Module 3: Robotic Sensory Systems

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World's First Robotics Cafe & Lounge

Source:
https://www.youtube.com/watch?v=imC4gqtP00s&feature=emb_logo

World's First Robotics Cafe & Lounge

Source: https://www.youtube.com/watch?v=vD4rQLuJGPY&feature=youtu.be

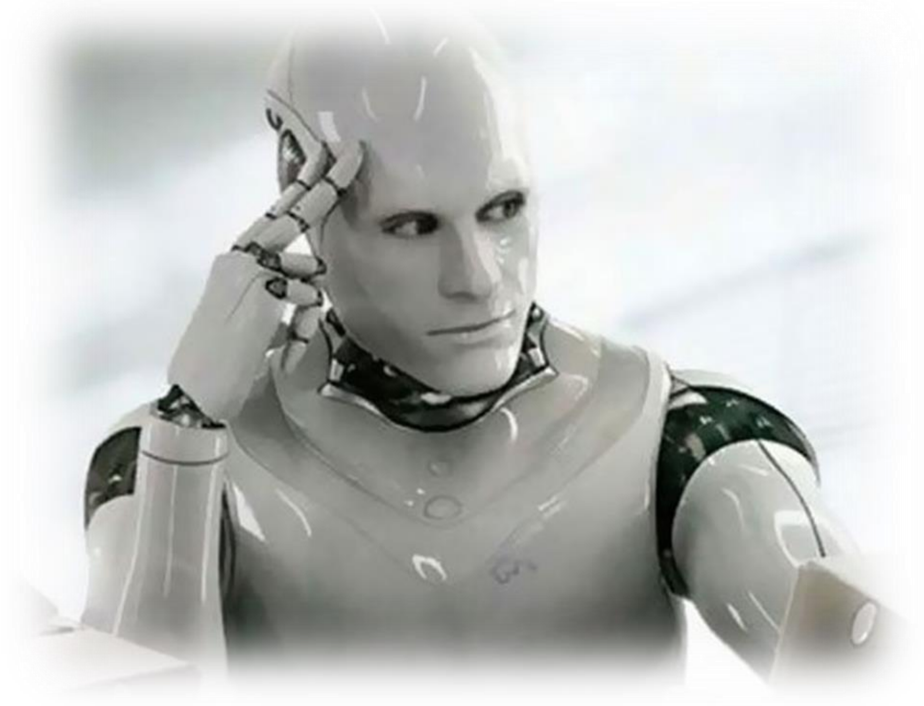
Objectives:

1. Understanding **advanced robotic sensory systems and their operations**
2. **Representing knowledge and uncertainty** in robotic systems

Topics

1. Robotic perception
2. Sensor and data fusion
3. Knowledge representation & reasoning
4. Uncertainty representation

Chapter 1: Robotic perception



Introducing Sensors

- **Definition:** Devices which provide **information** about the physical world
- Constitute the **perceptual** system of a robot
- **Key elements** as well as **limitations** in robotics
- Range from **simple to complex** depending on the amount of information they provide:
  - **A switch** is a simple on/off sensor
  - **A human retina** is a complex sensor consisting of more than a hundred million photosensitive elements (rods and cones)

Why Sense in Robotic Systems?

- Why not just program the robot to perform its tasks without sensors?
  1. Uncertainty
  2. Dynamic world
  3. Detection / correction of errors

Levels of Processing

- Finding out if a switch is open or closed
  - Measure voltage going through the circuit ⇒ **electronics**
- Using a microphone to recognize voice
  - Separate signal from noise, compare with store voices for recognition ⇒ **signal processing**
- Using a surveillance camera
  - Find people in the image and recognize intruders, comparing them to a large database ⇒ **computation**

What can be sensed from sensors?

- ***Direct Transduction***: e.g., electric and magnetic fields, mechanical strain, temperature, electromagnetic energy...
- ***Derived quantities***: e.g. distance, human presence, heading, air flow, molecular concentrations, air pressure, color...

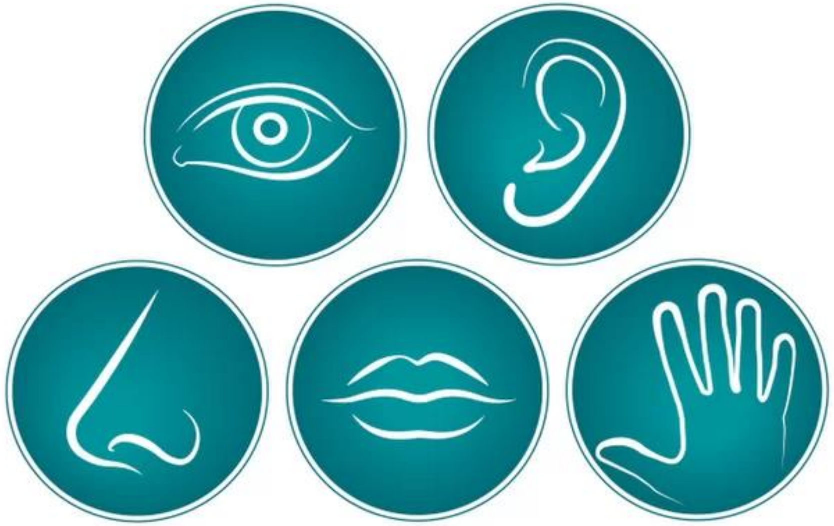
Human Sensory Systems (Examples)

Sense:

- Vision (Sight)
- Audition (Hear)
- Gustation (Taste)
- Olfaction (Smell)
- Tactition (Feel)

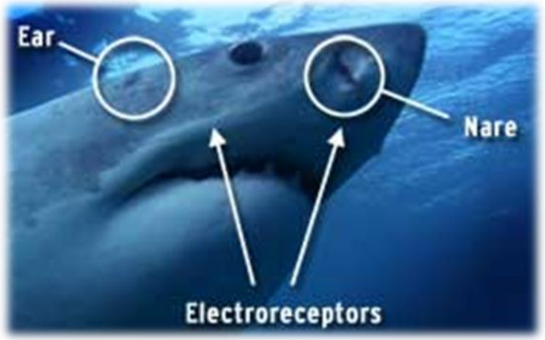
What sensed:

- EM waves
- Pressure waves
- Chemicals - flavor
- Chemicals - odor
- Contact pressure



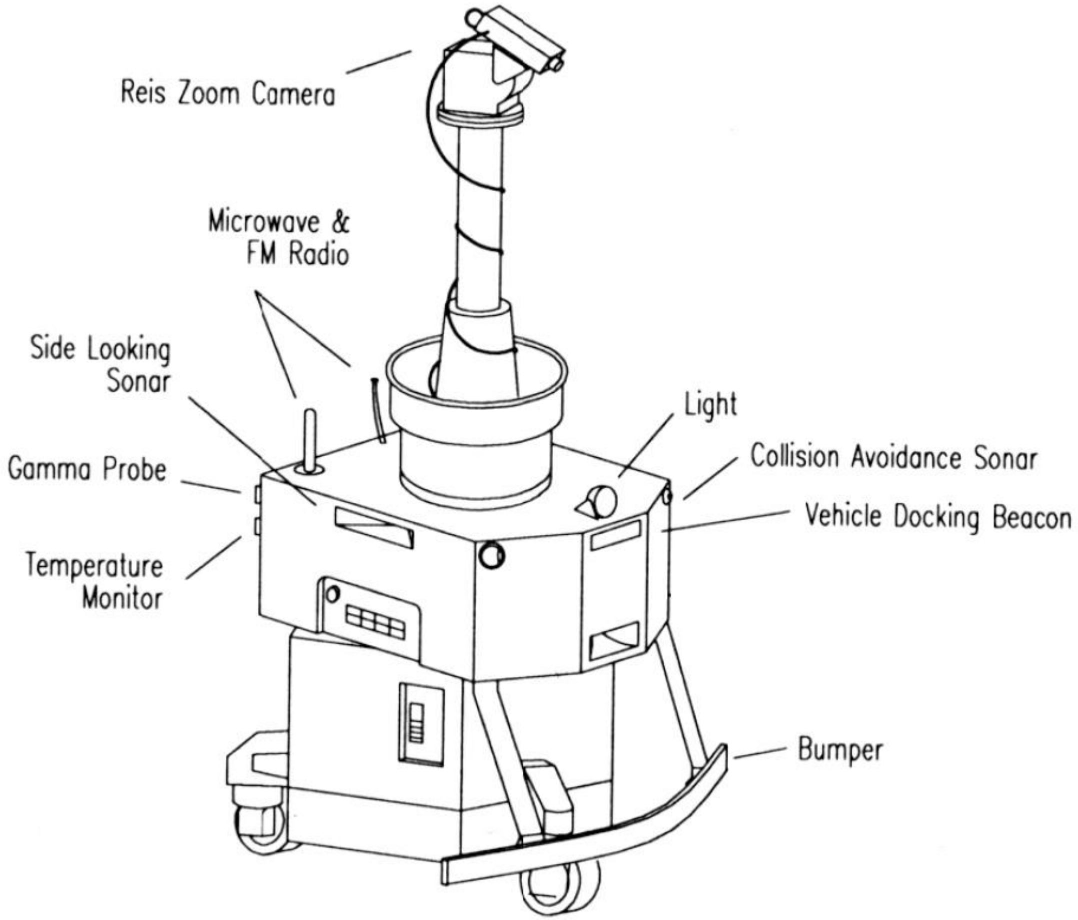
Animal Sensory Systems (“6th” Sense Examples)

- Magnetoception (birds)
- Electroception (sharks, etc.)
- Echolocation (bats, etc.)
- Pressure gradient (fish)



Designing Robotic Sensory Systems Similar to Humans' or Animals'?

- Human/Animal sensory systems adapted to functional needs and environment
- Similarly, **robots can use non-biological sensors which suit them to their 'ecosystems'**
- E.g. Programmable Humanoid NAO Evolution Robot, Sony Aibo Robot Dog



Designing Robotic Sensory Systems Similar to Humans' or Animals'?

- **Example (Programmable Humanoid NAO Evolution Robot):**

Source:
https://www.youtube.com/watch?v=NZEFjjsAbKU

Designing Robotic Sensory Systems Similar to Humans’ or Animals’?

