
Cognitive Robotics

01. Introduction

AbdElMoniem Bayoumi, PhD

Fall 2022

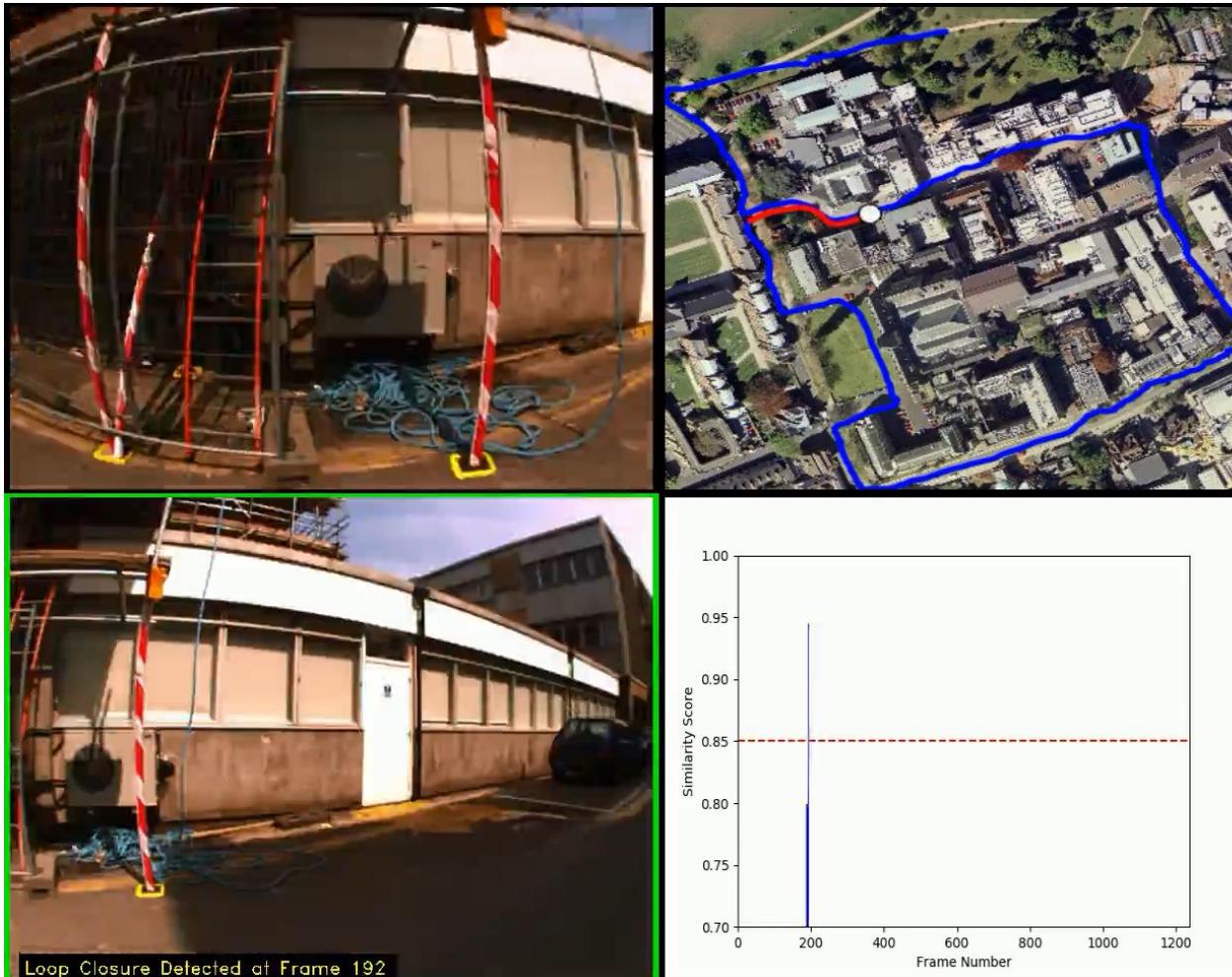
Acknowledgment

- These slides have been created by Wolfram Burgard, Dieter Fox, Cyrill Stachniss and Maren Bennewitz

Little bit about me

- Current Affiliation:
 - Cairo University, Faculty of Engineering
(Computer Engineering Dept.)
- Ph.D., University of Bonn, Germany
- Research Interests:
 - Deep learning
 - Navigation

