cis32-ai — lecture # 3 — mon-6-feb-2006

today's topics:

- simple agents
- behavior-based AI

Behavior-based AI

We can distinguish two approaches to AI:

- Classic AI:
  - Symbolic representations;
  - "Good Old Fashioned AI" (GOFAI).
- Behavior-based AI:
  - Representation-free;
  - "Nouvelle AI".

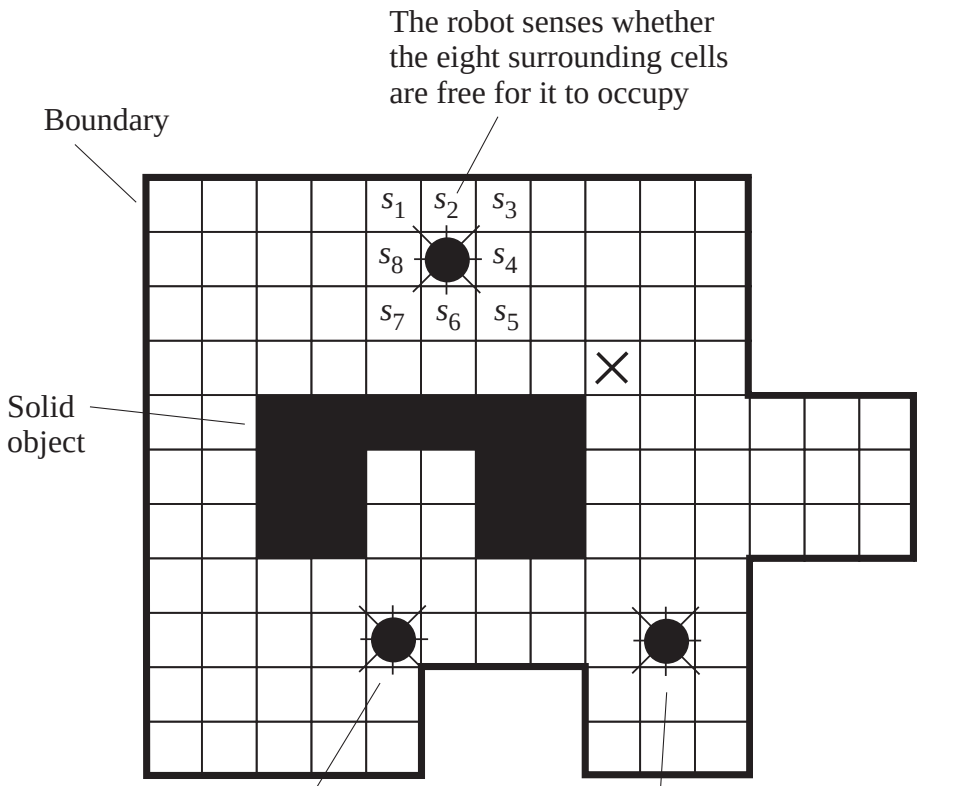
Classical models are *deliberative*. They involve what we recognise as thinking.

- Sense-Plan-Act:
  - Sense the world and figure out where we are;
  - Generate a plan to get where we want to go;
  - Translate plan into actions.
- Iterate until goals are achieved.
- Need some kind of world model, notion of goal etc.

Hypothesis is:

- Most activity isn't planned out; it is just reaction.
- Complex behaviors are just combinations of simple behaviors.
  - If we can string together enough simple behaviors we will get complex behavior.
- Can get further with this "bottom-up" approach than with the classical approach.
  - An artificial cockroach that works is better than an artificial human that doesn't.
- Elephants don't play chess.

Example



- Task:
  - Go to a cell adjacent to a boundary or object and follow its perimeter.
- Sensors:
  - Can sense if adjacent cells are occupied.
  - Each s_i has value 0 when that cell can be occupied. 1 otherwise.
- Thus at X, the sensors have value:

$$(0, 0, 0, 0, 0, 0, 1, 0)$$

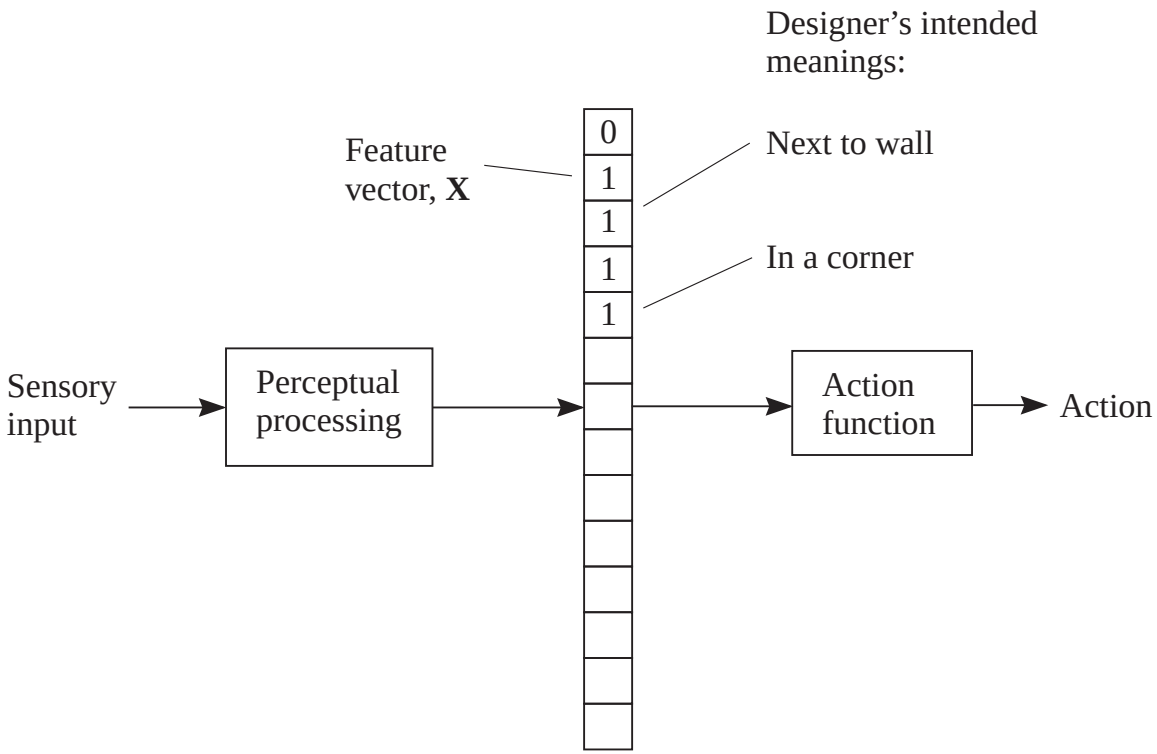
- In general we write $S = (s_1, s_2, s_3, s_4, s_5, s_6, s_7, s_8)$

- Actions:
  - north move up in grid.
  - east move right in grid.
  - south move down in grid.
  - west move left in grid.
- We write the set of all actions as A.
- These work provided the cell into which the robot tries to move is free.
- The task is then to come up with a function from a set of s_i to some action:

$$f : S \mapsto A$$

Perception & Action

In general, the situation is:



Features can be numerical, categorical, or binary-valued.

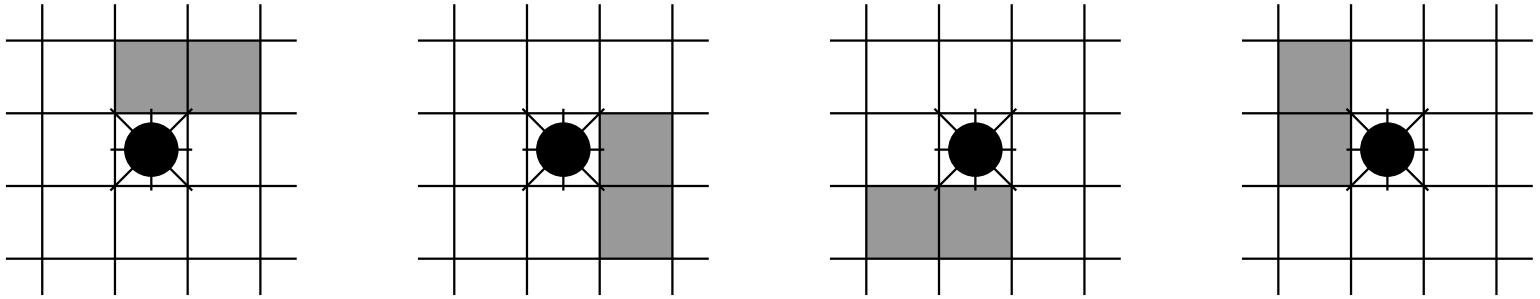
- The split between action and perception is arbitrary.
- Could make everything perception or everything action.
- The split is driven by the feature vector (just change the action function to get a different behavior).
- Once the split is decided, we have to:
  - Map sensor data to feature vector;
  - Map feature vector to actions.
- Thus we have split the function f above into:

$$g : S \mapsto X$$

and

$$h : X \mapsto A$$

- There are 256 different feature vectors.
- For boundary following, the following are the interesting cases:



x_1 x_2 x_3 x_4

In each diagram, the indicated feature has value 1 if and only if at least one of the shaded cells is *not* free.

- We can then define the feature vector in terms of x_i.
- This gives us a way of defining g.
- Of course, in real life, identifying features is not so easy...

- Now we have to define h.
- If all the x_i are 0, then the robot can move in any direction.
- We will make it go north if this is the case.
- Otherwise there is a boundary to follow.
- We follow it by:
  - If $x_1 = 1$ and $x_2 = 0$ then east
  - If $x_2 = 1$ and $x_3 = 0$ then south
  - If $x_3 = 1$ and $x_4 = 0$ then west
  - If $x_4 = 1$ and $x_1 = 0$ then north

- We can write these conditions as Boolean expressions.
- The condition for the robot to move east is:

$$x_1.\overline{x_2}$$

- And the condition for it to move north is:

$$\overline{x_1}.\overline{x_2}.\overline{x_3}.\overline{x_4} + x_4.\overline{x_1}$$

- We can also express the x_i as Boolean combinations of the sensor signals:

$$x_4 = s_1 + s_8$$

Production systems

- How do we represent the action function?
- One convenient representation is as a *production system*, a collection of *production rules*.
- Each rule is written as:

$$c_i \longrightarrow a_i$$

  with a *condition* part and an *action* part.

- A production system is a list of such rules:

$$\begin{aligned} c_1 &\longrightarrow a_1 \\ c_2 &\longrightarrow a_2 \\ &\vdots \\ c_n &\longrightarrow a_n \end{aligned}$$

- The condition can be any binary-valued function of the appropriate feature vector.
- For our example it is just a simple Boolean function.
- To select an action, we look through the rules until we find a c_i which evaluates to 1.
- Then we execute the associated a_i.
- The a_i can be a primitive action, a set of actions, or a call to another production system.
- Usually the last rule in the system has condition 1 (ie. it is an "else" production).

- Thus, for our example, we could have the production system:

$$\begin{aligned} x_4\overline{x_1} &\rightarrow \text{north} \\ x_3\overline{x_4} &\rightarrow \text{west} \\ x_2\overline{x_3} &\rightarrow \text{south} \\ x_1\overline{x_2} &\rightarrow \text{east} \\ 1 &\rightarrow \text{north} \end{aligned}$$

- This system will then run forever.
- It is what we call a *durative* procedure.

- Another kind of production system will have an overall goal.
- Imagine that we want the robot to follow the boundary until it finds a north-east corner (like the top-left corner in the example) and then stop there.
- We can define another item in the feature vector:

  $$x_5 = s_1 s_2 s_3 \overline{s_4 s_5 s_6} s_7 s_8$$

  and then write the production system:

  $$\begin{aligned} x_5 &\rightarrow \text{nil} \\ 1 &\rightarrow \text{b}-\text{f} \end{aligned}$$