- Example (Sony Aibo Robot Dog):

Source:
https://www.youtube.com/watch?v=lbSmyN1IsuE

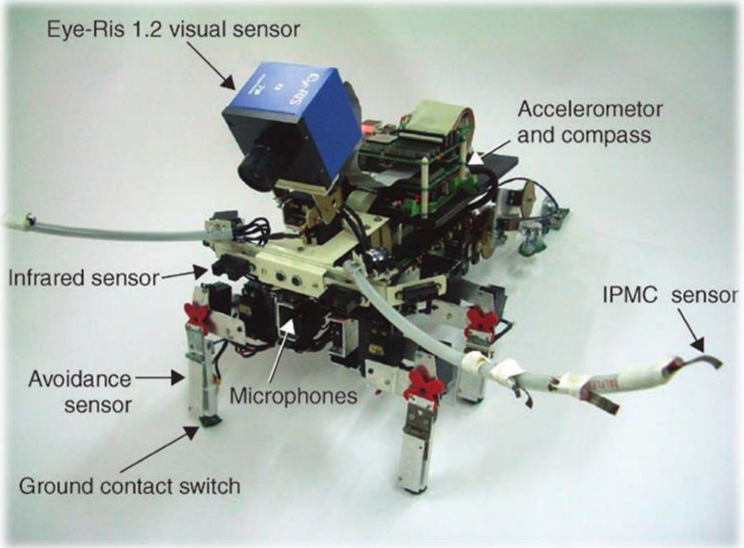
Robot Sensory Systems (Examples)

Sense:

- **Vision (Sight)**
- Audition (Hear)
- Gustation (Taste)
- Olfaction (Smell)
- Tactitions (Feel)
- Thermoception (Heat)

Possible Relevant Sensor:

- **Camera**
- Microphone
- Chemical sensors
- Chemical sensors
- Contact sensors
- Thermocouple



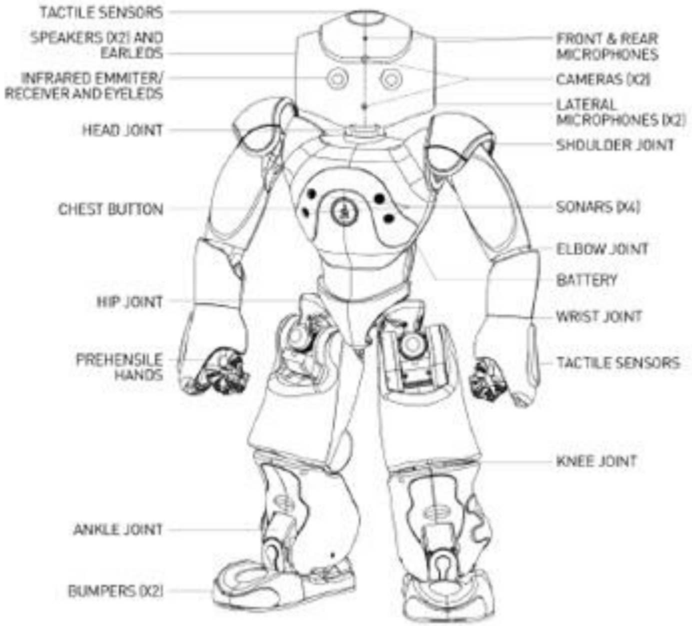
Robot Sensory Systems (Examples)

Sense:

- Equilibrioception
- Proprioception
- Magnetoception
- Electroception
- Echolocation
- Pressure gradient

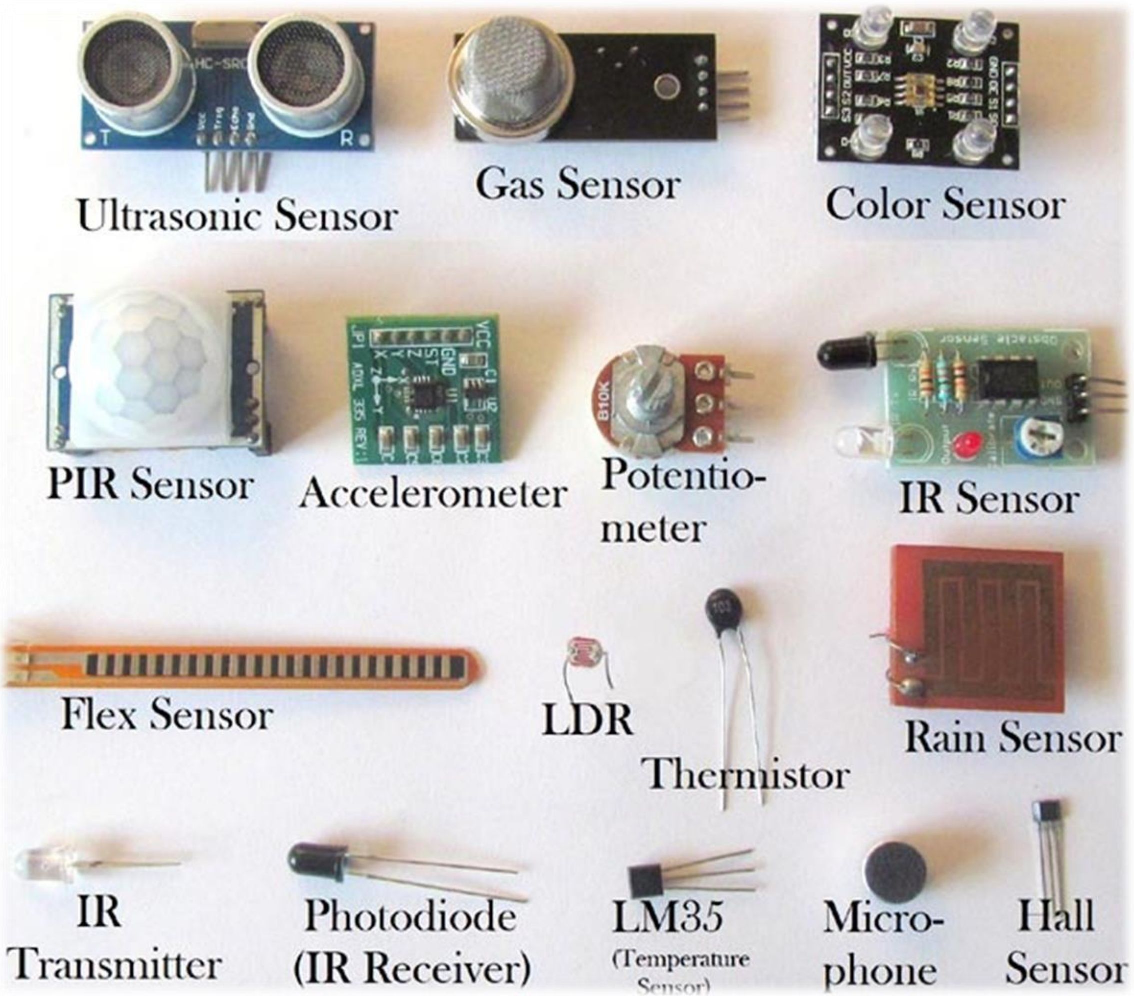
Possible Relevant Sensor:

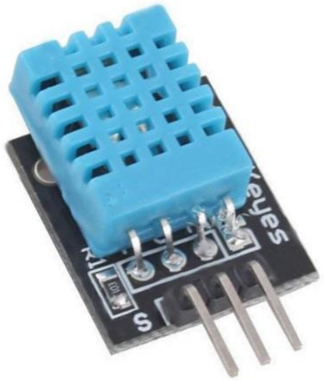
- Accelerometer
- Encoders
- Magnetometer
- Voltage sensor
- Sonar
- Array of pressure sensors?



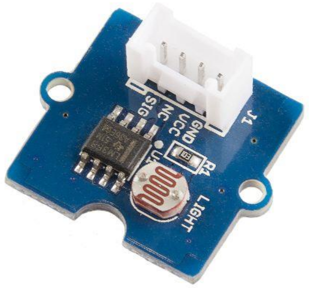
Programmable Humanoid NAO Evolution Robot

Sensors (Many types out there!)





