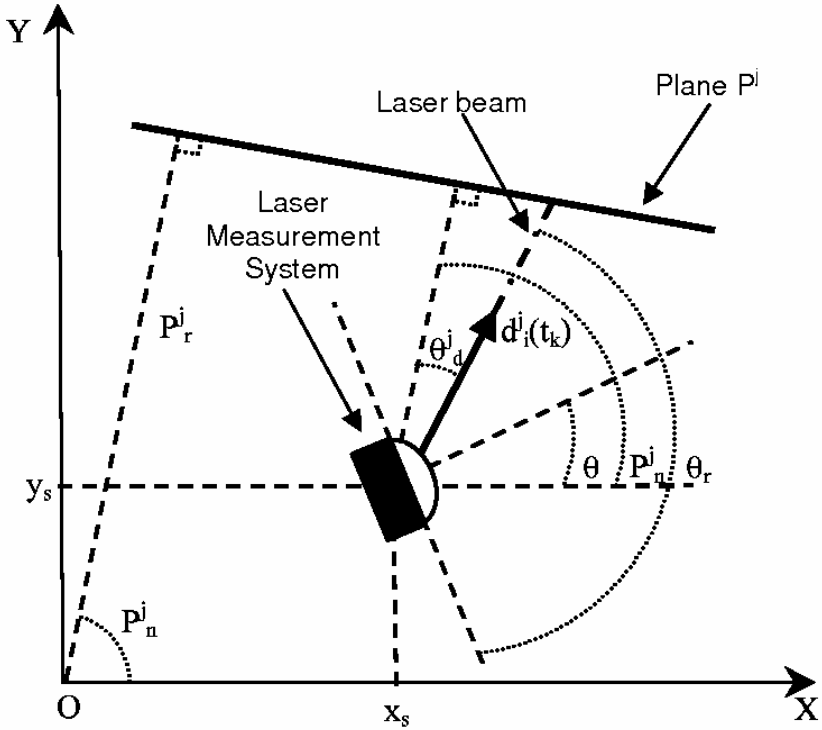
Position of the laser scanner referred to the inertial coordinate system:

$$
\begin{aligned}
x_s(t_k) &= x(t_k) + l\,cos\theta(t_k) \\
y_s(t_k) &= y(t_k) + l\,sin\theta(t_k) \\
\theta_s(t_k) &= \theta(t_k)
\end{aligned}
$$



Laser Measures

The walls and the obstacles in an indoor environment are represented by a proper set of planes orthogonal to the plane *X*-*Y* of the inertial system



Each plane is represented by the triplet:

- ✓ P_r^j : normal distance of the plane from the origin
- ✓ P_n^j : angle between the normal line to the plane and the *X*-direction
- ✓ $P_\nu^j \in \{-1,\ 1\}$ defines the face of the plane reflecting the laser beam

Expected distance of the laser center from the plane:

$$d_i^j(t_k) = \frac{P_\nu^j(P_r^j - x_s(t_k)cosP_n^j - y_s(t_k)sinP_n^j)}{cos\theta_d^j}$$

Stochastic State-Space Model

State vector: $X(t) = [X_1(t)^T, \theta(t)]^T$ where $X_1(t) = [x(t), y(t)]^T$

Measurement vector: $Z(k) := [Z_1(k)^T, Z_2(k)^T]^T$

- ✓ $Z_1(k) = [z_1(k), z_2(k)]^T$
  - ✓Measure provided by the encoders: $z_1 = \bar{\nu}(t_k)\Delta t_k + n_\nu(t_k)$
  - ✓Measure provided by the FOG: $z_2 = \theta_g^r(\cdot) + n_\theta(\cdot)$
- ✓ $Z_2(k) = [z_3(k), z_4(k), \cdots, z_{2+n_s}(k)]^T$
  - ✓Measure provided by the *i*-th laser reading: $z_{2+i}(k) = d_i^j(k) + n_{r,i}(k)$

Stochastic State-Space Model

Observation noise: $V(k) = [\, n_\nu(k), n_\theta(k), n_{r,1}(k), \cdots, n_{r,n_s}(k) \,]$

- ✓ White sequence $\sim N(0, R)$
- ✓ Covariance matrix of the independent errors affecting the sensor measures
  $R := \text{block diag}\,[R_1,\, R_2]$
  - ✓ $R_1 := \text{diag}[\sigma_\nu^2,\, \sigma_\theta^2]$
  - ✓ $R_2 := \text{diag}[\sigma_{r,1}^2,\, \sigma_{r,2}^2,\, \cdots,\, \sigma_{r,n_s}^2]$

The measure $z_2(\cdot)$ provided by the FOG is much more reliable than $z_1(\cdot)$ and $z_{2+i}(\cdot)$

- ✓ $\sigma_\theta^2 << \sigma_\nu^2,\ \sigma_\theta^2 << \sigma_{r,i}^2$ ➡ singularity of *R* ➡ $z_2(\cdot) = \theta_g^r(\cdot)$
- ✓ Lower order non singular EKF assuming $\sigma_\theta^2 = 0$

Known deterministic signal

Only $X_1(\cdot)$ is estimated as a function of $z_1(\cdot)$ and $Z_2(\cdot)$

Stochastic State-Space Model

The measure provided by the encoders is in terms of increments

Extended state $\bar{X}(k) := [X_1(k)^T, X_1(k-1)^T]^T$

Linearized and discretized dynamic state-space equation:

$$\bar{X}(k+1) = \bar{A}(k)\bar{X}(k) + \bar{L}(k)U(k) + \bar{B}(k)\theta_g^r(k) + \bar{D}(k) + \bar{W}(k) \qquad \text{(a)}$$

Measure equations:

- ✓ $z_1(k) = C_1(k)\bar{X}(k) + v_1(k)$ (b)

  expressed as a function of $x(k+1) - x(k)$ and $y(k+1) - y(k)$
- ✓ Linearization of $Z_2(k)$

  $$\bar{Z}_2(k) = C_2(k)\bar{X}(k) + V_2(k), \; C_2(k) := [c_1(k)^T, \quad c_2(k)^T, \quad \cdots, \quad c_{\bar{p}_k}(k)^T]^T \qquad \text{(c)}$$

Equations (a), (b) and (c) represent the linearized and discretized state-space form to which the classical EKF algorithm has been applied

Laser Scanner Reading Selection

Reduce the probability of an inadequate interpretation of erroneous sensor data

- ✓ Interferences produced by
  - ✓ presence of unknown obstacles in the environment
  - ✓ uncertainty on the sensor readings

Compare the actual laser sensor readings with their expected values

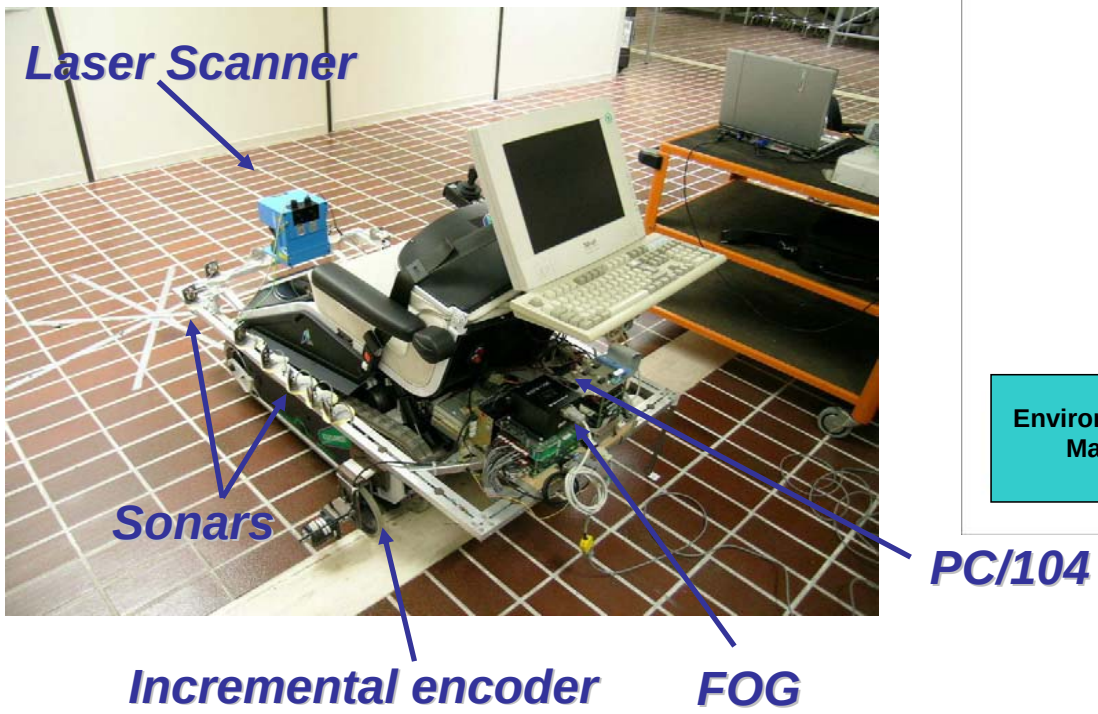
$$\gamma_i(k) = z_{2+i}(k) - \hat{d}_i^j \qquad \gamma_i(k) \sim N(0, s_i(k))$$

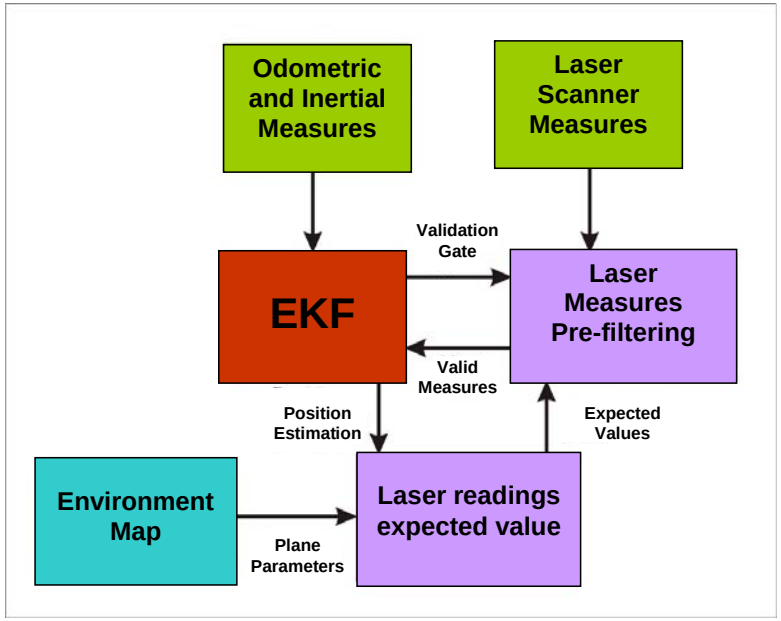
The current value $z_{2+i}(k)$ is accepted if $|\gamma_i(k)| \leq 2\sqrt{s_i(k)}$

- ✓ Variable threshold chosen as twice the standard deviation of the innovation process

EKF Implementation

The EKF has been implemented on the navigation module of the TGR Explorer powered wheelchair