Research Interests

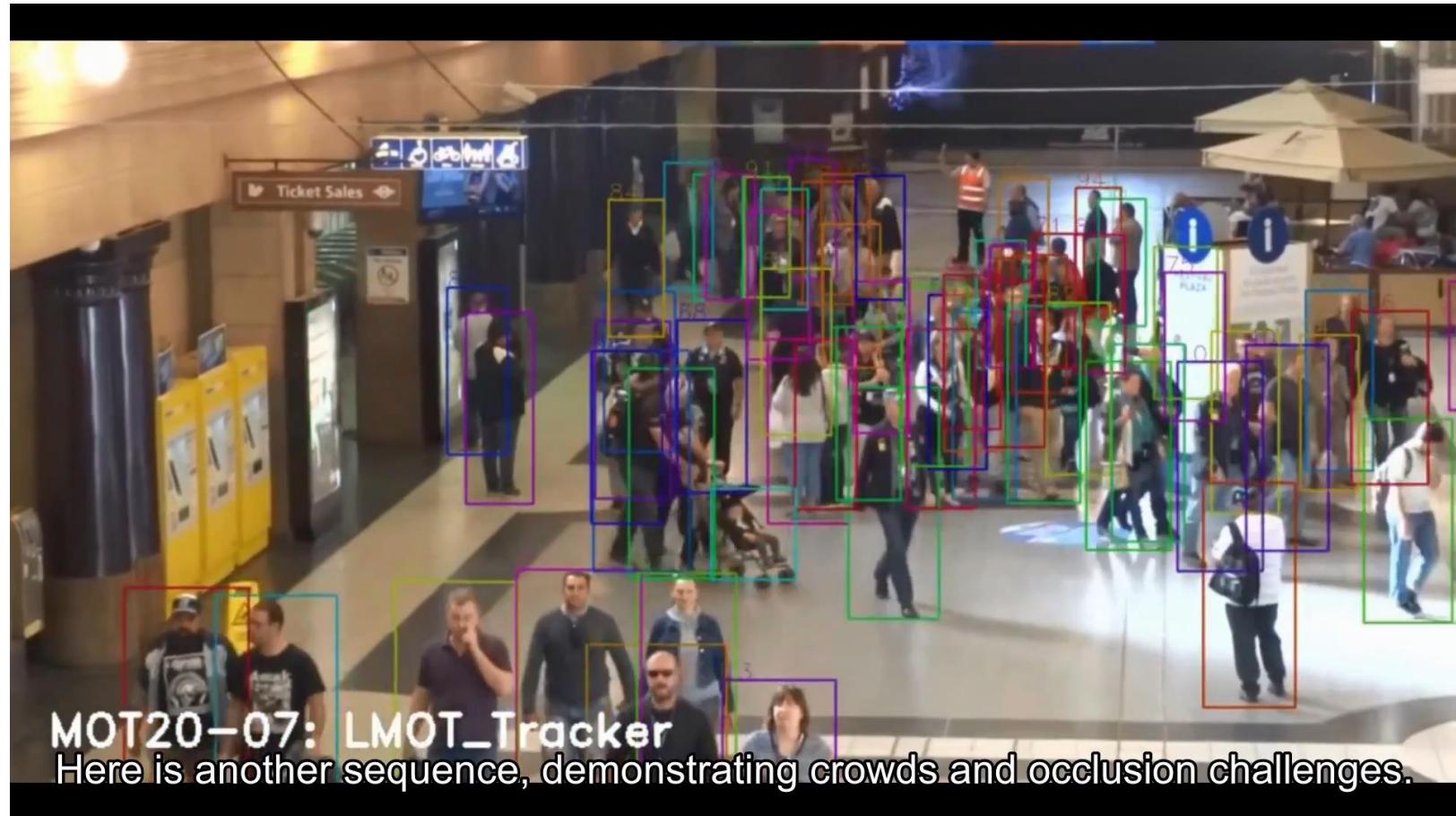


LoopNet: Where to Focus? Detecting Loop Closures in Dynamic Scenes

H. Osman, N. Darwish, and A. Bayoumi

In: IEEE Robotics and Automation Letters (RA-L), 2022, presented in ICRA 2022

Research Interests



MOT20-07: LMOT_Tracker

Here is another sequence, demonstrating crowds and occlusion challenges.

LMOT: Efficient Light-Weight Detection and Tracking in Crowds
R. Mostafa, H. Baraka, and A. Bayoumi
In: IEEE Access, 2022.

Administrivia

- Contacts:
 - abayoumi@cu.edu.eg
- Grading Policy:
 - Project: 20%
 - Assignments: 10%
 - Midterm: 10%
 - Final Exam: 60% (written & closed book exam)
- Slides: <https://shorturl.at/hoGQ4>



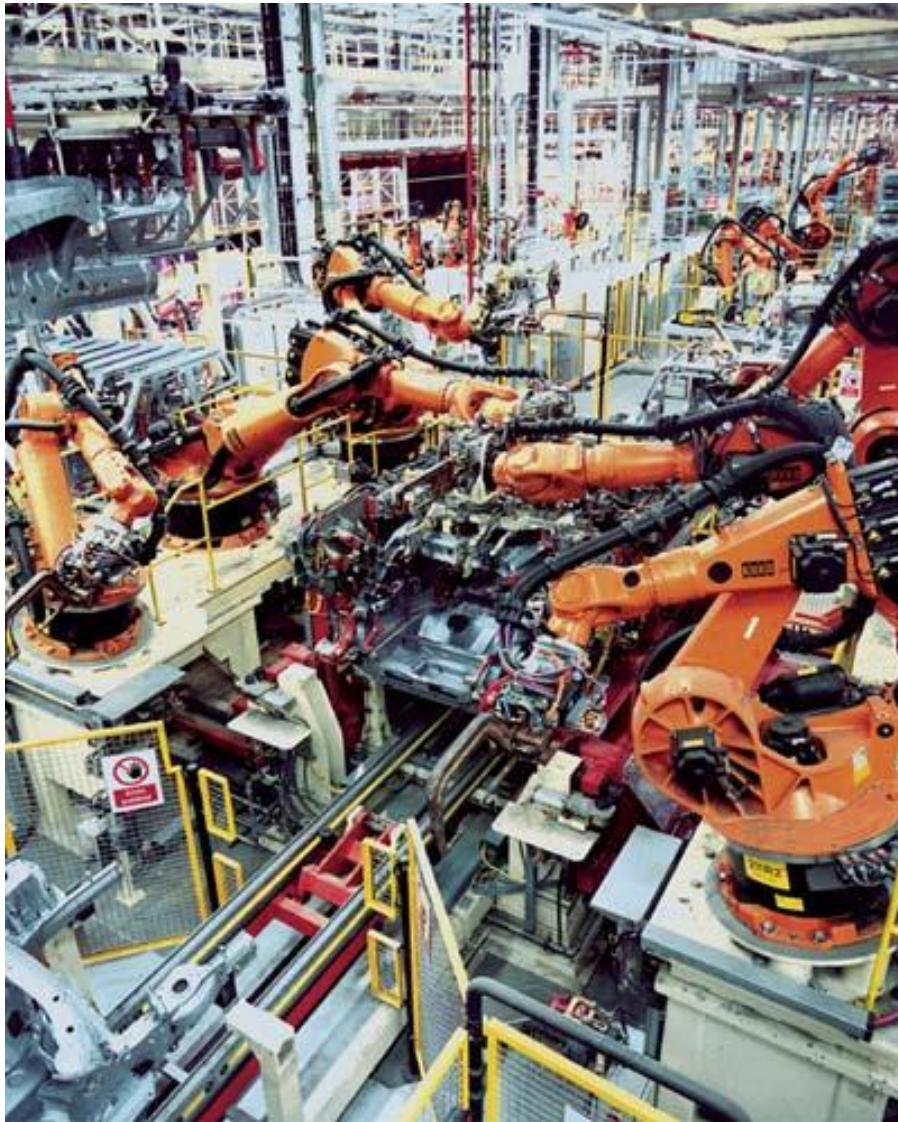
Administrivia

- Contacts:
 - abayoumi@cu.edu.eg
- Grading Policy:
 - Project: 15%
 - Assignments: 5%
 - Midterm: 10%
 - Final Exam: 70% (written & closed book exam)

Content of This Course

- Probabilities and Bayes
- The Kalman Filter
- The Extended Kalman Filter
- Probabilistic Motion Models
- Probabilistic Sensor Models
- Discrete Filters
- The Particle Filter, Monte Carlo Localization
- Mapping with Known Poses
- SLAM: Simultaneous Localization and Mapping
- SLAM: Landmark-based FastSLAM
- SLAM: Grid-based FastSLAM
- Path Planning and Collision Avoidance

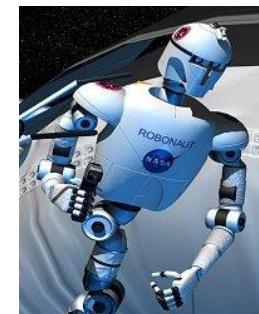
Traditional Robotics



- Controlled environment
- Well understood
- Millions of robots in mass production
- Not covered in this lecture

New Application Domains

- Flexible automation
- Mining, agriculture,...
- Logistics
- Household
- Medicine
- Dangerous environments
(Space, under water,
nuclear power plants, ...)
- Toys, entertainment