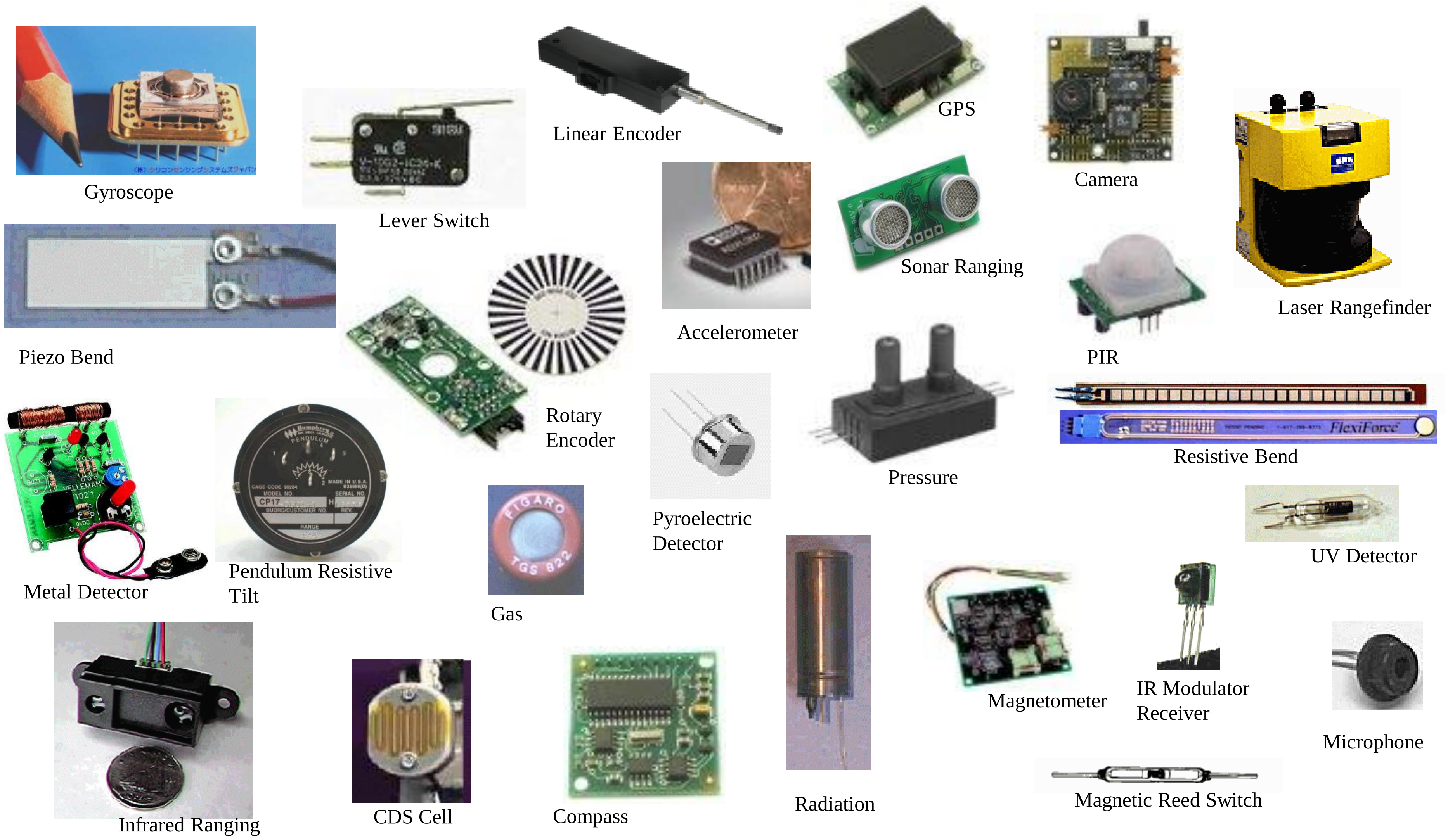
DHT11 – Temperature & Humidity Sensor



Light Sensor

Sound Sensor

Sensors (Many types out there!)



NUS Institute of Systems Science

Vision (Sight) in Robotic Systems

- Also known as **machine vision** (MV; aka computer vision or **EYES for the robots**)
- **Goal of MV** is to **develop programmes/algorithms that can automatically interpret images/videos**

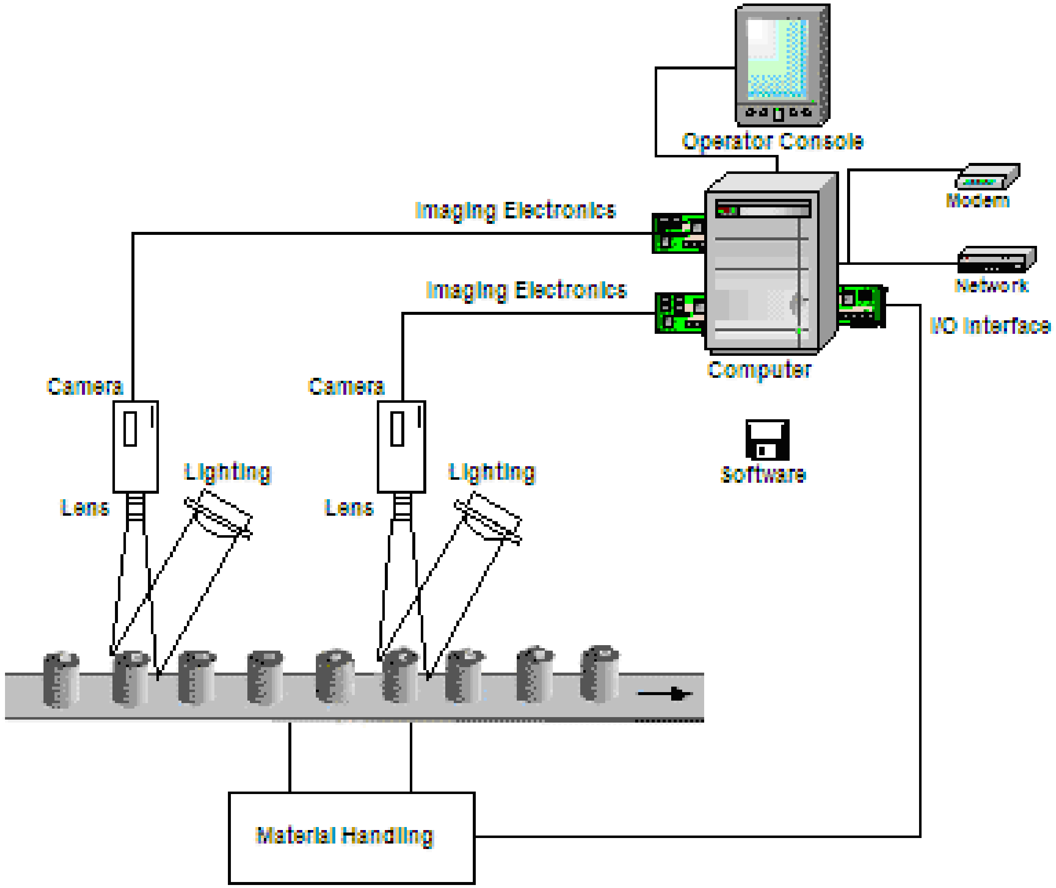
- **<u>Discussion Question:</u> Can MV match those of human's???**

Vision (Sight) in Robotic Systems

How does it generally work?

Requires:

- Must Have – a processor, camera or other forms of imaging sensors (e.g. radar, ultrasonic, laser, infra-red), software, imaging electronics
- Good to have – light source, hardware interface



Steps: (a) capture raw data, (b) process raw data, (c) analyse processed data, (d) feedback results

Vision (Sight) in Robotic Systems

Many various forms of Machine Vision (examples):

1. **2-D Machine Vision**
2. **2-D Deep Learning Machine Vision**
3. **Stereo (3-D; Depth) Machine Vision**
4. **Stereo (3-D) Deep Learning Machine Vision**

Increasing Complexity BUT Increasing Reliability

Vision (Sight) in Robotic Systems

- **2-D Machine Vision**

Vision (Sight) in Robotic Systems

- **2-D Deep Learning Machine Vision**

Vision (Sight) in Robotic Systems

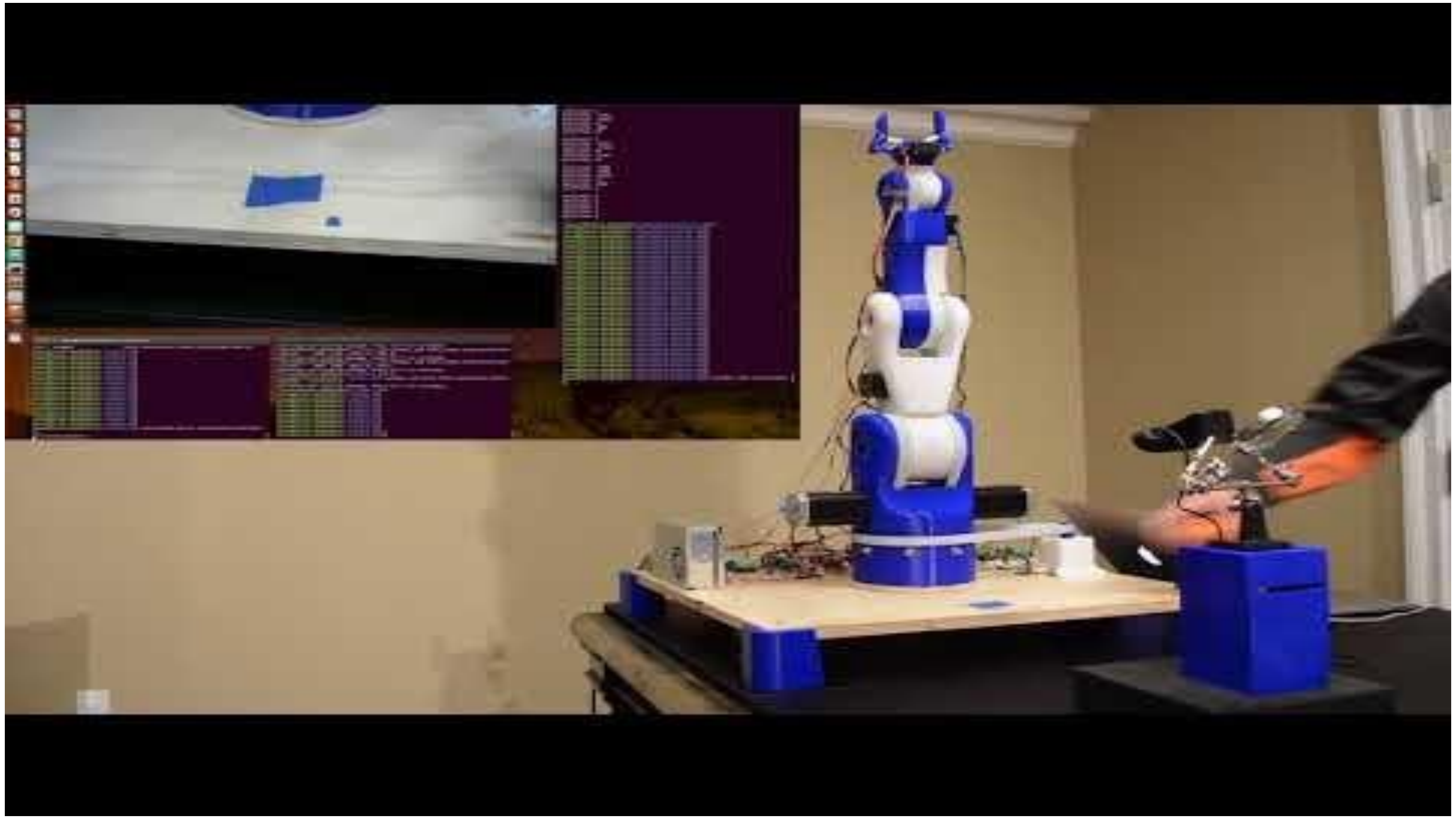
- **Stereo (3-D) Machine Vision**

Vision (Sight) in Robotic Systems

- **Stereo (3-D) Deep Learning Machine Vision**

Vision (Sight) in Robotic Systems

- **Application example: Object tracking & recognition**



Vision (Sight) in Robotic Systems

- **Application example: Object tracking & recognition**

Vision (Sight) in Robotic Systems

- **Application example: Physical Defect Inspection**

Label Printing

Bottle Seals

Robotic Perception Requirements

Robotic perception requires more than just sensors:

1. **Sensors**
   - Power and electronics
2. **Computation**
   - More power and electronics
3. **Connectors**
   - To connect it all

Robotic Perception Designs

- Historically robotic perception has been treated in isolation
  - For example, designing the sensory system of the robot first before considering the possible tasks that the robot needs to fulfil
- Generally it is not a good idea to separate:
  - What the robot senses
  - How it senses it
  - How it processes it
  - How it uses it

The Recommended Method

It is recommended to think of it as a single complete design:

- The **task(s)** the robot has to perform
- The most suitable **sensors** for the task(s)
- An **optimal mechanical design** that enables the robot to get the necessary sensory information for the task(s) (e.g. structure, shape and size of the robot, placement of the sensors)

A New Perceptual Paradigm

Robotic Perception without the context of actions is meaningless

- Action-oriented robotic perception

  How can perception provide the information necessary for behavior?