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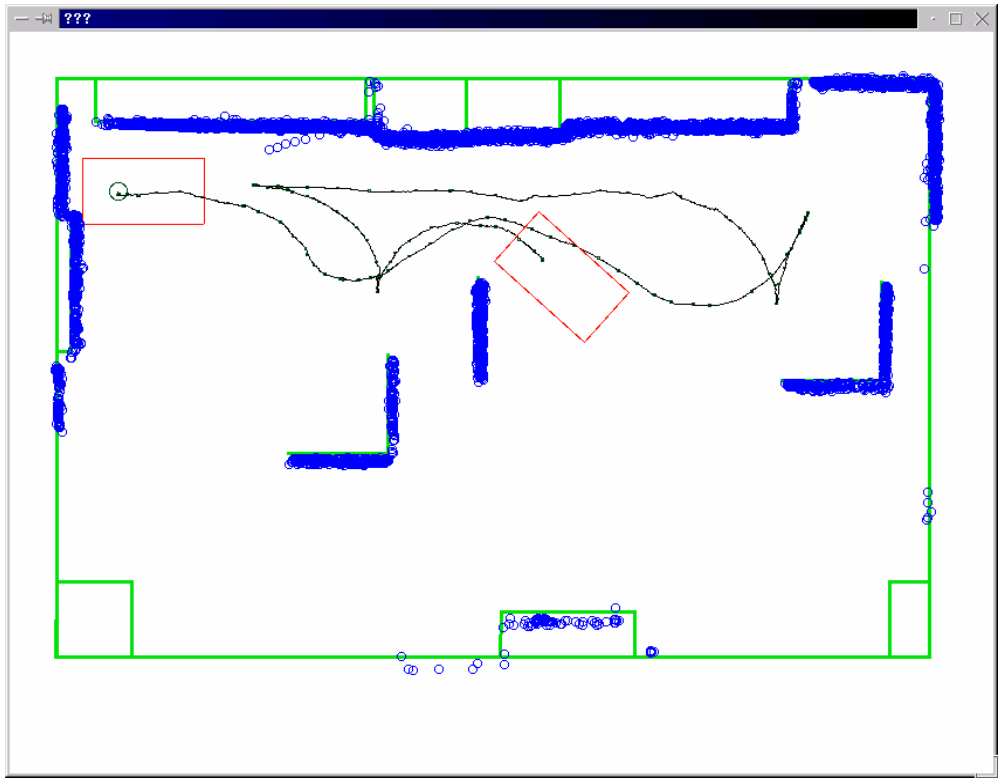
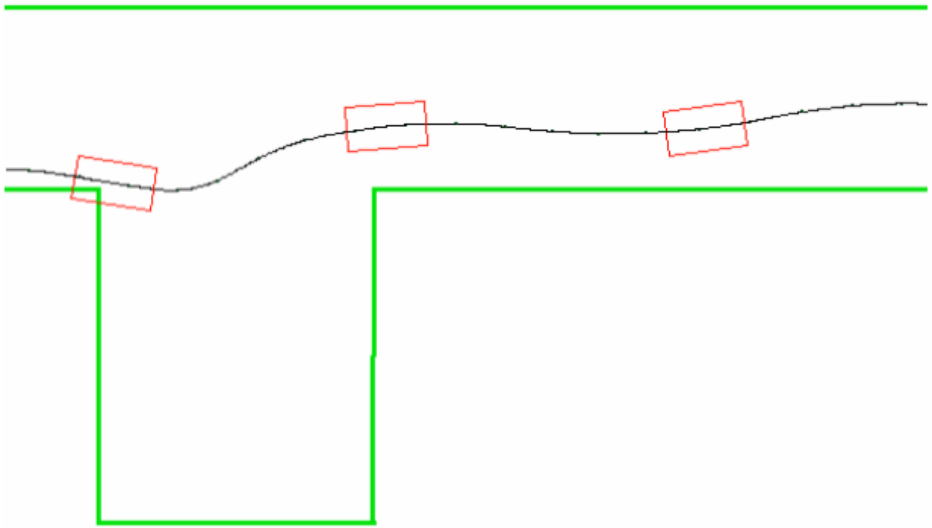