Cognitive Robotics

- Have cognitive functions normally associated with people or animals
- Interpret various kinds of sensor data
- Act purposefully and autonomously towards achieving goals
- Operate in dynamic real-life environments
- Exhibit a high degree of robustness in coping with unpredictable situations
- Key challenges
 - Systematic treatment of uncertainties
 - Perceiving the environmental state
 - Coordination of teams of collaborative robots in dynamic environments
 -

Tour Guide Robot Minerva (CMU + Univ. Bonn, 1998)



Autonomous Vacuum Cleaners



new improved version with mapping capabilities
and better cleaning strategies

Autonomous Lawn Mowers



not many cognitive capabilities required

DARPA Grand Challenge 2005



[Courtesy of Sebastian Thrun] 15

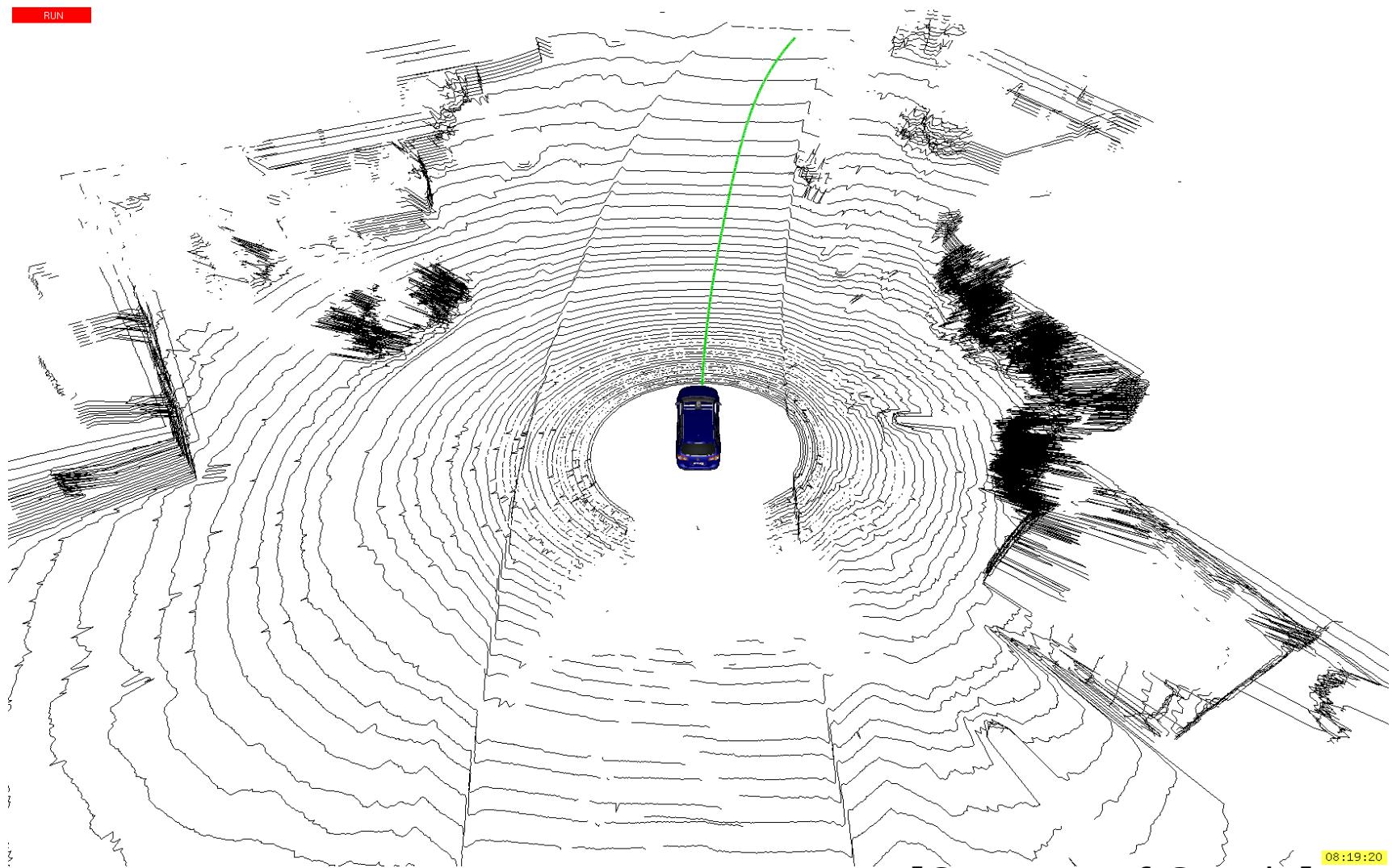
The Google Self-Driving Car



[Courtesy of Google]