  - Perceptual processing is tuned to meet motor activity needs
  - World is viewed differently based on the robot's intentions
  - Only the information necessary for the task is extracted

- Active robotic perception

  How can motor behaviors support perceptual activity?

  - Use motor control to enhance perceptual processing via sensor positioning
  - Intelligent data acquisition, guided by feedback and a priori knowledge

Using A Priori (*from before*) Knowledge of the World

- Perceptual processing can benefit if knowledge about the world is available
- Expectation-based perception (what to look for)
  - ❖Knowledge of the world constraints the interpretation of sensors
- Focus of attention methods (where to look for it)
  - ❖Knowledge can constrain where things may appear
- Perceptual classes (how to look for it)
  - ❖Partition the world into categories of interaction

Chapter 2: Sensor & data fusion

What is Sensor Fusion?

A man with a watch knows what time it is;
a man with two watches isn't so sure

- **Definition:** Combining multiple sensors to obtain better data about the environment
- Sensor fusion is a complex process
  - ➢ Different sensor accuracy
  - ➢ Different sensor complexity
  - ➢ Contradictory information
  - ➢ Asynchronous perception
- A strategy is needed to put the various data sets together and make sense of them for the given application

Neuroscientific Evidence

- Our brain process data from multiple sensory system
  - Vision, touch, smell, hearing, sound
- Individual sensory system use separate regions in the brain (e.g. sight, hearing, touch)
- Vision itself uses multiple regions
  - Two main vision streams: the **"what"** (object recognition) and the **"where"** (position information)
  - Pattern, color, movement, intensity, orientation

What Can We Learn from Biology?

Sensor function should decide its form

- Evolved sensors have specific **geometric** and **mechanical** properties (i.e. special sensors)
- Examples
  - Flies: complex facetted eyes
  - Birds: polarized light sensors
  - Bugs: horizon line sensors
  - Humans: complicated auditory (hearing) systems
- Biology uses clever designs to maximize the sensor's perceptual properties (e.g. range and accuracy)

Psychological Insights: Affordances

- **Affordances:** "*potentialities for action inherent in an object or scene*" (Gibson 1979, psychology)
- The focus of affordances is the **interaction** between the robot and its environment
- **Perception is biased by what needs to be done**
- Robot thinks – what is my task?
  - I see a chair because I want to sit on it
  - I see a chair as something to avoid
  - I see a chair as something to throw at my enemy

Psychological Insights: Affordances

- As a robot designer, you may not get the chance to manufacture new sensors
- But you will always have the chance to **design interesting ways of using the available sensors** to get the job done.
- It is often not only a chance but a necessity!
- Utilize the interaction with the world and **always keep in mind the task**

Sensor & Data Fusion

- **Different sensors have varying characteristics which affect their effectiveness**
- Effectiveness of sensors is dependent on the application
- Characteristics of sensors
  - Power required
  - Sampling speed
  - Active vs passive (e.g. SICK laser systems vs stereo vision)
  - Size
  - Cost (from a few cents to tens of thousands of dollars)
  - Range and accuracy (from 10-3 to 103 of metres)
  - Local vs global (e.g. range sensors vs GPS)

Sensor & Data Fusion

- **<u>Definition:</u> The process of integrating together different sensory data from multiple sources into the same representation framework**
- **Two general approaches:**
  - Supra-feature-vectors – Rosenblum and Gothard, 1999
    - Features from individual sensors combined into a suprafeature-vector, which is then classified
  - Features from individual sensors classified first
    - Individual classifications are merged thereafter

Sensor Fusion Example: Xiaomi Mi Robot

Source: https://www.youtube.com/watch?v=nlpKUa7P2Rc

Sensor Fusion Example: Xiaomi Mi Robot

- **Equipped with 12 different sensors** that prevent the robot from bumping into things and falling down (off the stairs):

1. **Laser Distance Sensor (precise distance and position)**
2. Ultrasonic radar sensor (distance of other objects)
3. Cliff sensor
4. Gyroscope (orientation)
5. Accelerometer
6. Collision sensor
7. Electronic compass
8. Drop sensor
9. Fan speed sensor
10. Speedometer (speed)
11. Dustbin sensor
12. Wall sensor

Let's do this together: Designing a Robotic Sensory System that will detect and recognize people

- Break into groups
- In your groups, design a robotic sensory system that will **detect** and **recognize** people.
- **As part of the design process, you are to:**
    1. Recommend the sensor type(s) that is required for this given application; you are not required to name the sensor model/brand, stating the generic type will do (e.g. light, temperature, humidity)
    2. If necessary, explain the enhancement(s) required for your sensor type(s) in order to achieve the objective
    3. Explain why you choose each sensor type(s) and the respective enhancements (if any)
    4. Create a simple decision flowchart to illustrate the decision process involving your chosen sensor(s)/enhancement(s) that will lead you to achieve the objective
    5. Conclude what you have learnt from this group project

RECAP – RATIO’s Barista & Bartender Robot

What sensors are involved here?

Source: https://www.straitstimes.com/asia/east-asia/hand-it-to-the-robot-to-make-that-perfect-latte

Chapter 3: Knowledge representation & reasoning

Difference between Artificial Intelligence (AI) & Knowledge Representation & Reasoning (KR&R)

- AI is the study and development of systems that demonstrate intelligent behaviour (focus on how we think)
- KR&R is **the study of ways to represent and reason with <u>information</u> in order to achieve intelligent behaviour (focus on what we know)**

Introducing Knowledge Representation & Reasoning

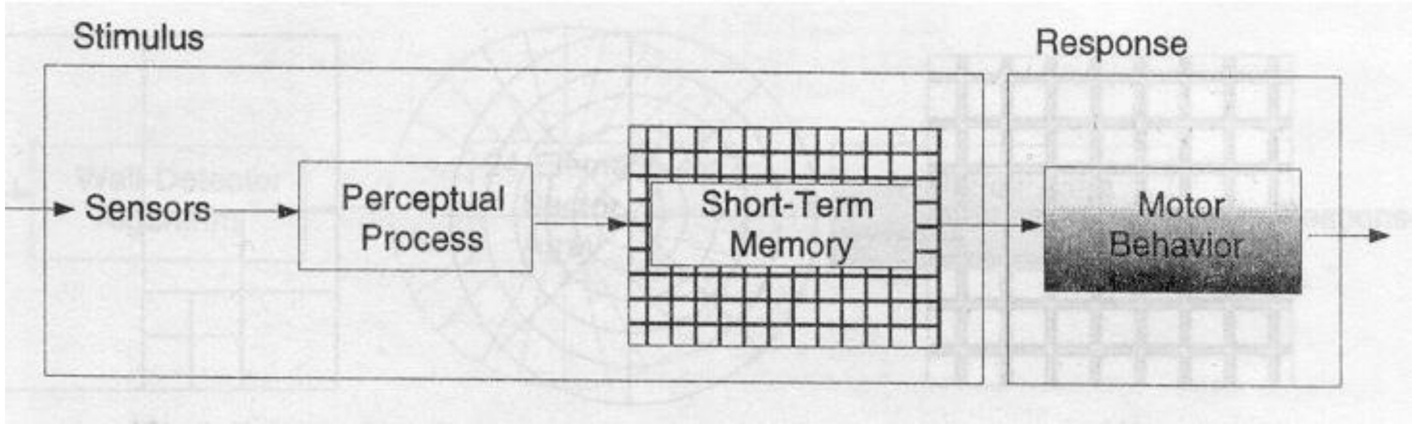
- There are many ways to approach the topic of intelligence and intelligent behavior
  - *neuroscience*, *psychology*, *evolution*, *philosophy*
- KR suggests an approach to understanding intelligent behavior that is radically different
  - Instead of studying humans very carefully (biology, nervous systems, psychology, sociology, etc.), it argues that what we need to study is ***what humans know***
  - It is taken as a given that what allows humans to behave intelligently **is that they know a lot of things about a lot of things and are able to apply this knowledge as appropriate to adapt to their environment and achieve their goals**

Introducing Knowledge Representation & Reasoning

- **KR&R focuses on the knowledge**, not on the knower. We ask the following: "*what any agent—human, animal, electronic, mechanical—would need to know to behave intelligently, and what sorts of computational mechanisms might allow its knowledge to be manipulated*"
- KR made available in several ways to the control system for behaviour-based robotic systems:
  1. Short-term behavioral memory
  2. Sensor-derived cognitive maps (a type of long-term memory map)
  3. A priori map-derived representation (a type of long-term memory map)