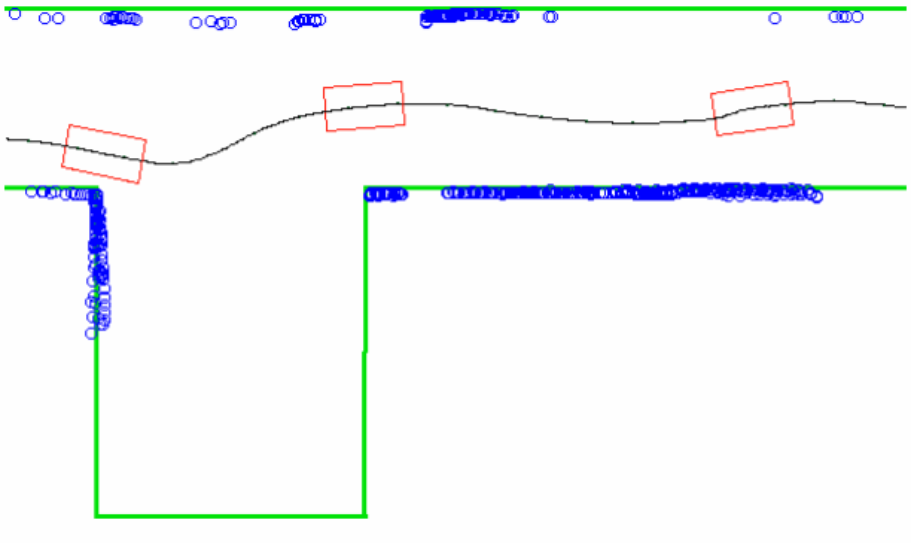
Experimental Results

- 115 m length trajectory
- Uncertainties on the environment model
- T_C=0.4 s

EKF without laser measures



EKF with laser measures



Experimental Results

- 115 m length trajectory
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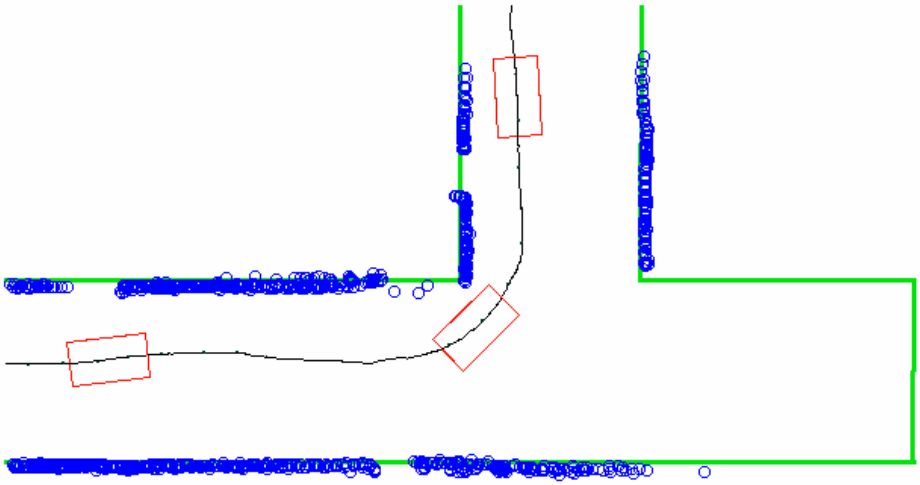
EKF without laser measures

EKF with laser measures



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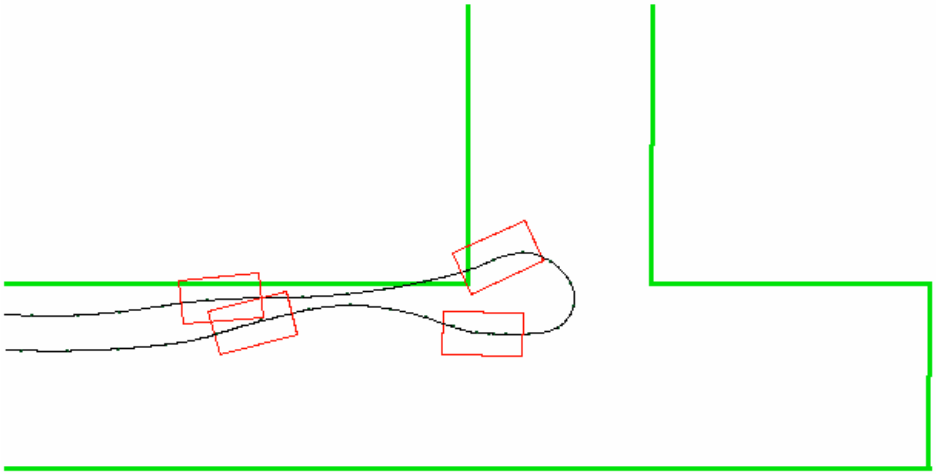
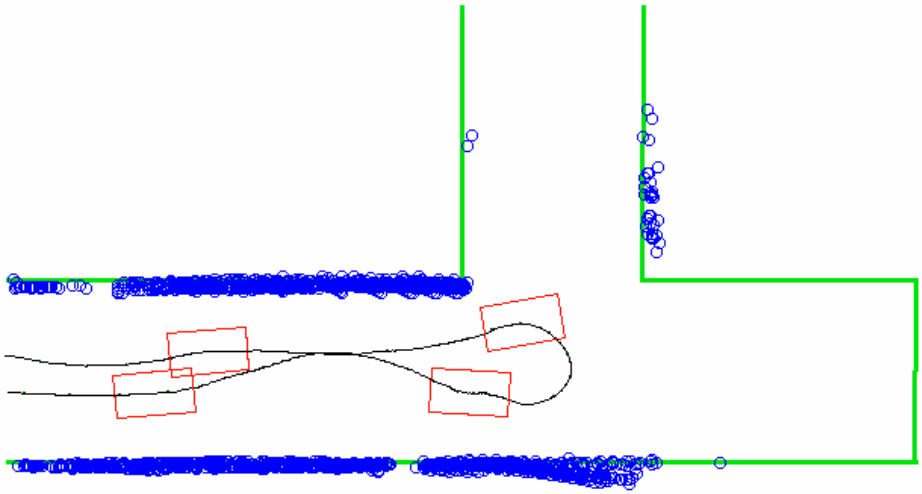
EKF without laser measures



EKF with laser measures



Comments

- ✓ The proposed algorithms show several applications of Kalman filtering to mobile robot localization, in situations where different kinds of sensory devices are available
- ✓ Adaptively estimating the unknown state noise statistics from data improves the convergence and performance of the Kalman filter
- ✓ When the available sensor accuracies differ significantly from each other, this fact must be suitably taken into account
- ✓ Tests have been performed in different known environments and suitable trajectories have been realized (also with different set of sensors and real-time implementations)
- ✓ A suitable integration of proprioceptive and exteroceptive sensory data allows a highly accurate estimate of robot location

Part 4: “A Kalman Filter for Simultaneous Localization And Map building”

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Simultaneous Localization and Map Building (SLAM)