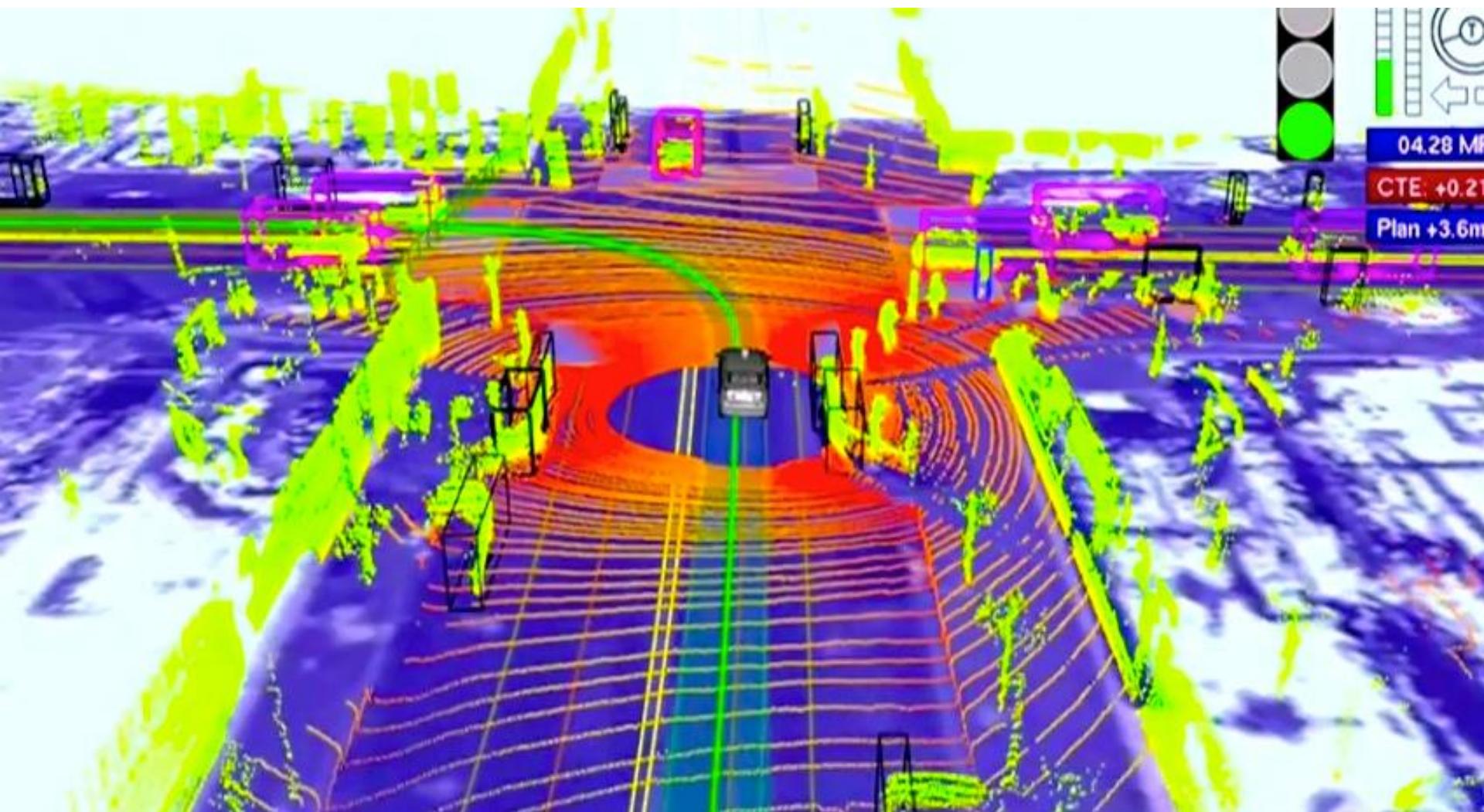
The Google Self-Driving Car

RUN



[Courtesy of Google]

The Google Self-Driving Car



[Courtesy of Google]

Driving in the Google Car



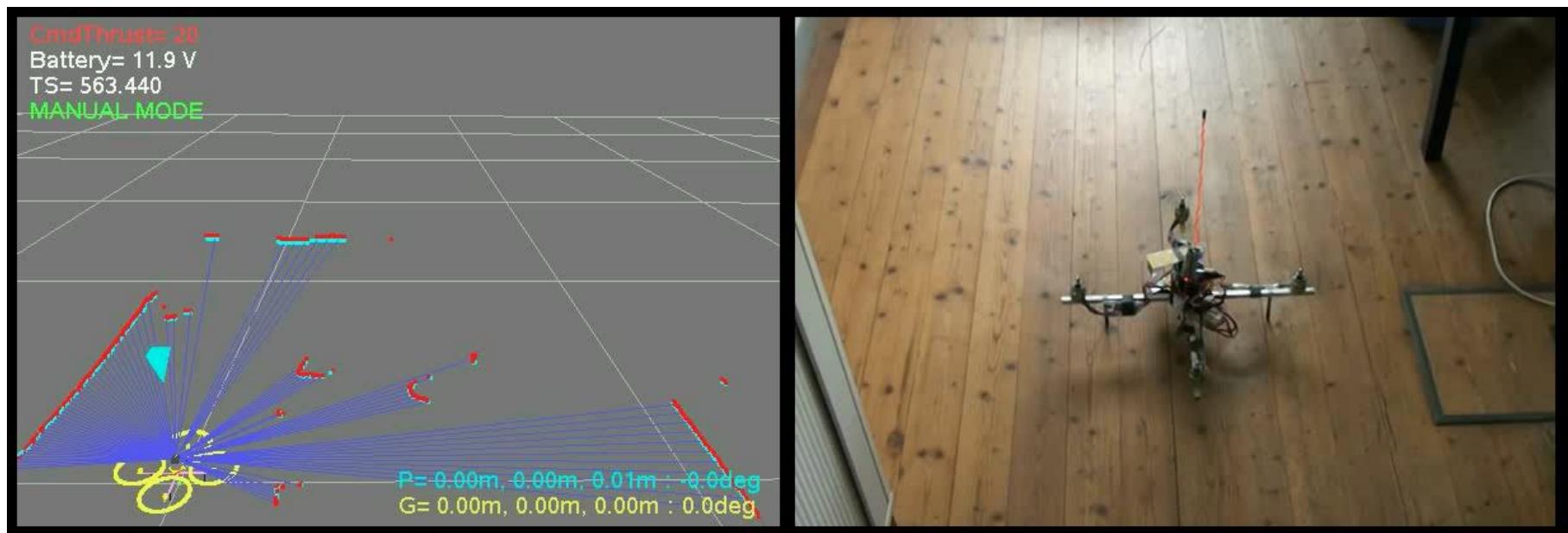
[Courtesy of Google]