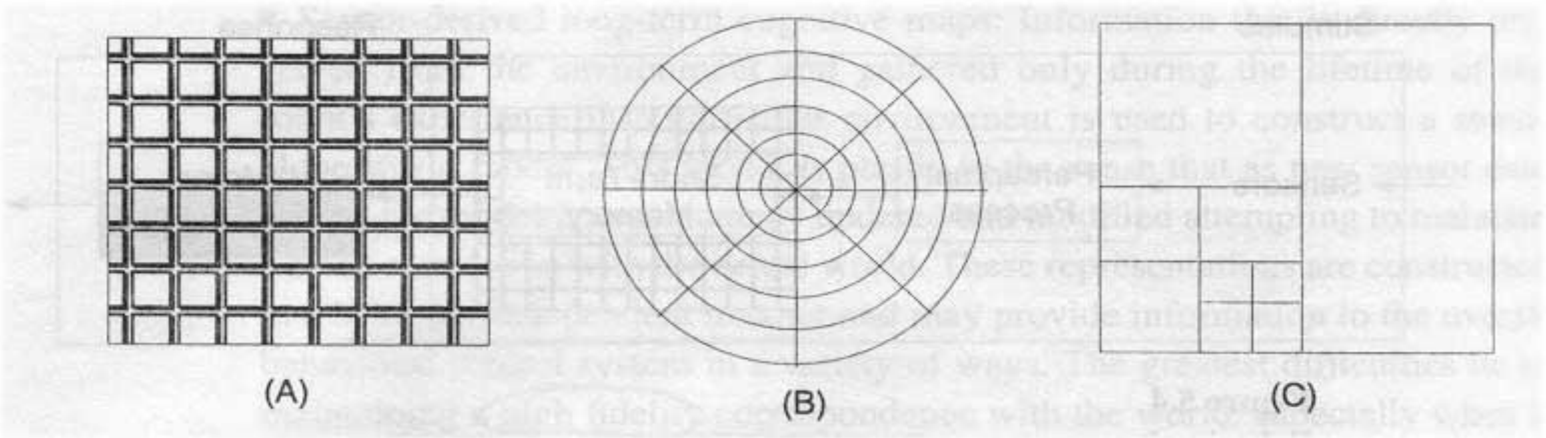
Short-term behavioural memory

- Behavioural memory **reduces the need for frequent sensor sampling** in reasonably stable environments and it **provides recent information** to guide the robot that is outside of its sensory range
- **Characteristics:**
  - **Used in support of a single behaviour** in a behavioural control system, like **obstacle avoidance (passing temporary objects like pedestrians/cars)**
  - Served as **a buffer and translator for a limited number of previous sensing data**
  - **Transitory and suitable for dynamic environments**



Short-term behavioural memory

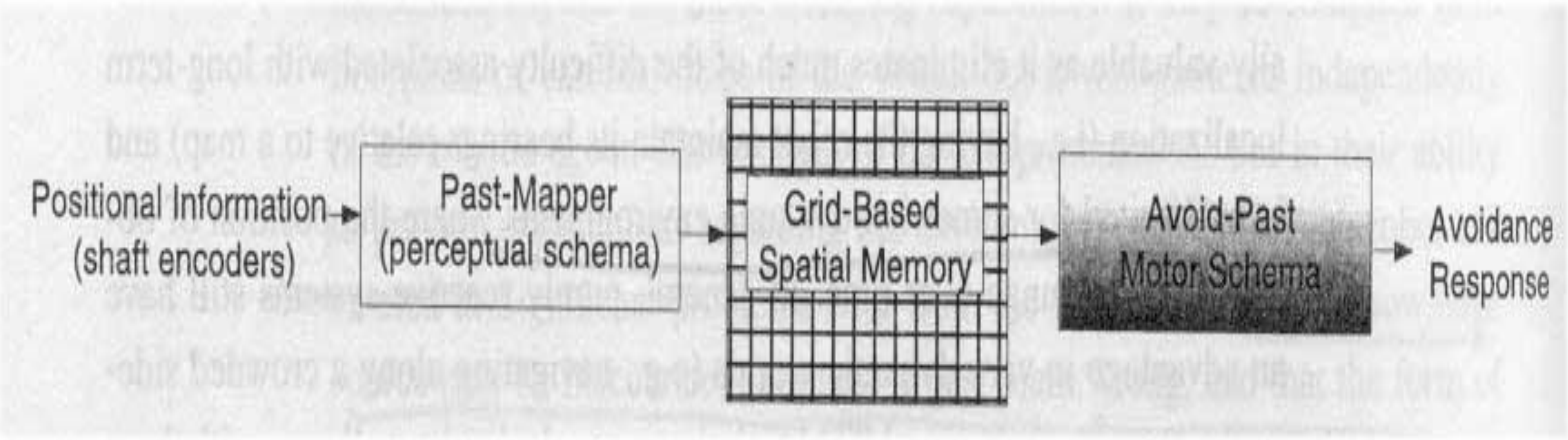
- Grid representations for the navigable space:
  - Resolution: the amount of area each grid unit covers (e.g., inch, meter)
  - Shape: square or radial sectors
  - Uniformly: the same size or variable size (quadtrees)



Regular grid | Sector grid | Quadtree

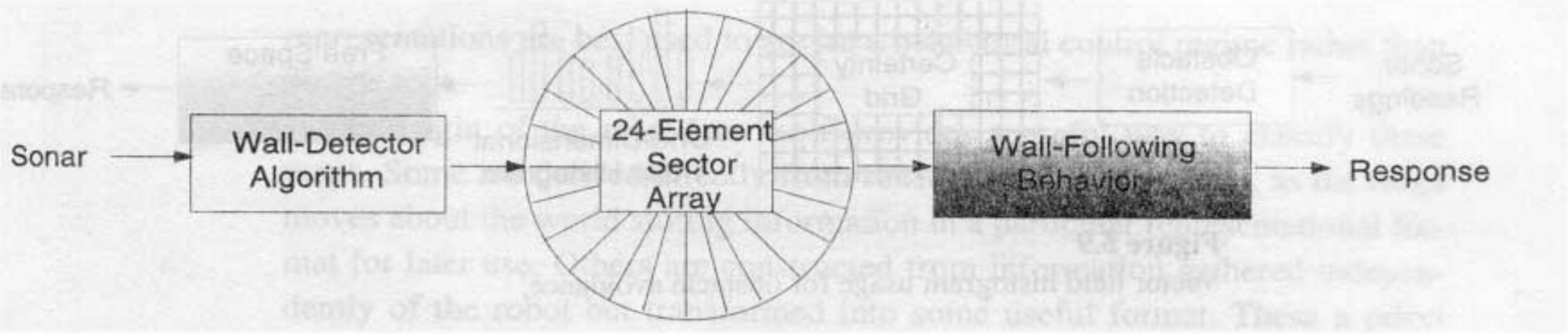
Short-term behavioural memory

- Avoid-past: using dead reckoning information based on shaft encoder readings
- **A regular grid stores sensory information concerning where the robot has recently been to**



Short-term behavioural memory

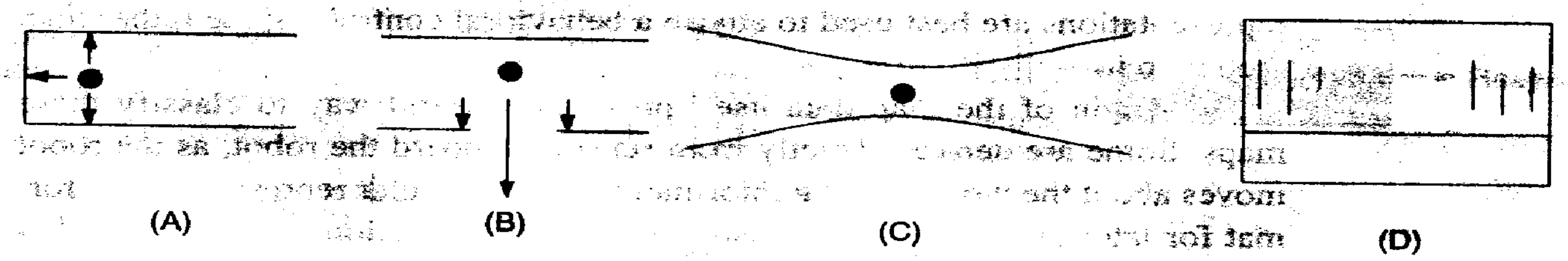
- **Wall memory**
  - Uses an array of elements (ultrasonic sensors) to increase confidence over time that the robot is near a wall
  - The memory readings are then used to support a wall-following behaviour
- **Action memory**
  - Stores information about both the environment (e.g., wall) and the most recent robot response
  - To get the direction, a weighted average of past responses to bias the immediate reactive response



Sensor-derived long-term cognitive maps

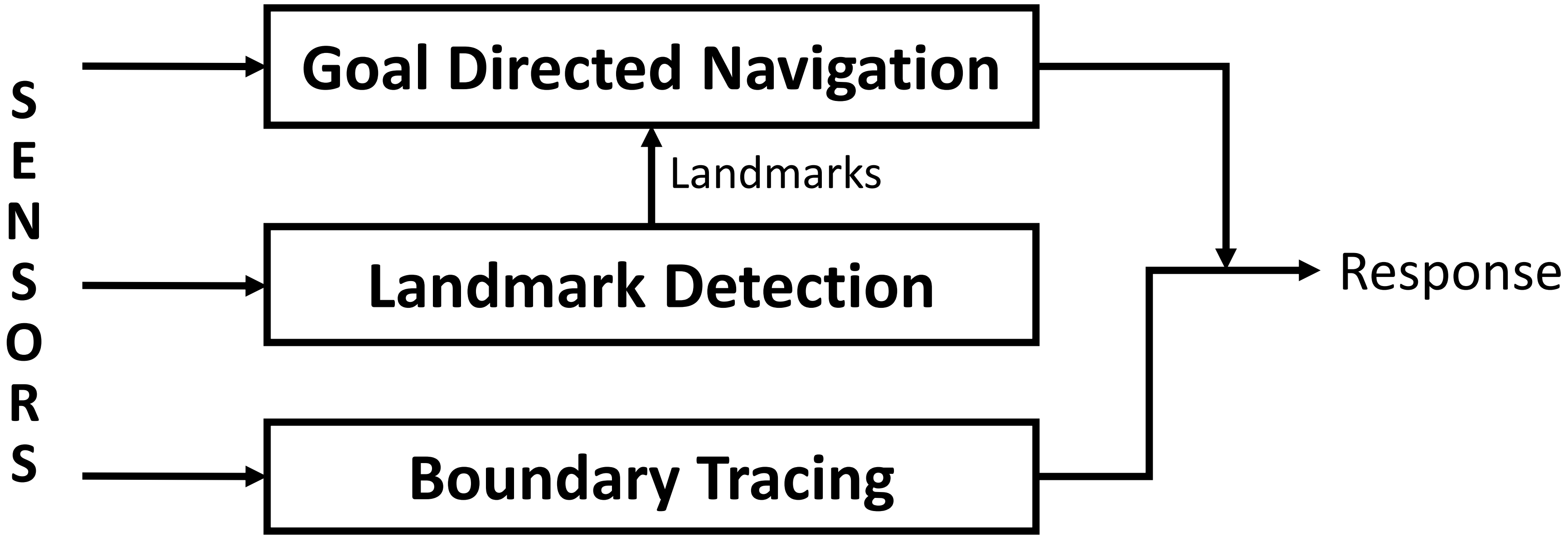
- Provide information **directly gleaned from the robot's experiences within the environment**
- **Qualitative representations:** Relatively tolerable to the inherent inaccuracies in robot motion and sensor readings
- Distinctive places:
  - ➢One of the hallmarks of qualitative navigational techniques
  - ➢Regions with characteristics that distinguish them from their surroundings

