A Real Time Controller for Social Contingency Detection

Javier R. Movellan

Machine Perception Laboratory
Institute for Neural Computation
UC San Diego

&

Intelligent Robotics and Communication Laboratory
ATR, Kyoto, Japan.

September 14, 2004
1. Structure of the Talk

- Introducing the Machine Perception Lab.
- Probabilistic Functionalism.
- Social Contingency Detection.
- Infomax Controller.
- Real Time Demo.
Structure of...

Goals

On the Need...

Probabilistic...

Real Time...

Contingency...

A Control...

Conclusions

Contact...

Home Page

Title Page

Page 3 of 33

Go Back

Full Screen

Close

Quit
2. Goals

Understand the problems faced by the brain when interacting with the world.


Machine Perception Toolbox

Develop an Architecture that can sustain autonomous interaction with Humans:
1. Dynamic integration of information.
2. Real Time Control
3. Combination of Multiple Modalities.
4. Multiple Time Scales
3. On the Need for Scientific Reform in Focus, Methods, and Education

- The traditional issues of interest in the cognitive sciences (the faculties of the mind) are of little use for a problem critical to understand human nature.

- The traditional methods in the cognitive and social sciences have tended to produce scholastic feuds that slowed down progress.

- There is a need for a paradigm shift: Focus on understanding the computational problems underlying real time interaction with the world and the solutions found by the brain.
4. Probabilistic Functionalism

- Focused on the study of the problems faced by organisms when interacting with the world and understanding the solutions they found.

- Usually there are multiple ways to implement the same solution. The functional approach encapsulates implementation level issues and focuses on problem level issues (David’s Marr Computational Level of Analysis).

- Functional Models consist of: (1) A probabilistic formulation of the world and an objective function that formalizes the problem at hand; (2) An optimal solution to that problem. This is done using the tools of probability theory and stochastic control.

- The model is evaluated by comparing the behavior of the optimal solution with some desired behavior (e.g., observed behaviors in organisms).

- The model is refined based on what we learned on the evaluation.
We will explore how these ideas can be applied in practice by focusing on the problem of Social Contingency Detection.
5. **Real Time Social Interaction as a Control Problem**
• Actuators: Lungs, vocal cords, facial muscles, hands.
• Sensors: Eyes, ears, tactile sensors.
• Long time delays when compared with control of physical objects.
• High uncertainty.
• No explicit turn taking but more like a continuous dance.
• Real time pressure.
• Minimal Representations.
• Time constants in the order of 40 milliseconds.
• A perfect problem for the theory of stochastic optimal control.
6. Contingency Detection and Social Development

John Watson (1972) conducted an experiment in which 2-month-old infants learned to move their heads on a pressure sensitive pillow to activate a mobile above their cribs. After 4 days, each day with 10 minutes of exposure to this controllable mobile, infants exhibited vigorous social smiles, positive affect, and cooing when the mobile was present. These social behaviors appeared notably less in a control group for which the mobile moved in a non-contingent manner.

Watson proposed that contingency was a perceptual property used by infants to identify other humans and that in fact it was more powerful than other morphological properties of human faces (like the presence of eyes).

J. S. Watson (1972) Smiling cooing and “the game”, Merrill-Palmer Quarterly, 18:323.
By about 4 months of age infants prefer to interact with objects which are responsive but not perfectly controllable suggesting, at least qualitatively, a preference for levels of responsiveness typical of social interactions. (Bahrick and Watson, 1985; Watson, 1985).

Bigelow found that 4-5 month infants produced more contingent vocalization and social responses towards strangers which best approximated the level of responsiveness found in mother-infant interaction. Strangers that were more responsive or less responsive than mom were less preferred.

Bigelow A. E. (1999) Infant’s sensitivity to imperfect contingency in social interaction, in P. Rochat: Early social cognition: understanding others in the first months of life


- 28 infants, mean age 10.5 months.
  1. **Experimental group:** Infants interact with contingent robot for 3.5 minutes. Robot periodically turns to side boxes and interacts with them.
  2. **Control group:** Robot plays same behaviors as in experimental group but now driven by time (non-contingent). Also no contingency with the side boxes.

- Dependent variables: (1) Vocalization rate. (2) Following the robot’s “line of regard”.

![Diagram of robot and boxes]
• Experimental Group = 10.33 vocs per minute, Control Group = 1.84 vocs per minute $p < .002$, one tail).

• Infants in the experimental group looked proportionally more in the direction specified by the robot’s rotation (Experimental group = 32.29 %, Control group = 18.35 %, $p < .04$,

• Infants could tell in a few seconds whether or not the robot was responsive.

• Their behavior appeared to be very active. Did not conform to standard models of learning I was used to.

• We did not have a formal approach to understand what was happening from the point of view of learning theory. Our results were interpreted by others from the Theory of Mind point of view.
Movellon & Watson (1987) Infant Behavior and Development
Movellon & Watson (2002) ICDL
6.2. Modeling Contingency Detection

- Should work in a few seconds.
- Should be active.
- Should use the statistics of social interaction (time delays) predictability...
7. A Control Problem

Consider a simple organism with a single binary sensor and a single binary actuator refreshed at discrete times $t_1, t_2 \cdots$

- $Y_t$. Sensory observation at time $t$.
- $U_t$. Action at time $t$.
- $X_t$. Hidden state of the world at time $t$

- $p(y_t | x_t, u_t)$. Causal model.
- $p(x_{t+1} | x_t)$. State dynamics.