Obelix Experiment: Uni Freiburg

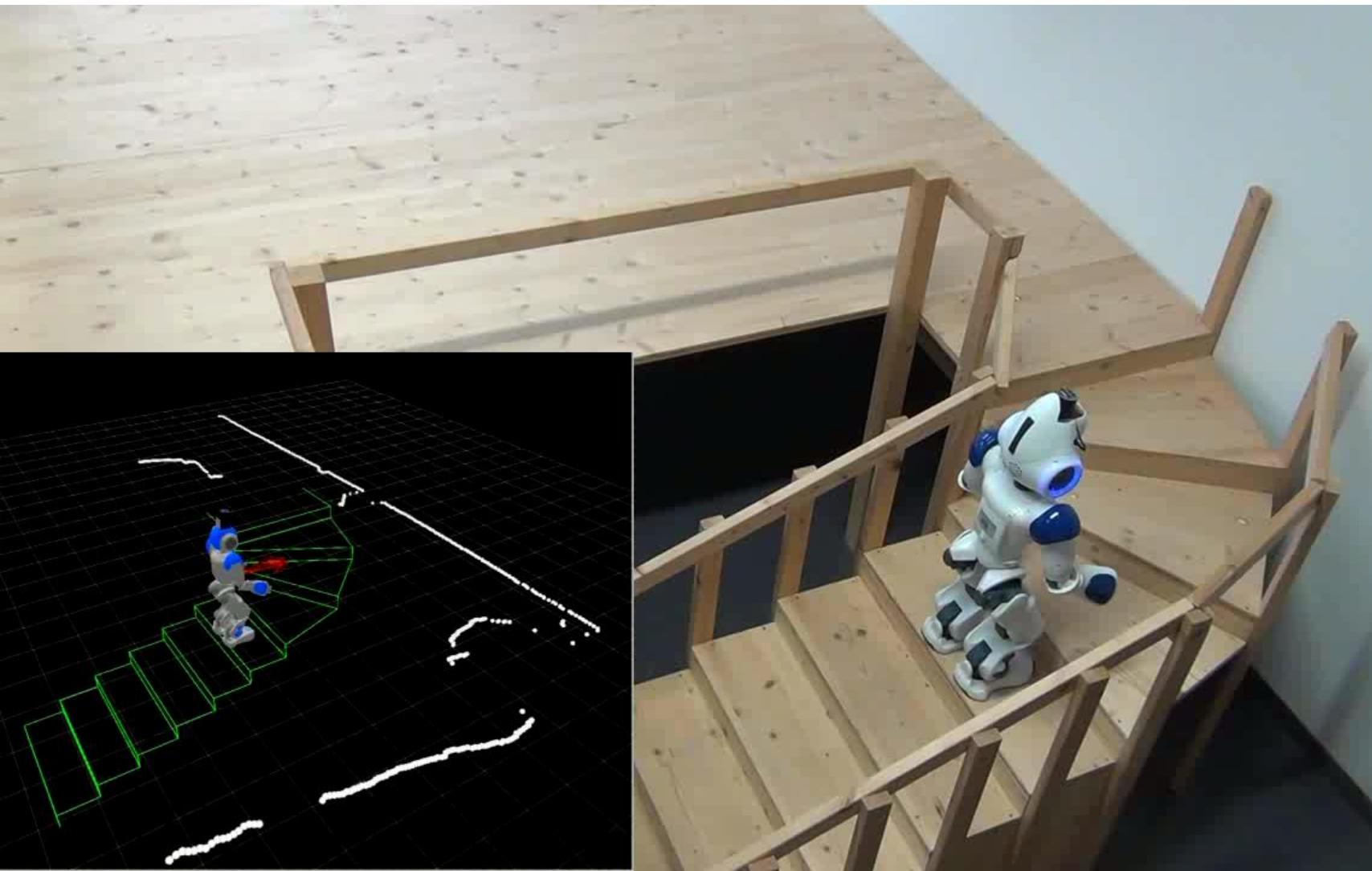


[Courtesy of AIS, Freiburg] 20

Autonomous Quadrotor Navigation

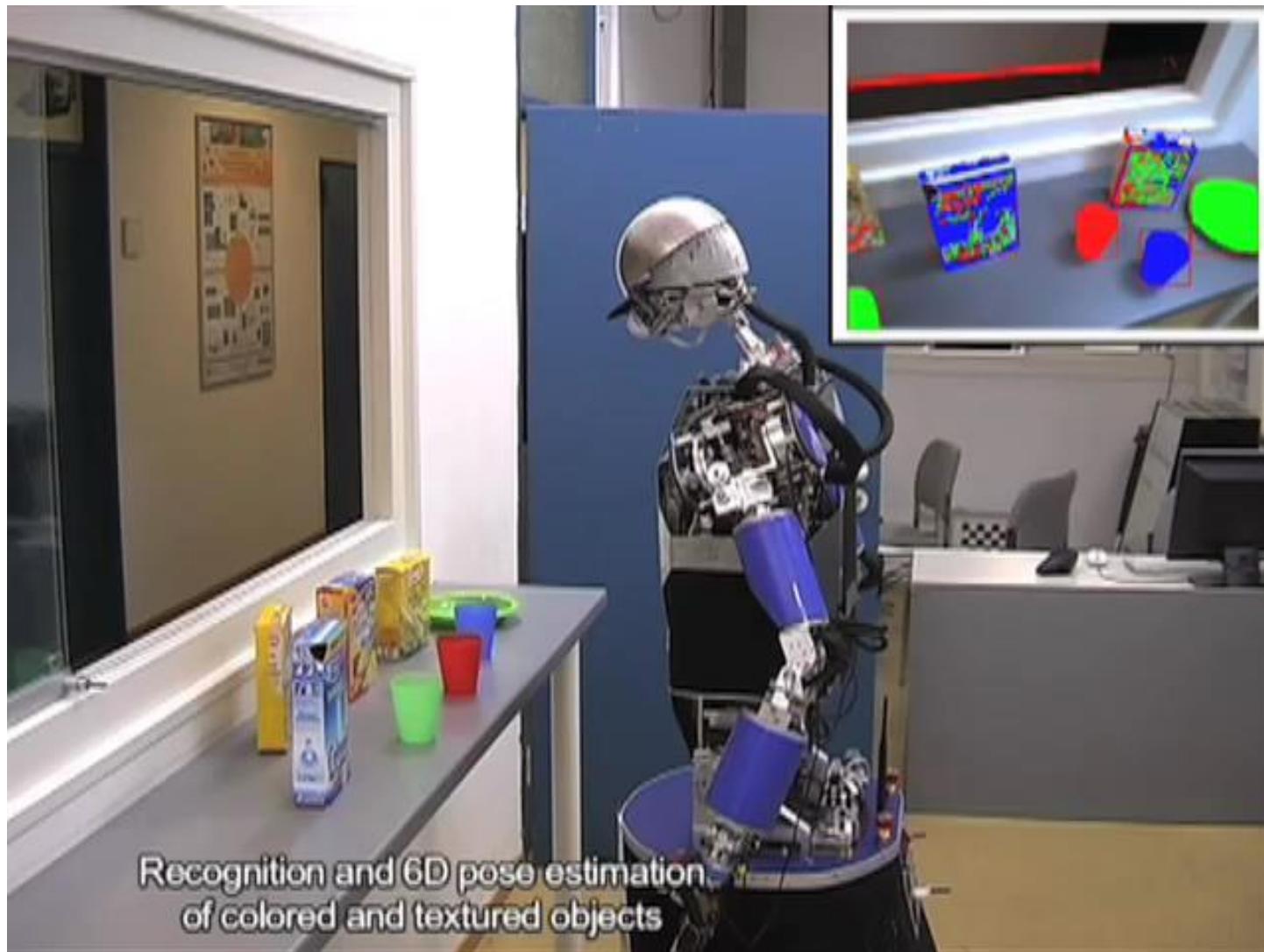


Stair Climbing (HRL)



4x

Interaction, Object Grasping



[Courtesy of T. Asfour et al.]

Towel Folding



[Courtesy of P. Abbeel et al.] 24

Cognitive Robot Cosero

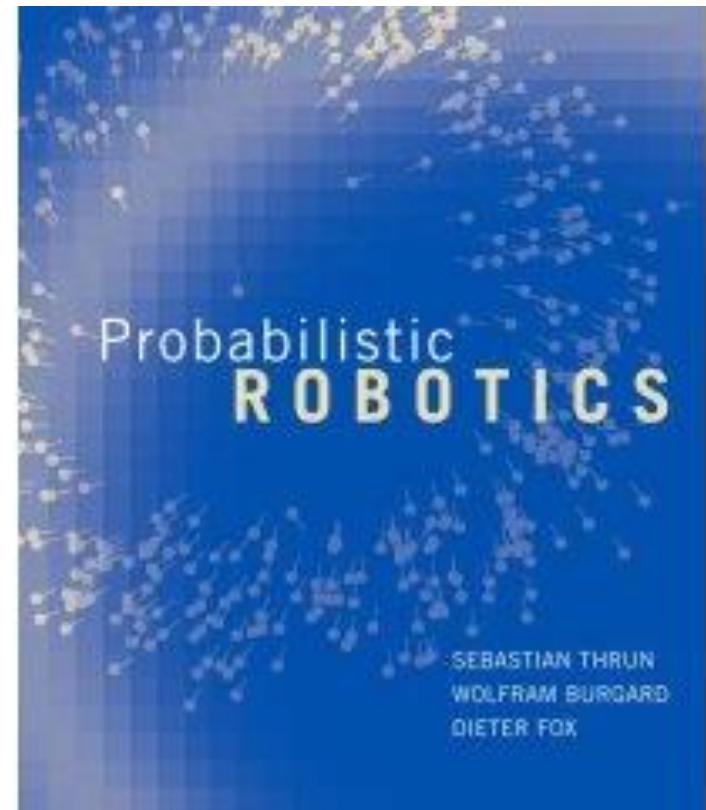
AIS Lab Uni Bonn (Sven Behnke)