End of hall | Doorway | Hallway constriction | Visual constellations



Sensor-derived long-term cognitive maps

- Behaviour-based navigation by qualitative maps
  - Integration of qualitative maps and behaviour-based robotic systems in subsumption-based system (below)
  - Boundary tracing, landmark detection, goal-directed navigation and map learning

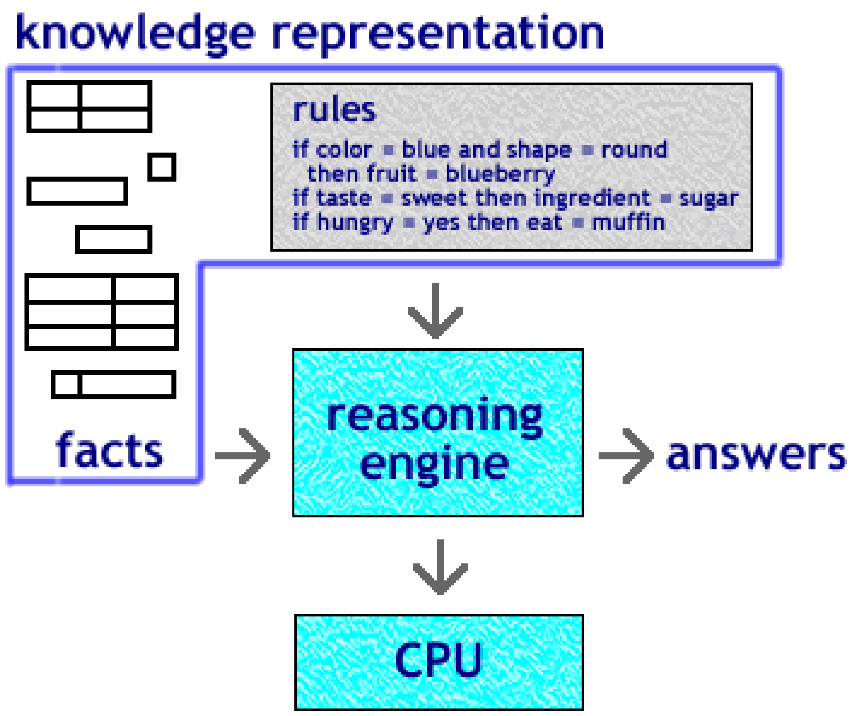


A priori map-derived representation

- A priori map-derived representations
  - **A priori maps: constructed from data obtained independently from the robotic agent itself**
  - Easier to compile data directly without forcing the robot to travel through the entire environment ahead of time
  - These data may be available from standard sources
  - Precompiled sources of information may be encoded for the robot's use
- Perils to the accuracy:
  - Errors may be introduced in the process of encoding the new data
  - The data may be relatively old compared to recent robotic sensor readings
  - The frame of reference for the observations may be incompatible with the robot's point of view

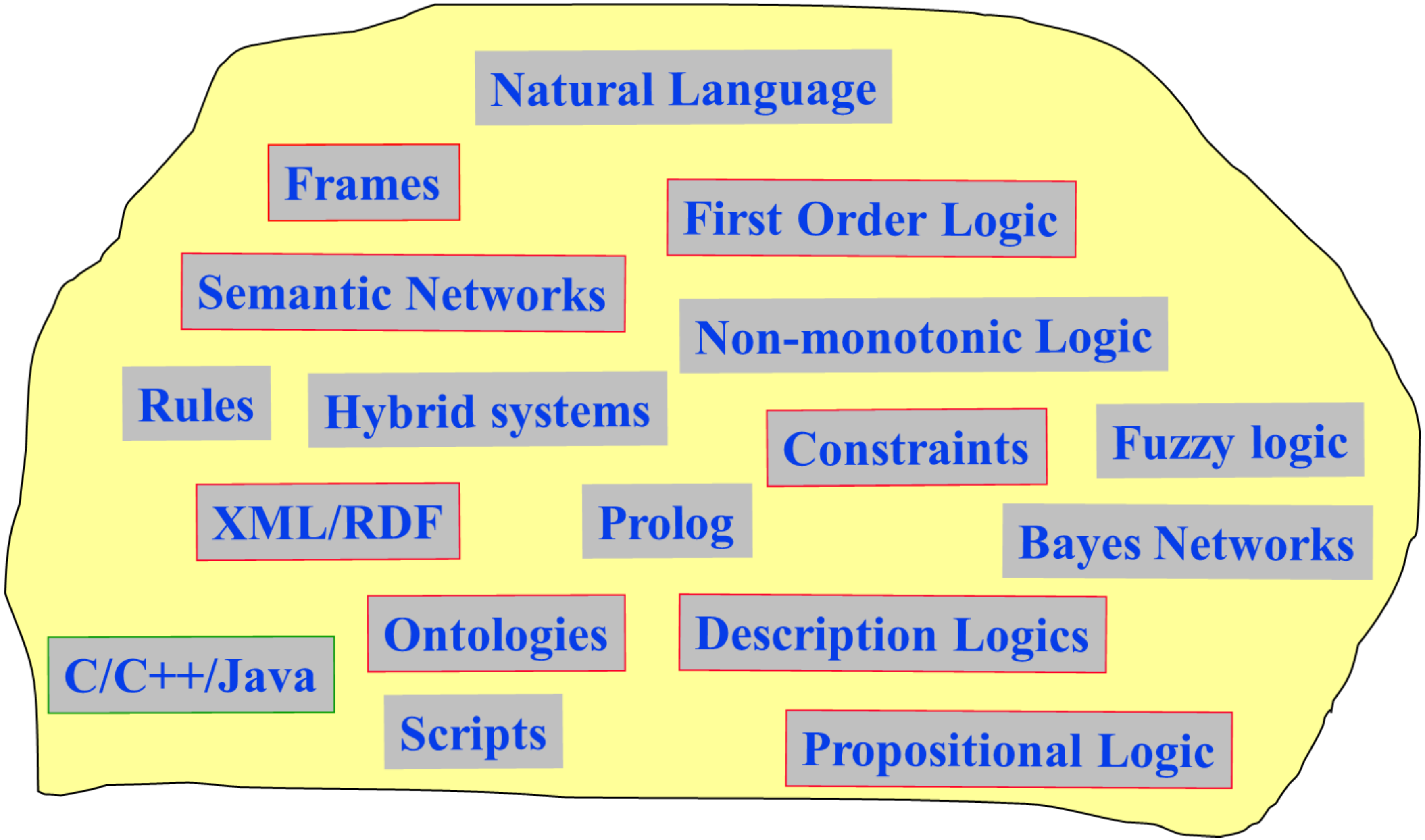
How can Knowledge be represented?

- **Symbolic methods**
  - ➢ Declarative Languages (Logic)
  - ➢ Imperative Languages (C, C++, C#, Java, etc.)
  - ➢ Hybrid Languages (Prolog)
  - ➢ Rules (IF/ELSE, AND, OR)
  - ➢ Frames
  - ➢ Semantic Networks
  - ➢ …



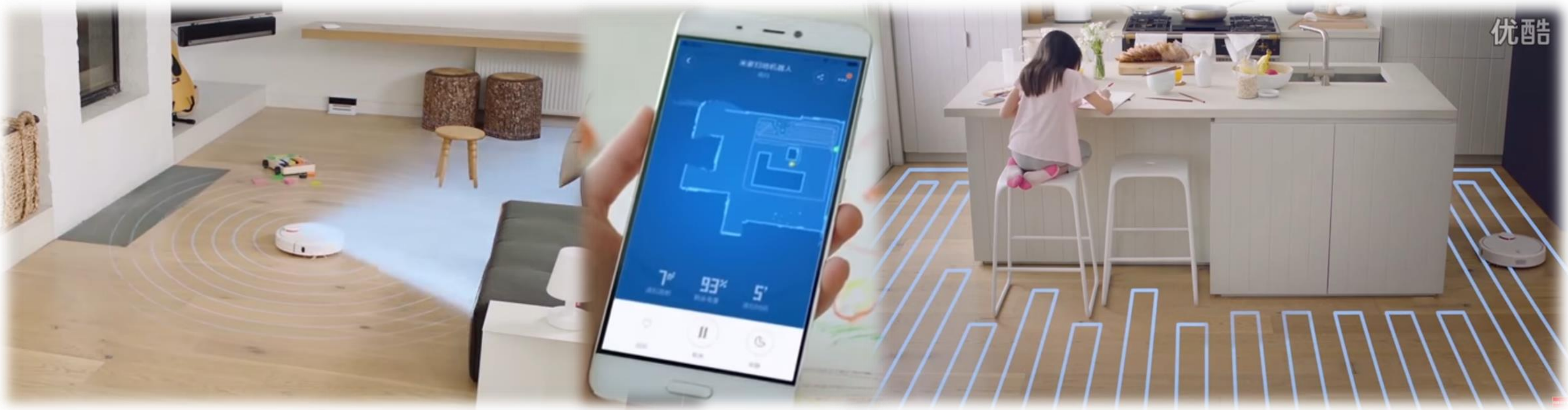
- **Non – symbolic methods**
  - ➢ Neural Networks
  - ➢ Genetic Algorithms