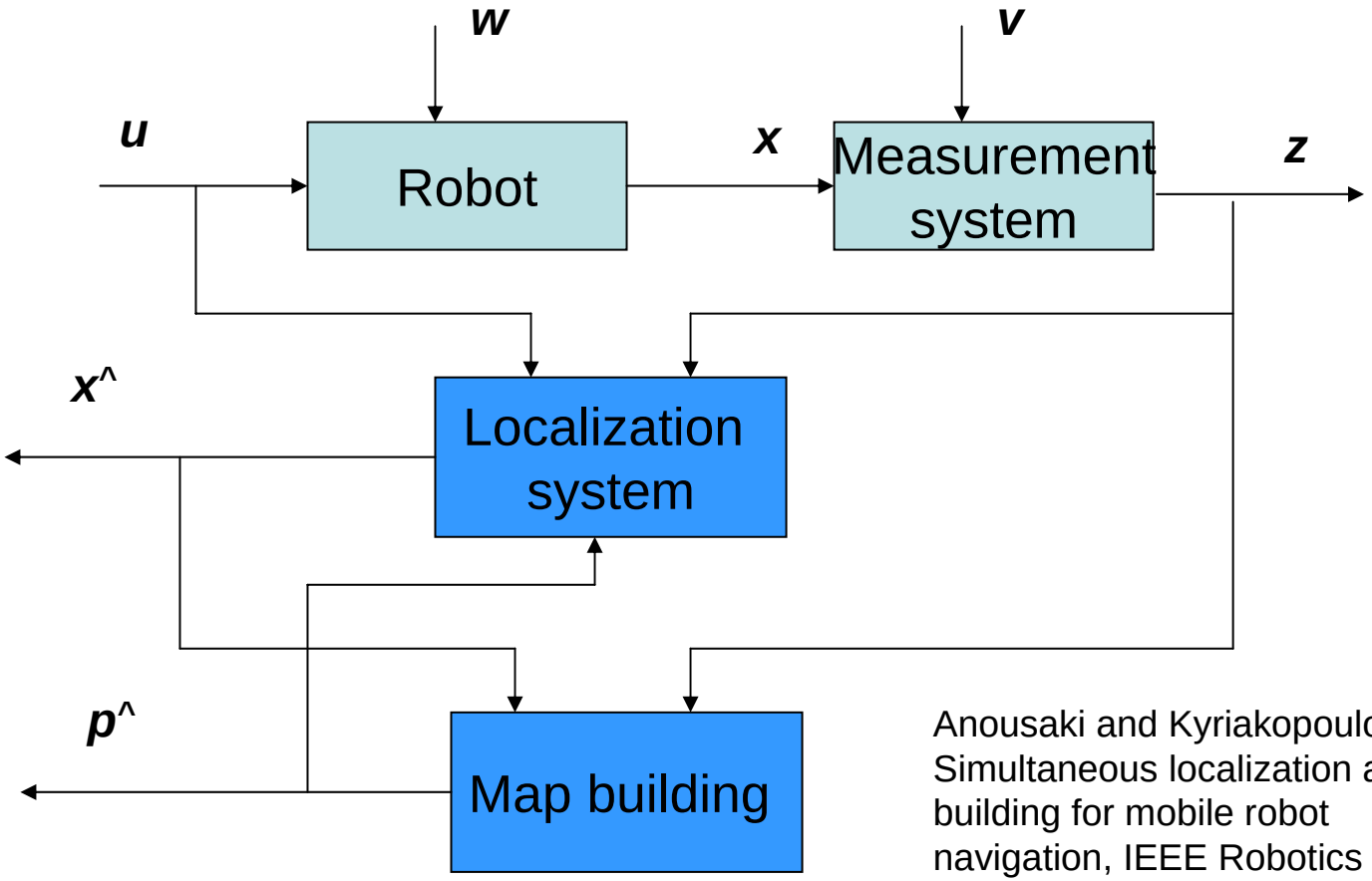
It is an "open problem": (I) for the localization of a mobile robot a map of the environment is required; (II) for the map building it is necessary to have a good estimate of the robot pose

Two approaches are mainly investigated:

i) Extended Kalman Filter and "stochastic map" (feature-based SLAM)

ii) Probabilistic approach (particle filter)

In the following our approach to the feature-based SLAM is presented and discussed. Also for this problem the main tool is the Extended Kalman Filter (EKF)



Anousaki and Kyriakopoulos, 1999, Simultaneous localization and map building for mobile robot navigation, IEEE Robotics & Automation Magazine, pp.42-53.

Background:

Gamini et al., 2001, A solution to the simultaneous localization and map building (SLAM) problem, IEEE Trans. Robotics and Automat., pp. 229-241

EKF and map defined by landmarks (outdoor application with range sensor)

Gamini et al., 2001, Map management for efficient simultaneous localization and mapping (SLAM), Autonomous robots, pp. 267-286

(outdoor application)

Castellanos et al., 2001, Multisensor fusion for simultaneous localization and map building, IEEE Trans. Robotics and Automat., pp. 908-914

EKF and landmarks (laser and vision system)

Zunino and Christensen, 2001, navigation in realistic environment, Proc. SIRS

EKF and stochastic map (sonar)

Folkesson, Jensfelt, Christensen, Vision SLAM and the Measurement Subspace, Proc. ICRA, Barcelona, April 2005

Methodologies for SLAM

Technologies for SLAM

Our approaches to SLAM

- ✓ The robot pose and environment feature locations can be simultaneously estimated using odometric, inertial and sonar range measures

  Ippoliti et al., Improving the robustness properties of robot localization procedures with respect to environment features uncertainties, Proc. of ICRA 2005, Barcelona, Spain, pp. 1463-1470

- ✓ Sonar measures can be used not only to provide distance information, but also to obtain an occupancy grid map; a probabilistic method is proposed for fusing the features extracted from it with data provided by a video camera, thus improving the performance with respect to an approach using odometric and sonar range measures only

  Bonci et al., Sonar and video data fusion for robot localization and environment feature estimation, proc. of CDC-ECC'05, Seville, Spain

Simultaneous estimation of robot location and environment features

State-space model whose state vector contains both the state variables of the wheelchair model and the state variables of landmarks

↓

Algorithm for the simultaneous on-line estimation of both the vehicle position and the environment features

↓

Computationally efficient solution to the localization problem

Simultaneous estimation of robot location and environment features

The algorithm operates in a stochastic framework, and is based on the ascertainment that the angular measure $\theta_g(t_k)$ provided by the FOG is much more reliable than the angular measure $y_\omega(t_k)$ obtainable by encoders

The estimation algorithm is an EKF defined on the basis of:

- ✓ a stochastic state-space model derived from:
  - ✓ the kinematic model of the unicycle vehicle
  - ✓ environment geometric features
- ✓ a measure equation containing:
  - ✓ the incremental measure of the encoders $y_\nu(t_k)$
  - ✓ the angular measure of the gyroscope $\theta_g(t_k)$
  - ✓ distance measures provided by the set of sonar sensors from environment planes