- Manipulation tasks in domestic environments
- Human-robot interaction



Probabilistic Robotics

- Authors:
 - Sebastian Thrun
 - Wolfram Burgard
 - Dieter Fox
- MIT Press, 2005



<http://www.probabilistic-robotics.org>

Probabilistic Robotics

Key Idea

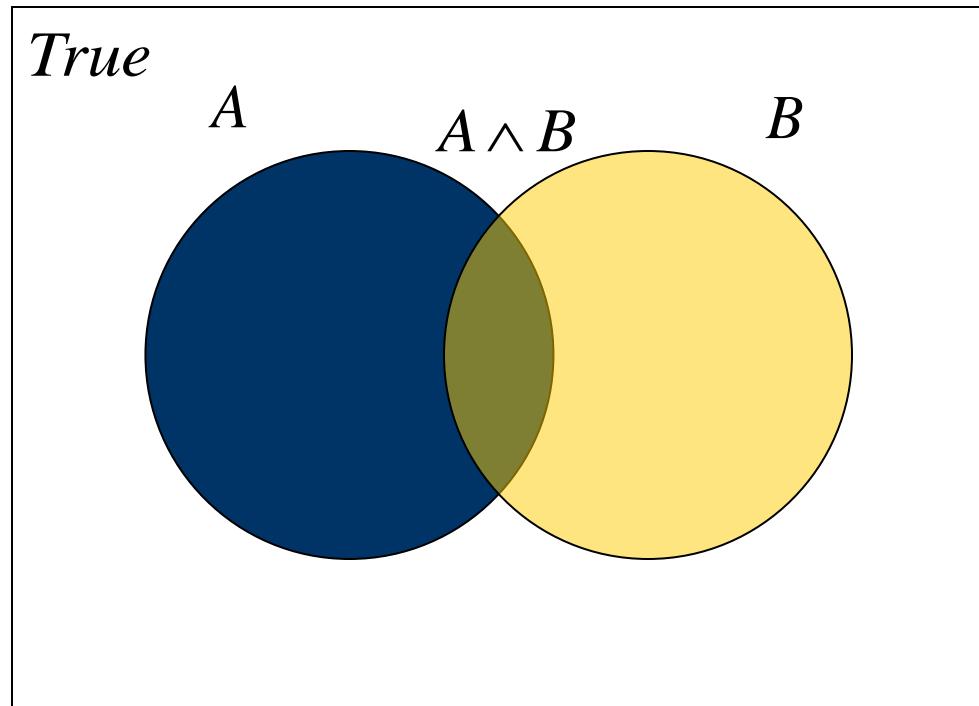
- **Explicit representation of uncertainty**
- Using the calculus of probability theory
- Perception = state estimation
- Action = utility optimization

Axioms of Probability Theory

- $P(A)$ denotes the probability that proposition A is true
- $0 \leq P(A) \leq 1$
- $P(\text{True}) = 1 \quad P(\text{False}) = 0$
- $P(A \cup B) = P(A) + P(B) - P(A \cap B)$

A Closer Look at Axiom 3

$$P(A \cup B) = P(A) + P(B) - P(A \cap B)$$



Using the Axioms

$$\begin{aligned} P(A \cup \neg A) &= P(A) + P(\neg A) - P(A \cap \neg A) \\ P(True) &= P(A) + P(\neg A) - P(False) \\ 1 &= P(A) + P(\neg A) - 0 \\ P(A) &= 1 - P(\neg A) \end{aligned}$$

Discrete Random Variables

- X denotes a **random variable**
- X can take on a countable number of values in $\{x_1, x_2, \dots, x_n\}$
- $P(X=x_i)$ or $P(x_i)$ is the **probability** that the random variable X takes on value x_i
- $P(\cdot)$ is called **probability mass function**
- For example:

$$P(Room) = \langle 0.7, 0.2, 0.08, 0.02 \rangle$$

/ | \ \backslash

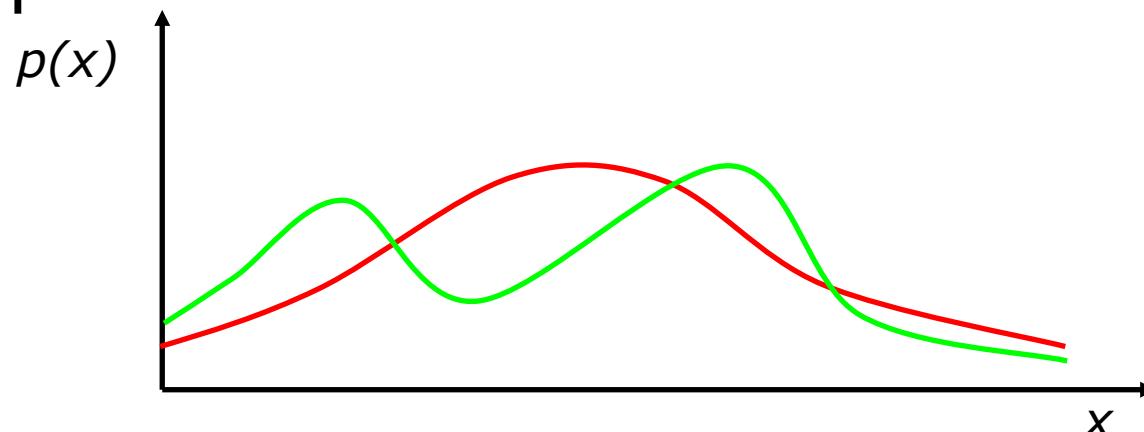
office, lecture hall, seminar room, kitchen

Continuous Random Variables

- X takes on values in the continuum
- $p(X=x)$ or $p(x)$ is a probability density function

$$P(x \in [a, b]) = \int_a^b p(x) dx$$

- For example:



The Probability Sums up to One

Discrete case

$$\sum_x P(x) = 1$$

Continuous case

$$\int p(x)dx = 1$$

Joint and Conditional Probability

- $P(X=x \text{ and } Y=y) = P(x,y)$
- If X and Y are **independent** then
$$P(x,y) = P(x) P(y)$$
- $P(x | y)$ is the probability of **x given y**
$$P(x | y) = P(x,y) / P(y) \quad \text{conditional probability}$$
$$P(x,y) = P(x | y) P(y) \quad \text{product rule}$$
- If X and Y are **independent** then
$$P(x | y) = P(x)$$

Law of Total Probability

Breaking the problem into simple pieces.