Symbolic Methods of KR



KR&R Example: Xiaomi Mi Robot

- **Utilizes the Laser Distance Sensor to create an interior map** within the house **(sensor-derived long-term cognitive maps)** and then **automatically builds the most efficient cleaning path**

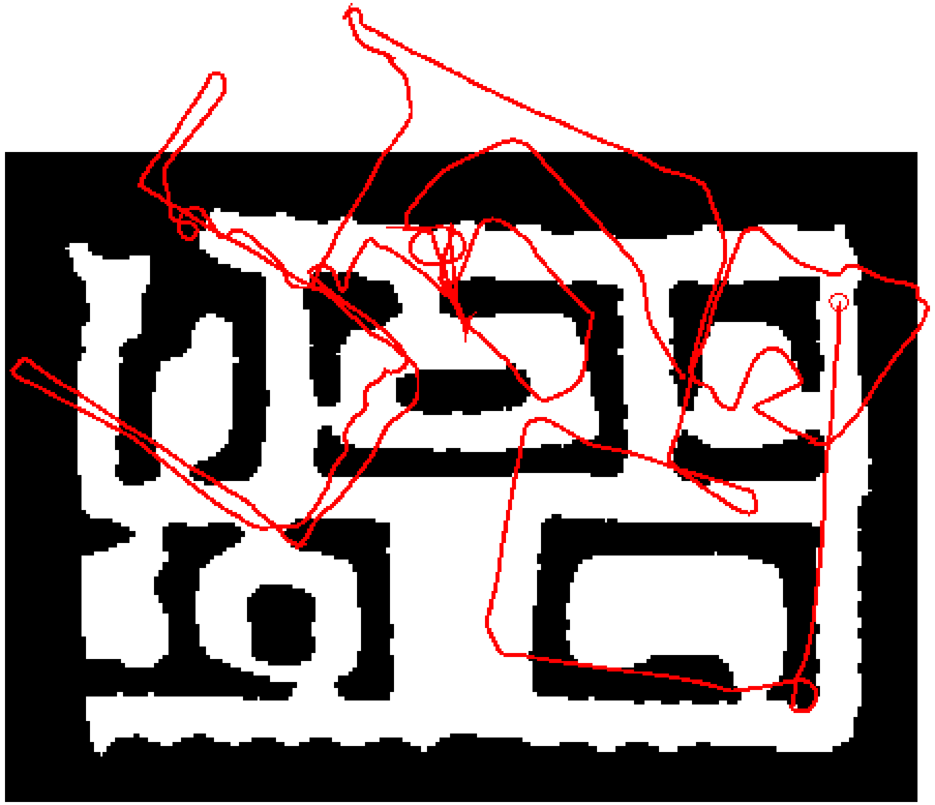


Chapter 4: Uncertainty representation

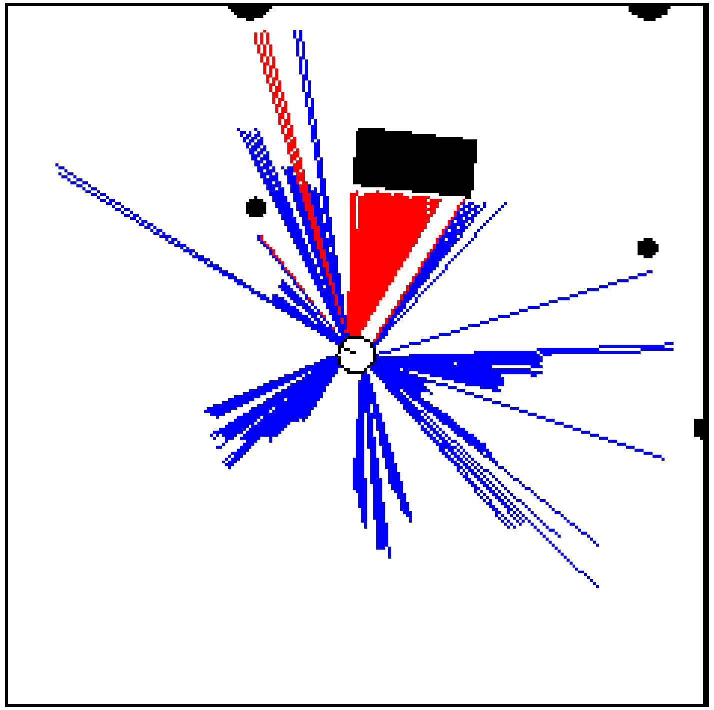
Uncertainty is Inherent/Fundamental

- Uncertainty arises from **four major factors:**
  - ➢Environment is stochastic, unpredictable
  - ➢Robots actions are stochastic
  - ➢Sensors are limited and noisy
  - ➢Models are inaccurate, incomplete

Nature of Sensor Data



Odometry Data



Range Data

Approaches in representing uncertainty

1. **Probability theory**
   - Conditional Probability
   - Bayesian Reasoning (e.g. Bayesian Classifiers, Bayesian Belief Networks)
2. **Maintaining multiple hypothesis**
3. **Machine Learning techniques**
   - E.g. Bayesian Learning, Reinforcement Learning, ANNs
4. **Fuzzy Sets and Fuzzy Logic**
5. **Rough Set representations**

Approaches in representing uncertainty

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Introducing Probabilistic Robotics

- **Key idea: Explicit representation of uncertainty using the calculus of probability theory**

- Perception = state estimation
- Action = utility optimization

Advantages and Disadvantages

Advantages:

- Can accommodate inaccurate models
- Can accommodate imperfect sensors
- Robust in real-world applications
- Best known approach to many complex robotics problems

Disadvantages:

- Computationally demanding
- False assumptions
- Approximate

Actions

- Often the world is dynamic since
  - actions carried out by the robot
  - actions carried out by other agents

- **How can we incorporate such actions?**

Typical Actions

- The robot **turns its wheels** to move
- The robot **uses its manipulator** to grasp an object

- **Actions are never carried out with absolute certainty**
- In contrast to measurements, **actions generally increase the uncertainty**

Modelling Actions using Conditional Probability

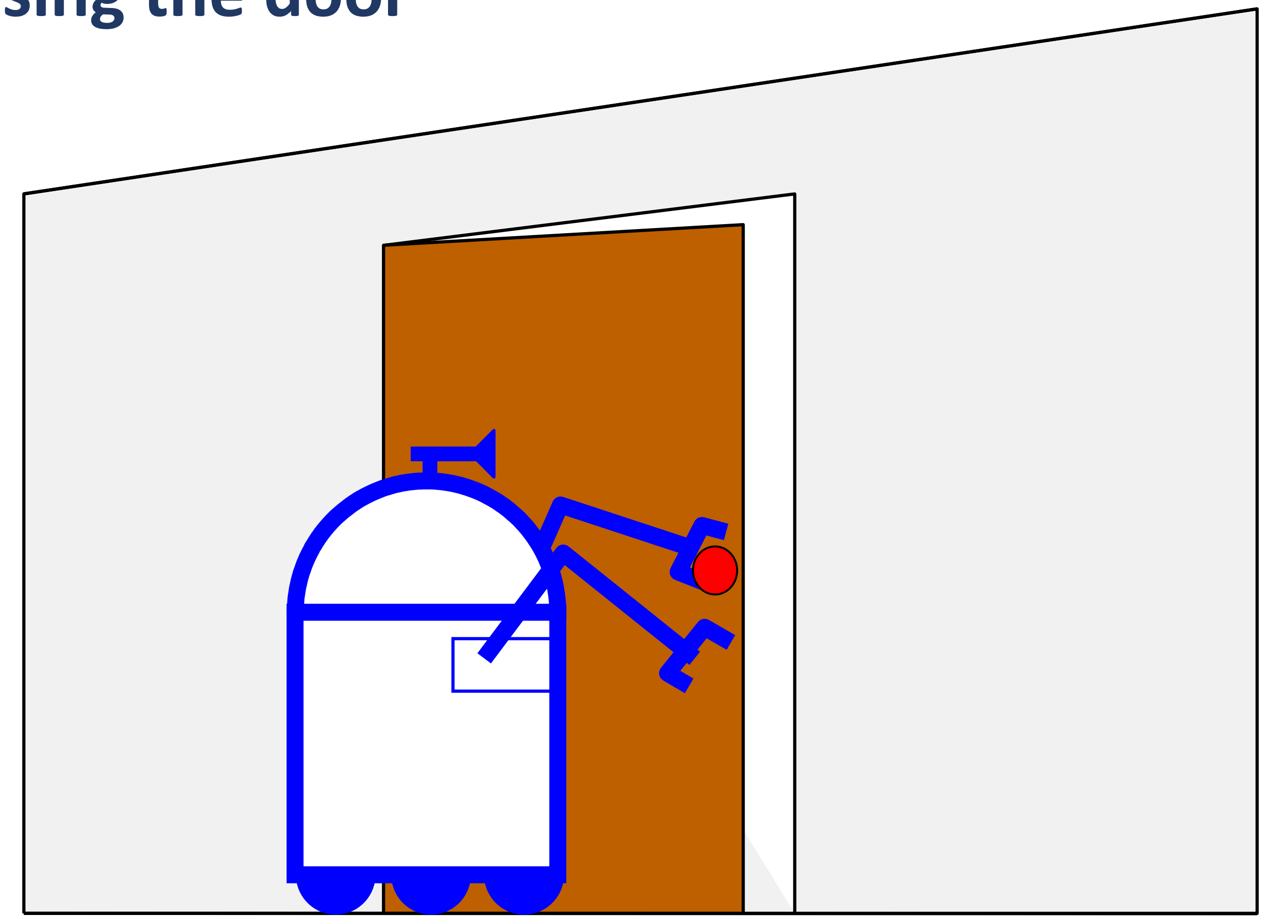
- To incorporate the outcome of an action *u* into the current "belief", we use the conditional pdf

$$P(x|u,x')$$

- This term specifies the pdf that ***executing u changes the state from x' to x***