Assume during past interactions with the world, our system has learned in an unsupervised manner that there are two types of situations (contingency clusters).
7.1. Causal Model: Two Causal Clusters

Situation 1 (External Agent Present)

- Action
- Self Feedback
- Prob Sensor On
- Time
- External Agent
- D1
- D2
- R1
- R2
- R3

Situation 2 (External Agent Absent)

- Action
- Self Feedback
- Prob Sensor On
- Time
- Background Activity
- R1
- R3
- D1
7.2. Model parameters:

- The relevant time delays $D_1, D_2$ are known from past experience.
- The self feedback rate $R_1$ is known from past experience.
- The response rates for agents $R_2$ and background activities $R_2$ are treated as Beta random variables. Their prior can be set to be uninformative.
- The type of contingency situation (agent vs no agent) is treated as a random variable with a given prior.

The hidden state $X_t$ consists of the type of cluster we are exposed to $H_t$, and the “unknown” response rates $R_2, R_3$. The unknowns are modeled using Beta distributions.
7.3. InfoMax Control

We want actions that maximize the expected information return about which cluster we are currently exposed to, i.e., we want to find a sequence of actions $u_{t+1} \cdots u_T$ which maximize the mutual information between the cluster variable $H$ and the observables

$$Q(u_t) = I(H, Y_tY_{t+1:T} \mid u_{1:t-1}y_{1:t-1})$$

$I$ Mutual Information

$H$ The hypothesis of interest

$Y_{t+1:T} = Y_{t+1} \cdots Y_T$ Future Sensor Values

$u_{1:t-1} = u_1 \cdots u_{t-1}$ Past Actions

$y_{1:t-1} = y_1 \cdots y_{t-1}$ Past Sensor Values

Interpretation: At each time a sequence of actions that is expected to produce a sequence of sensations highly informative about the hypothesis of interest.
7.4. A Bare-Bones Architecture

- Real Time Controller computes a summary of $Y_1, \ldots, Y_t, U_1, U_t$ and maps it into an action $U_{t+1}$.
- Intention Manager sets utility functions.
- Optimization engine adapts controller to optimize utility.
7.5. The Optimal Controller

We wrote a program to search for the optimal controller for this situation. It took 2 days of a G5 to find the optimal controller for $T = 40$, a huge table lookup. We then performed regression analysis to understand what the controller was doing. Turns out 97% of the entries in the controller could be predicted by the following rules:

- Do not make any actions during the period from the last past action and $D_1 + D_2$.

- Compute the entropy of the posterior distribution for $R_2$ and $R_3$ if the uncertainty about $R_2$ (agent rate) is 9 times larger than the uncertainty about $R_3$ (background rate) then act. Otherwise do not act.

Javier should not forget to explain why this is a good control plan.
7.6. The Controller In Action

Experimental Group (Contingency)
Control Group (No Contingency)
Infomax at Work.
Control Group: Difficult Case
7.7. Real Time Implementation

30 Hz Synchronized AV Capture (QuickTime) → Face Detector (C++)

0.01 Hz Infomax Binarization (Java) → Optimization Engine (MatLab off-line)

6 Hz Real Time Controller (Java)

Binary Sensory Inputs → Changes Priors

Sounds → 6 Hz Real Time Controller (Java)
7.8. Critique of the Current Model

- Surprisingly effective considering it uses a 6bps input channel and 6bps output channel.
- Robot’s intention is to learn, not to communicate, yet it sustain interesting communication episodes with humans. Suggests we may not want to focus on c
- Currently the structure of the hypotheses (causal clusters) is set by hand. In the future these will be causal clusters learned in an unsupervised manner.
- Rewrite the controller so that it’s intention is to “understand” the world not just the two causal hypotheses.
- $D1, D2$ are fixed and known, it would be interesting to treat it as unknown random variables.
- The actions and observations are binary.
• Only one action channels and one observation channel.
• The hypothesis is stationary.
• The goal of this system is just to discover whether contingency exists. A consequence of this is that system may be good at asking questions but not that good at responding to questions.
• The model does not consider the fact that humans change the background rate. Changes in background rate are in fact informative about the presence of humans. This has a very negative effect on first time interactions.
7.9. Model Refinement

- Modify model to include knowledge that humans can cause changes in background rate.
- Learn the model using reinforcement learning methods.
- Understand the effects of delays and uncertainty.
- Coupling with Face Detection: Learn how responsive objects look like.
- Neural mechanisms (started pilot study with Kawato’s Laboratory in Japan).
8. Conclusions

- It is useful to study social interaction at a functional level decoupled from implementation issues. (A Kalman controller is a Kalman controller regardless of how it is implemented).

- It is useful to conceptualize social interaction as a real time control problem.

- The approach provides new avenues to understand social development.

- It suggests potential experiments to understand neural mechanisms underlying social interactions.

- It suggests an interesting architecture for communication robots: Probabilistic; Reactive; Intention-based.
9. Contact Information

- movellan@mplab.ucsd.edu
- http://mplab.ucsd.edu