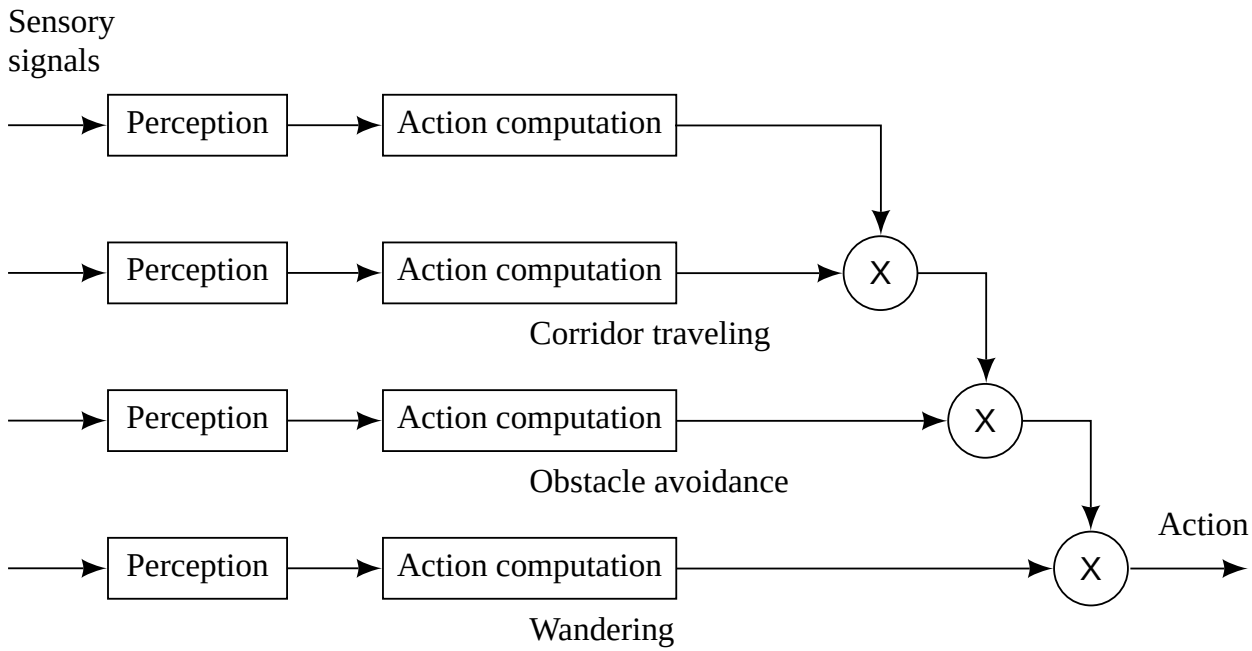
  where nil is an action which does nothing, and b-f is a call to the previous production system.

- There are three points to make about this.
- First, in goal-achieving production systems, the topmost rule identifies the situation we are aiming for.
- Once this is acheived, we need do nothing more.
- Second, conditions and actions lower down the production system lead towards the achievement of the topmost condition.
- Indeed, action a_i is intended to bring about c_j where $j < i$.
- Third, we can build up a hierarchy of production systems, where systems lower in the hierarchy move the robot towards meeting the conditions of productions in systems higher up.
- This gives us a means of procedural abstraction.

- Systems of rules like this are call *teleo-reactive* (T-R) programs.
- Every action in a T-R program works towards the achievement of a condition higher in the program.
- It is typically easy to write such programs.
- T-R programs are also very robust.
- Even in the face of faulty sensor readings, carefully constructed T-R programs will get back on track.

Subsumption Architecture

- Another approach to combining simple sensory-driven behavior:



- Each module receives sensory information directly from the world.
- If the sensory inputs match the preconditions of a module, it executes.
- Modules can *subsume* each other (in the picture upper modules can subsume lower ones).
- When module i subsumes j, then if i's precondition is met, the program of i replaces that of j.
- So in the example:
  - The robot wanders until it has to avoid an obstacle;
  - Avoids an obstacle until it is travelling in a corridor.

- Subsumption architecture started with Brooks.
- Idea is that:
  - Build basic behavior;
  - When that is refined, add a subsuming behavior;
  - When that is refined, add another;
  - ...
- So far as I know, the maximum "stack height" is not *that* high.
- However, there are other ways of making the approach more sophisticated.

- We can make the approach more flexible:
  - Rather than having a fixed set of behaviors, construct a task specific set.
  - (Plan, but in terms of behaviors not actions.)
- We can improve on subsumption.
  - Rather than having one behavior replace another, merge behaviors.
  - (Imagine being able to do a weighted sum of actions.)
- Both these features are available in Saffiotti's THINKING CAP.

- How could we program this?
- As follows:

```
if <some condition>
   then <some action>
   else if <another condition>
           then <another action>
           else ...
```

- Here actions higher up in the compound if statement take precedence.

Summary

- This lecture introduced stimulus-response agents.
- These do not think; they just act.
- We looked at two approaches to implementing such systems.
  - Production rule systems.
  - Subsumption architecture.