Modelling Actions using Conditional Probability

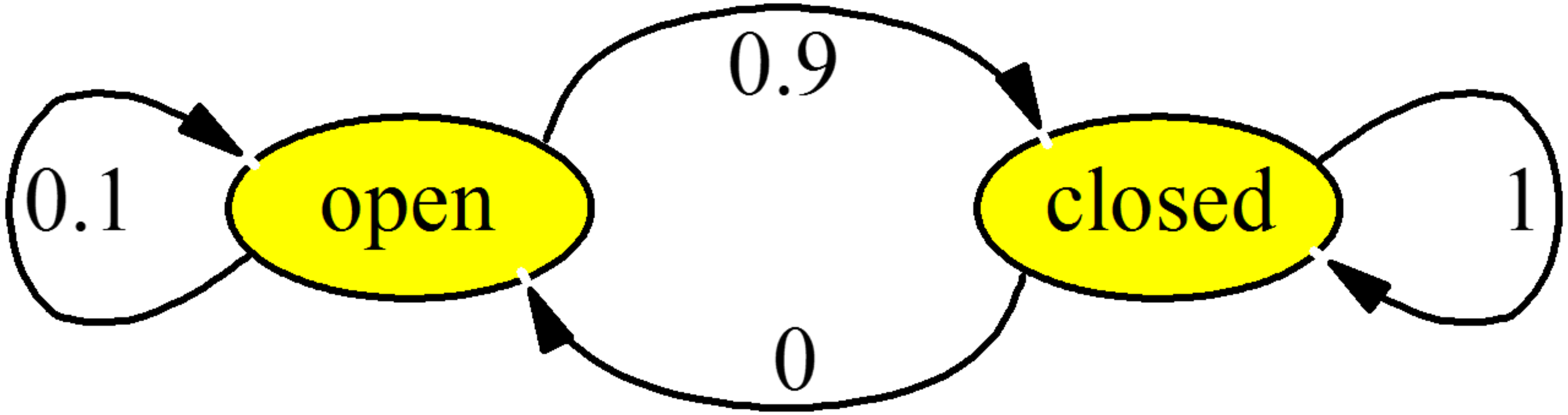
- **Example: Closing the door**



Modelling Actions using Conditional Probability

- **State Transitions**

P(x|u,x') for *u* = "close door":



If the door is open, the action "close door" succeeds in 90% of all cases.

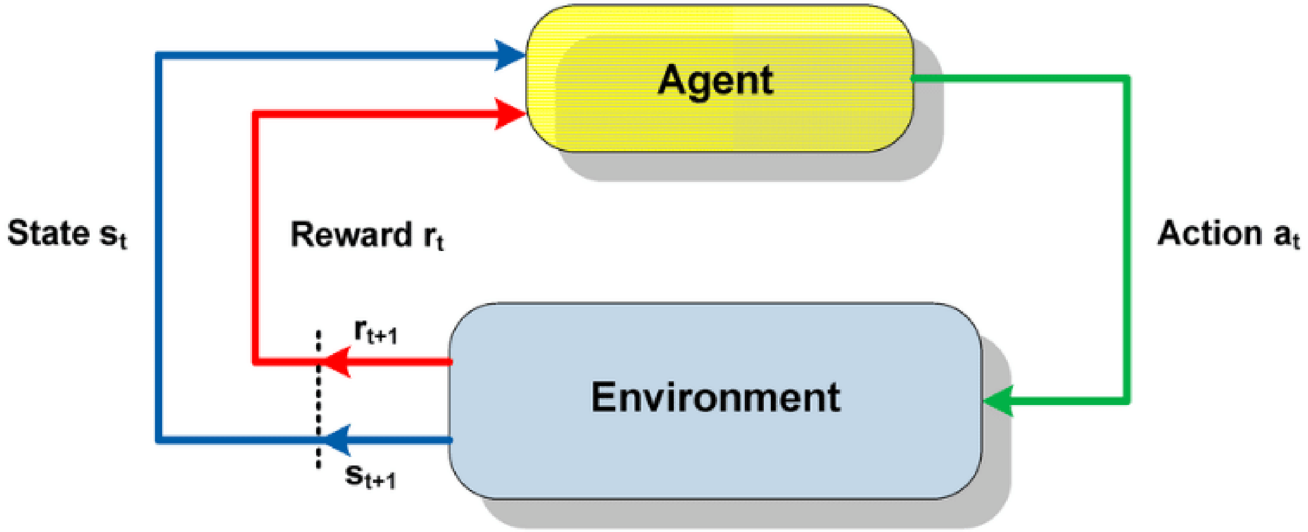
Introducing Reinforcement Learning

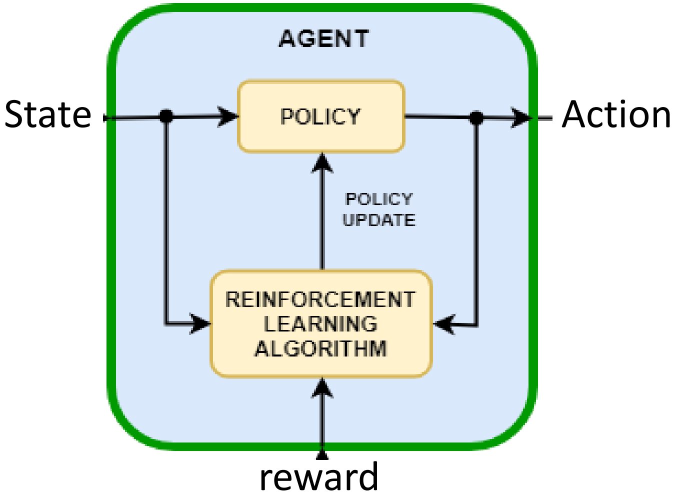
Imagine playing a new game whose rules you don’t know; after a hundred or so moves, your opponent announces, “You lose”.

-Russell and Norvigd

Introduction to Artificial Intelligence

Introducing Reinforcement Learning



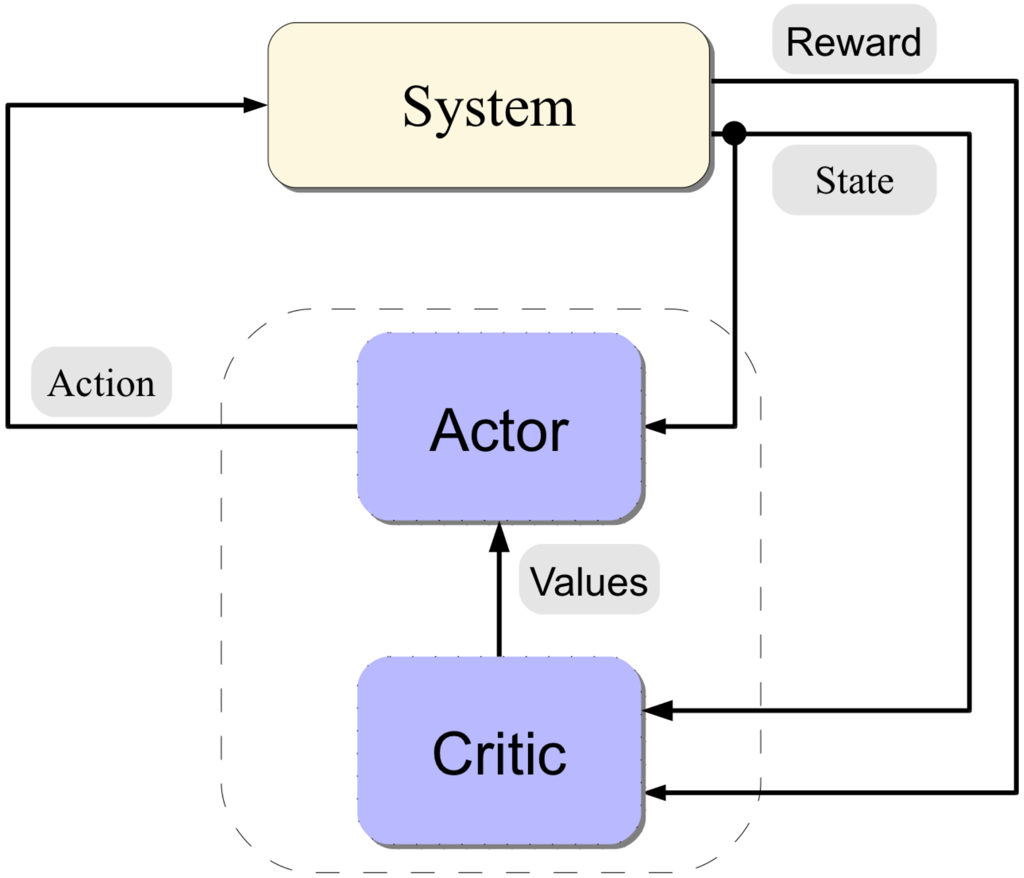


- Agent represent the policy and RL algorithm
- Environment represents the physical robot
- Action represent the motor movements
- State represent the observation data obtained from the sensors
- Reward functions describe how the robot should behave; amount of reward given is dependant on the state

- In lame man terms, this is a trial and error framework; **"learn by doing"**
- Unlike Conditional Probability method, the transition model and reward function are initially unknown (**Model-free**)
- **Goal: to learn an optimal policy**

Introducing Reinforcement Learning

Actor-critic learning configuration



Reinforcement Learning – Pros & Cons

Pros:

- Can occur in much less generous environments (uncertainty); E.g. no model of environment
- Save development time (less dependence on knowledge)
- Adaption to environment
- Suitable for complex behaviour in complex domains

Cons:

- Learning/training speed can be slow; depends on desired state
- Unpredictable behaviour
- Computation time and memory requirements (can lead to higher costs)

Chapter 5: Summary & Conclusions

Summary & Conclusions

- **Robotic perception** requires (a) **sensors**, (b) **computation**, and (c) **connectors**
- **Utilizing only one sensor type may not be sufficient** AND/OR may not optimize the results for a given application; highlights the **importance of sensor and data fusion**
- **Obtaining data and utilizing the obtained data is important when applying the Knowledge Representation & Reasoning** (KR&R) method (what is known)
- **Probability theories and reinforcement learning techniques can be utilized to solve uncertainty challenges** in robotic systems/applications

Pop Quiz

Pop Quiz at Kahoot!

- Go to www.kahoot.it or download the Kahoot! App
- Key in the given Game PIN on the screen
- Answer the questions as instructed on screen

Thank you!

Questions?