Simultaneous estimation of robot location and environment features

The measure $z_1(\cdot)$ provided by the encoders is in terms of increments

Extended state $\bar{X}(k) := [X_1(k)^T, X_1(k-1)^T]^T$

$\widetilde{X}(k) := [\ \bar{X}^T(k), \quad X'^T(k)\ ]^T$ where

$X'(k) := [P_r^1, P_n^1, P_r^2, P_n^2, \cdots, P_r^{n_p}, P_n^{n_p}]^T$

Dynamic state-space equation:

$$\widetilde{X}(k+1) = \widetilde{A}(k)\widetilde{X}(k) + \widetilde{L}(k)U(k) + \widetilde{B}(k)\theta_g^r(k) + \widetilde{D}(k) + \widetilde{W}(k) \qquad \text{(a)}$$

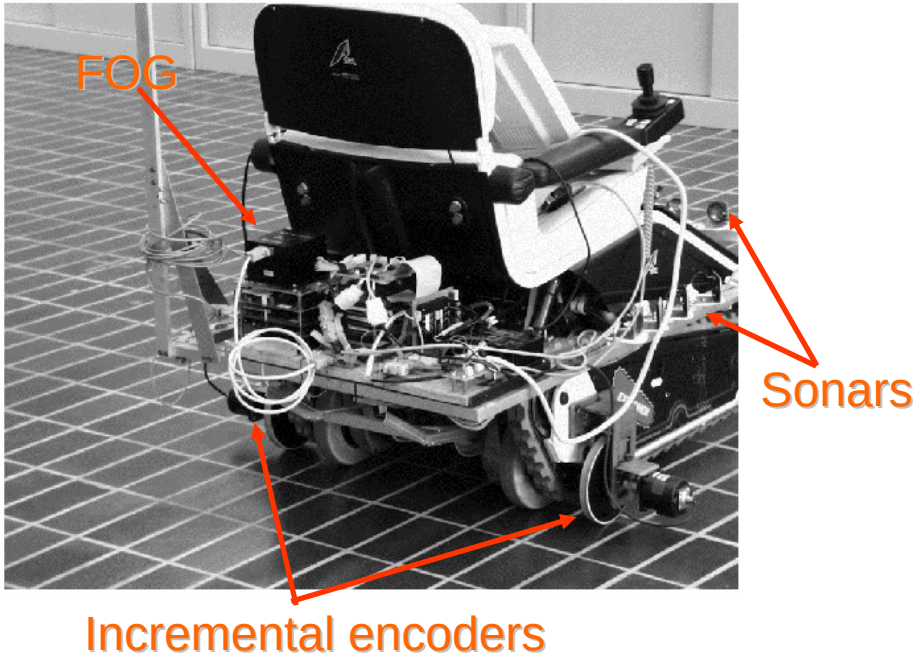
Measure equations:

- ✓ $z_1(k) = \widetilde{C}_1(k)\widetilde{X}(k) + v_1(k)\ ,\ \widetilde{C}_1(k) = [\,C_1(k), \quad 0_{1,2n_p}\,]$ (b)
  expressed as a function of $x(k+1) - x(k)$ and $y(k+1) - y(k)$
- ✓ $\bar{Z}_2(k) = \widetilde{C}_2(k)\widetilde{X}(k) + V_2(k)\ ,\ \widetilde{C}_2(k) = [\,\widetilde{c}_1(k)^T, \quad \widetilde{c}_2(k)^T, \quad \cdots, \quad \widetilde{c}_{p_k}(k)^T\,]^T$ (c)

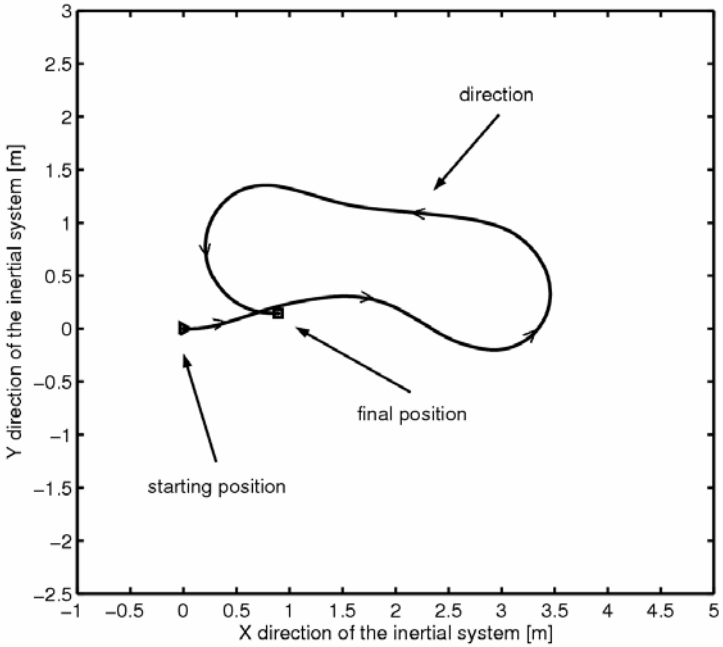
Equations (a), (b) and (c) represent the linearized and discretized state-space form to which the classical EKF algorithm has been applied

Experimental results

The EKF has been implemented on the navigation module of the TGR Explorer powered wheelchair