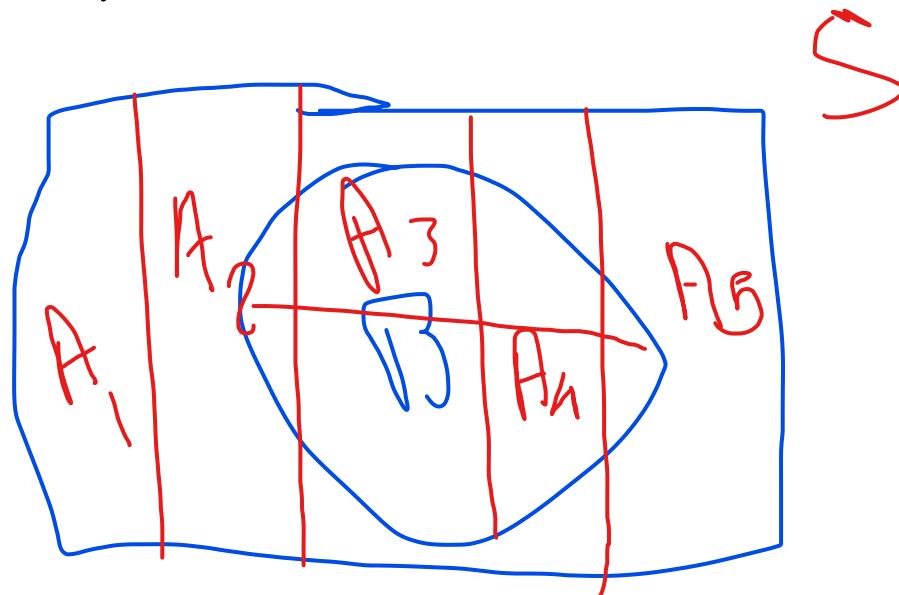
Divide and conquer

Discrete case

$$P(x) = \sum_y P(x | y)P(y)$$

Continuous case

$$p(x) = \int p(x | y)p(y)dy$$



Marginalization

Discrete case

$$P(x) = \sum_y P(x, y)$$

Continuous case

$$p(x) = \int p(x, y) dy$$

Bayes' Rule

solve a question mn harvard course sheet.

hwa 3ml a? hwa 2alk since $P(x|y) = P(x,y) / P(y)$

w bema en brdo $P(y | x) = P(y,x) / P(x)$

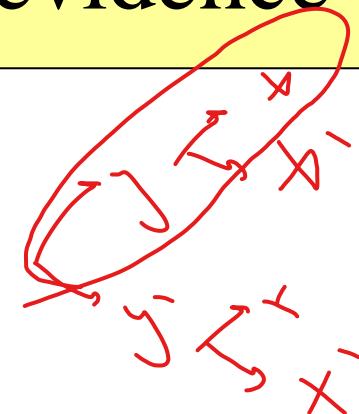
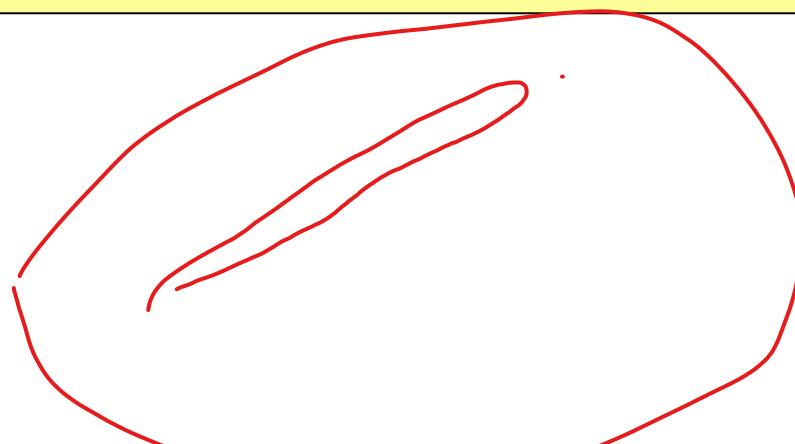
yeb2a mmkn n2ol $P(x|y) = P(y|x) P(x) / P(y)$

akny bgeb el relation bs bl3ks, w da byfr2 kter gedan w mofed fe est5damat ktera.

$$P(x, y) = \underbrace{P(x | y)P(y)}_{\Rightarrow} = \underbrace{P(y | x)P(x)}$$

$$P(x|y) = \frac{P(y | x)P(x)}{P(y)} = \frac{\text{likelihood} \cdot \text{prior}}{\text{evidence}}$$

posterior



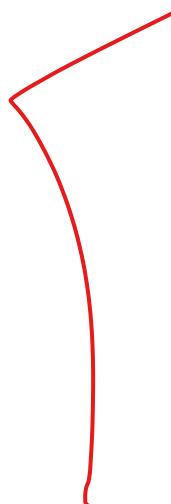
Normalization

U 1
c 4

$$P(x|y) = \frac{P(y|x)P(x)}{P(y)}$$
$$= \eta P(y|x)P(x)$$

$$\eta = P(y)^{-1} = \frac{1}{\sum_z P(y|z)P(z)}$$

Algorithm:



$$\forall x : \text{aux}_{x|y} = P(y|x)P(x)$$

// compute
// unnormalized posterior

$$\eta = \frac{1}{\sum_x \text{aux}_{x|y}}$$

// compute
// normalization factor

$$\forall x : P(x|y) = \eta \text{aux}_{x|y}$$

// normalize posterior

Bayes' Rule with Background Knowledge

$$P(x | y, z) = \frac{P(y | x, z) P(x | z)}{P(y | z)}$$

without knowing z , we will just have

$$p(x | y) = p(y | x) p(x)$$

$$p(y)$$

now we know that z already occurred, so just make a conditional probability with it in your consideration.