Experimental results

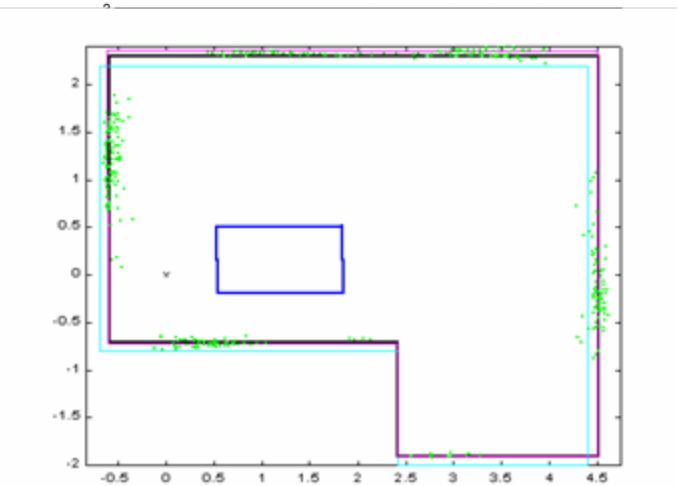


Trajectory of the vehicle estimated by the proposed algorithm

	x	y	θ
AC	$0.91\,m$	$0.145\,m$	$6.2832\,rad$
EC	$0.8935\,m$	$0.1446\,m$	$6.2873\,rad$
E	$0.0165\,m$	$0.0004\,m$	$0.0041\,rad$

Detected estimate errors (E) in correspondence of the final vehicle configuration = distance between the actual (AC) and the corresponding estimated (EC) configuration

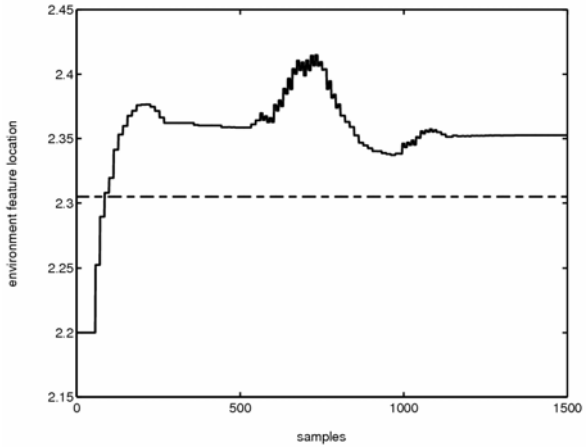
Experimental results



- ✓ The continuous lines are the actual (true) locations of environment map landmarks
- ✓ Dotted and dashed lines represent the initial and final estimates of environment map landmarks respectively
- ✓ The dots are the actually used sonar measures

	L_1	L_2	L_3	L_4	L_5
IE	$0.12\,m$	$0.105\,m$	$0.11\,m$	$0.095\,m$	$0.095\,m$
FE	$0.0475\,m$	$0.0476\,m$	$0.07\,m$	$0.0523\,m$	$0.034\,m$

Differences in module between the actual locations of environment landmarks and their initial (IE) and final (FE) estimates



A typical estimate (continuous line) of environment geometric feature location

- ✓ As the vehicle progresses through the environment, the error in landmark location estimate decreases monotonically to a lower bound
- ✓ The dashed line represents the actual environment geometric feature location

Data Fusion

The performance of the considered approach to SLAM can be improved by the use of more reliable measures

For example the reliability of exteroceptive measures could be increased by the data fusion of complementary sensors, as considered in the problem of map building: data fusion between sonar readings and video data

Hough Transform

The CCD video camera can be used for extracting the walls and obstacle borders, which are straight lines in the *XY* plane

For detecting straight lines representing environment features, the Hough Transform (HT) is used

Straight line equation: $\rho = u\cos\phi + v\sin\phi$

ρ : distance between the straight line and the origin of the coordinate system in the image plane
ϕ : orientation of the line
u, v : coordinates of whatever edge point belonging to the line

The edge points are detected by an orthogonal differential operator

For each detected edge point the parameters (ρ, ϕ) are estimated and quantized, and the accumulator array $H(\rho, \phi)$ is increased accordingly

Eventually, the peaks of $H(\rho, \phi)$ identify the parameters of the highest probability lines

Occupancy grid map

The values of the cells in the grid are updated by a probabilistic fusion of sonar readings

Straight line segments can be found in the occupancy grid as aligned cells with high probability of occupation

By interpreting a grid and its probabilities as an image with different levels of intensity (grey level), it is possible to apply the HT to detect straight lines and to associate a probability to each detected line

Video and ultrasonic data fusion

Matching between the lines extracted from the video data and from occupancy grid is performed for environment features belonging to the part of the floor visible from the CCD camera (here called "visible space")

The proposed matching algorithm is based on the combination of the line probabilities encoded in both Hough accumulators

All the straight lines detected from the portion of the occupancy grid corresponding to the portion of floor falling in the "visible space" are matched with the straight lines detected from the video image by projecting the straight lines of the video image on the floor plane

The existence probability of the straight lines is stored in both Hough accumulators

The matching algorithm is based on the combination of the line probabilities encoded in both Hough accumulators; a Bayesian estimator is considered

The idea is to validate the straight lines detected by the vision system with the sonar probabilistic map

Ultrasonic and video data fusion

Also data video measures are included in the measurement equation

Vector $Z(k)$ is composed of three subvectors:

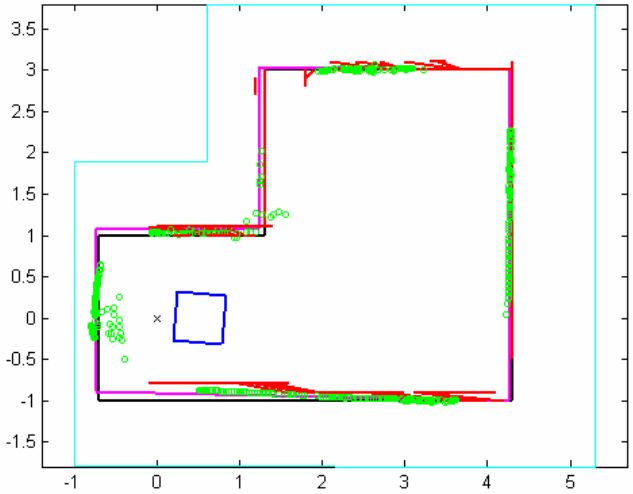
- ✓ $Z_1(k) = [z_{o,1}(k),\ z_{o,2}(k),\ z_{o,3}(k)]^T$ (odometric measures)
  - ✓ $z_{o,1}(k) = x(k) + v_{o,1}(k)$ $\quad z_{o,1}(k) = \hat{x}(k-1|k-1) + \Delta x(k)$
  - ✓ $z_{o,2}(k) = y(k) + v_{o,2}(k)$ $\quad z_{o,2}(k) = \hat{y}(k-1|k-1) + \Delta y(k)$
  - ✓ $z_{o,3}(k) = \theta(k) + v_{o,3}(k)$ $\quad z_{o,3}(k) = \hat{\theta}(k-1|k-1) + \Delta\theta(k)$
- ✓ $Z_2(k) = [z_{f,1}(k),\ z_{f,2}(k),\ \ldots,\ z_{f,2n_{fm}}(k)]^T$ (data fusion measures)
  - ✓ $z_{f,2i-1}(k) = P_r^i(k) + v_{f,2i-1}(k)$ $\quad z_{f,2i-1}(k) = \rho_i(k)$
  - ✓ $z_{f,2i}(k) = P_n^i(k) + v_{f,2i}(k)$ $\quad z_{f,2i}(k) = \phi_i(k)$
- ✓ $Z_3(k) = [z_{s,1}(k),\ z_{s,2}(k),\ \ldots,\ z_{s,n_{sm}}(k)]^T$ (sonar measures)

The observation noise is a white sequence with zero mean and covariance *R*, where *R* is a diagonal matrix

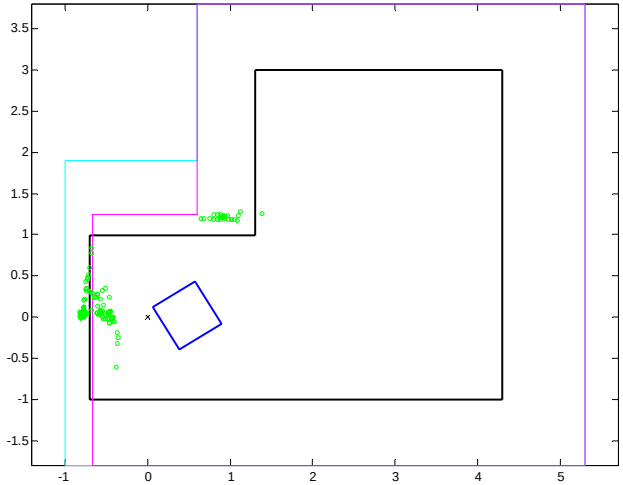
Fusion measure selection is analogous to the procedure previously recalled

Ultrasonic and video data fusion

- ✓ Black lines: actual (true) locations of environment map landmarks
- ✓ Cyan lines: initial estimates of environment map landmarks
- ✓ Magenta lines: final estimates of environment map landmarks
- ✓ Green dots: actually used sonar measures
- ✓ Red lines: actually used fusion measures



With fusion measures

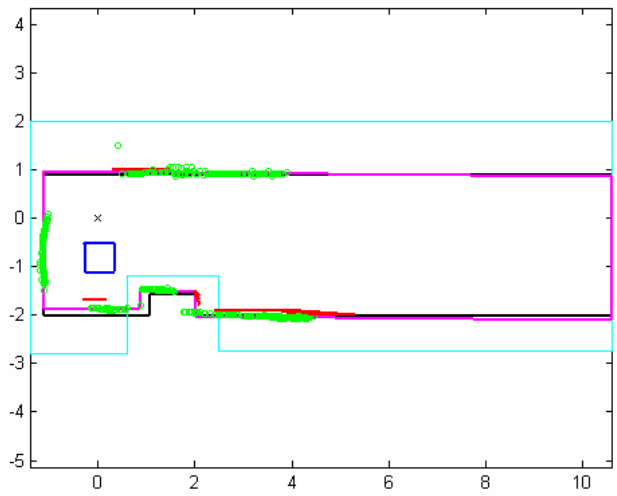


Without fusion measures

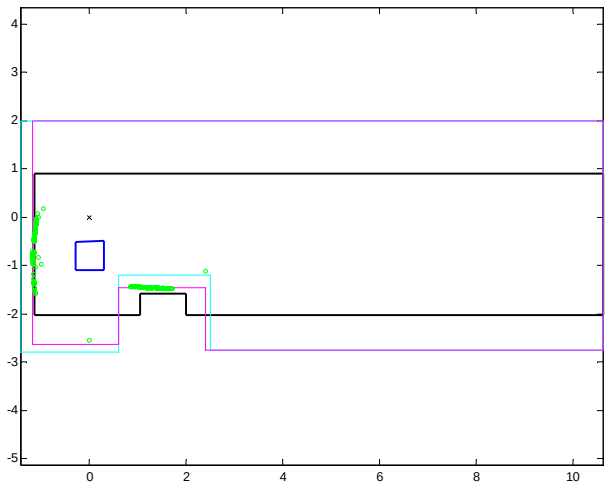
The algorithm using fusion data performs better than the one using sonar range measures only, especially when the initial estimate of landmarks differs from the real value by about 1 m

Ultrasonic and video data fusion

Even in a less structured environment the algorithm using fusion data shows satisfactory performances, while the one using sonar measures only is unable to correct an initial erroneous estimate of landmark locations



With fusion measures



Without fusion measures

Comments

- ✓ The proposed algorithms for SLAM operate in a stochastic state-space form where sensor and model uncertainties are intrinsically taken into account
- ✓ The vehicle trajectory estimate is highly accurate and robust with respect to uncertain physical parameters and not exactly known initial conditions
- ✓ All available information and uncertainties are collected into the state-space representation
- ✓ The solution has a recursive structure and requires a modest computational effort