Conditional Independence

$$P(\underline{x}, \underline{y} | z) = P(x | z)P(y | z)$$

A: F C
 $P(A | F, !C) = 1$

Equivalent to $P(\underline{x} | z) = P(x | z, y)$

When z is known,
 y does not tell us
anything about x

and $P(\underline{y} | z) = P(y | z, \underline{x})$

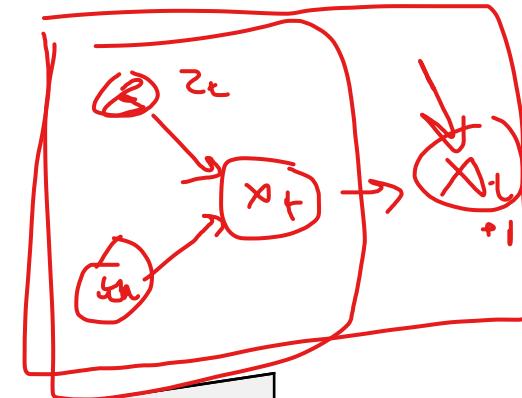
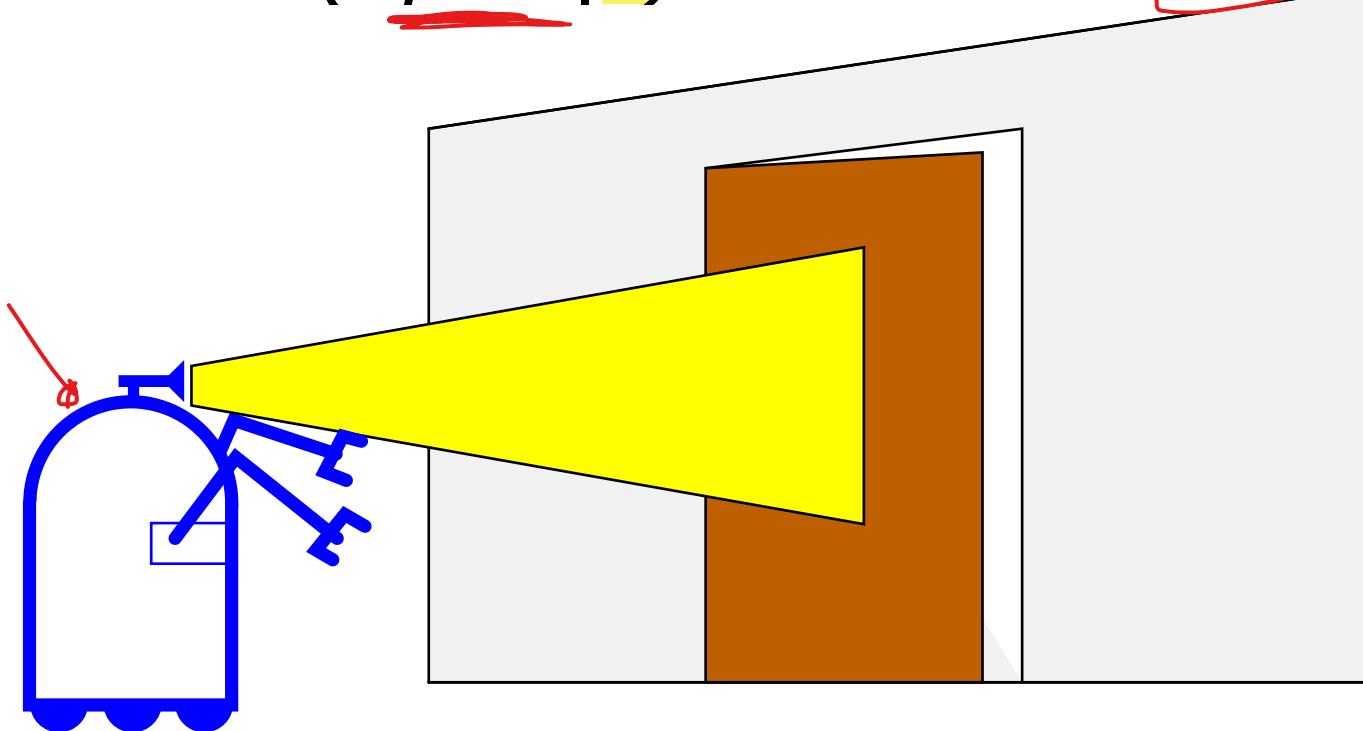
When z is known,
 x does not tell us
anything about y

if we know that we have a conditional independence, does this implies, that the original events are independent?

if we now that the original events are independent, does this mean that we have conditional independence?

Simple Example of State Estimation

- Suppose a robot obtains a measurement \underline{z}
- What is $P(\underline{\text{open}} | \underline{z})$?



Causal vs. Diagnostic Reasoning

- $P(open|z)$ is **diagnostic**
- $P(z|open)$ is **causal**
- Often **causal** knowledge is easier to obtain **count frequencies!**
- Bayes' rule allows us to use causal knowledge:

$$P(open | z) = \frac{P(z | open)P(open)}{P(z)}$$

$p(\neg z | \text{open}) =$

Example

- $P(z | \text{open}) = \underline{\underline{0.6}}$ $P(z | \neg \text{open}) = \underline{\underline{0.3}}$
- $\underline{\underline{P(\text{open})}} = P(\neg \text{open}) = \underline{\underline{0.5}}$

$$P(\text{open} | z) = \frac{P(z | \text{open})P(\text{open})}{P(z | \text{open})p(\text{open}) + P(z | \neg \text{open})p(\neg \text{open})}$$

$$P(\text{open} | z) = \frac{0.6 \cdot 0.5}{0.6 \cdot 0.5 + 0.3 \cdot 0.5} = \frac{0.3}{\underbrace{0.3 + 0.15}_{0.45}} = \underline{\underline{0.67}}$$

- z increases the probability that the door is open

Combining Evidence

- Suppose our robot obtains another observation z_2
- How can we integrate this new information?
- More generally, how can we estimate $P(x / z_1, \dots, z_n)$?



Recursive Bayesian Updating

$$P(x | z_1, \dots, z_n) = \frac{P(z_n | x, z_1, \dots, z_{n-1}) P(x | z_1, \dots, z_{n-1})}{P(z_n | z_1, \dots, z_{n-1})}$$

Markov assumption:

Last measurement z_n is independent of previous measurements z_1, \dots, z_{n-1} if we know the state x

$$P(x | \underline{z_1, \dots, z_n}) = \frac{P(z_n | x) P(x | z_1, \dots, z_{n-1})}{P(z_n | z_1, \dots, z_{n-1})}$$

$$p(x | z_1, z_2) = \frac{p(x | z_1) p(x | z_2)}{p(x)}$$

$$\text{summ } (p(x) p(z|x))$$

$$= \eta \left[\prod_{i=1}^n P(z_i | x) \right] P(x)$$

Example: Second Measurement

lw fket da, hytl3lk nfs el equation el fo2.

$$P(\underline{\text{open}}|z_2, z_1) = \frac{P(z_2|\text{open})P(\text{open}|z_1)}{P(z_2|\text{open})P(\text{open}|z_1) + P(z_2|\neg\text{open})P(\neg\text{open}|z_1)}$$

This is the normalization factor.

$$P(\text{open} | z) = P(z | \text{open})P(\text{open})$$

$$\hline P(z | \text{open}) P(\text{open}) + P(z | \neg\text{open}) p(\neg\text{open})$$

$$P(\text{open}|z_2, z_1) = P(z_2 | \text{open}, z_1) p(\text{open}|z_1)$$

$$\hline \underline{P(z_2 | z_1)}$$

$$p(z_2 | z_1) = p(z_2 | \text{open}) p(\text{open} | z_1) + p(z_2 | \neg\text{open}) p(\neg\text{open} | z_1)$$

Summary



- Probabilities allow us to model uncertainties in a systematic way
- Bayes' rule allows us to compute probabilities that are hard to assess otherwise
- Under the Markov assumption, recursive Bayesian updating can be used to efficiently combine evidence

Acknowledgment

- These slides have been created by Wolfram Burgard, Dieter Fox, Cyrill Stachniss and Maren Bennewitz