4 : Hardware

In this lecture consider Hard A Life

- Includes some 'real robots' and simulated ones
- We mention some of the early work done here
  - Seven dwarves – simple robots that can learn and interact
- Also a variety of work done elsewhere
  - Robots that swarm, self replicate and flock

We also outline methods for learning, including

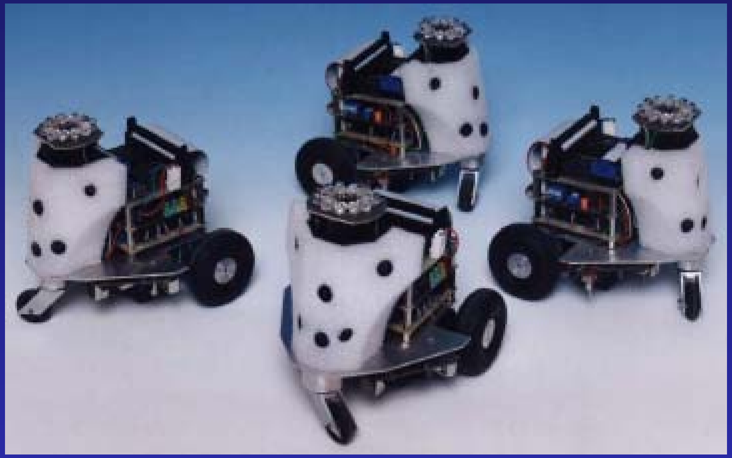
- Finite State Automata, Markovian Domains, Machine Learning
  - Reinforcement Learning; Cognitive Learning; Mental Acting
  - Temporal Difference Learning; Q Learning
- Evolutionary Robotics … Learning Classifier Systems

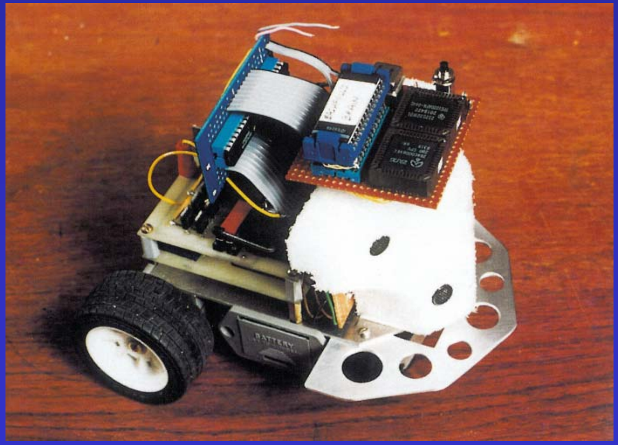
Robotics in Cybernetics

Perceive environment (ultrasonics) and act (motors drive wheels)

Program series of rules for obstacle avoidance /following

Then KW wanted to demonstrate real time learning in public lecture





Learn by trial and error – fuzzy automata

Interesting to observe 'emergent' behaviour (from rules)

Demonstrate benefit of sharing experiences – locally/USA

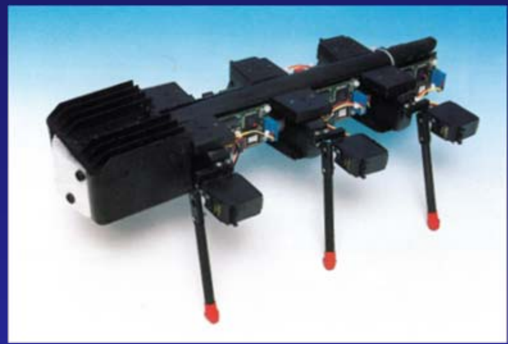
Also flocking behaviour, finding 'food'

Other Reading Robots

Six legged 'Elma'

Controller each leg

Off line, GAs evolve 'gait'



Tracked robots –rugged

Engaging Robots: Innovative Outreach for Attracting Cybernetics Students
Richard Mitchell, Kevin Warwick, Will N Browne, Mark N Gasson and Jim Wyatt IEEE Transactions on Education, vol. 53, no. 1, February 2010

Flocking Robots

"The Swarmbots have already shown their ability to co-operatively explore and navigate, for example searching an area in the most efficient way without central co-ordination."
www.defensetech.org/

http://www.youtube.com/watch?v=Kk40ZnuzNNw

NB: Better fish
http://uk.youtube.com/watch?v=eO9oseiCTdk&NR=1

Swarm Bots

Much work on implementing swarm intelligence on Robotics
Commercial / Govt funded projects

http://news.bbc.co.uk/1/hi/technology/7548190.stm

SYMBRION - Symbiotic Evolutionary Robot Organisms
I-SWARM
SWARM-BOTS

http://uk.youtube.com/watch?v=e44hA6IBtkA&NR=1

iRobot and Frontline Robotics : teaching how to work together.

See http://www.irobot.com/

Issues in Swarms

Collective intelligence
- Self-organisation
- Goal switching

Morphology – structures of A-Life
- Heterogeneous or homogenous robots
- Global or local control

Hardware
- Scaling i.e., miniaturisation
- Communication
- Power e.g., storage and recharging

Infrastructure
- Operating system
- Visualisation & tracking

Issues in Swarms: Scaling

Large-scale

Mine disposal, search & rescue, cleaning

http://dilab.eecs.utk.edu/index.html

Miniaturised-scale

Medical applications, repair, surveillance

http://groups.csail.mit.edu

Self Replicating / Repairing

Cornell University's

self-replicating robot modules : cubes about 4" inches on a side.

Able to swivel along a diagonal.

http://www.youtube.com/watch?v=gZwTcLeelAY

ckBot: Self-Assembly after Explosion + Dynamic Rolling

Decentralized, fault-tolerant system with structural isomorphism.

http://uk.youtube.com/watch?v=uIn-sMq8-Ls

Slug Bot

http://news.bbc.co.uk/1/hi/sci/tech/503149.stm

Once robot collected a load of slugs it must return to the static fermentation station before battery fully flat.

Next we give an overview of methods used for learning..

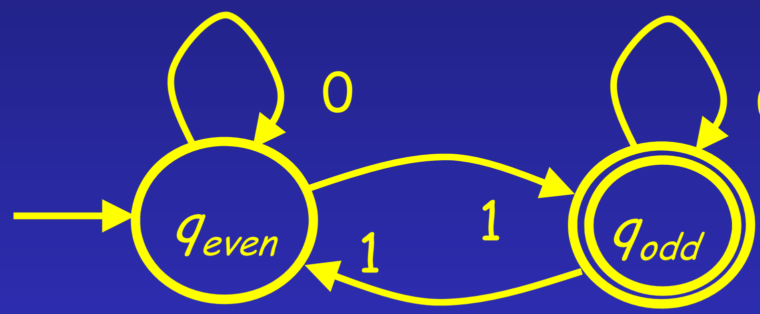
Finite State Automata

A model of a system which has states; current set by past

Conditions exist for Transitions – often set by inputs

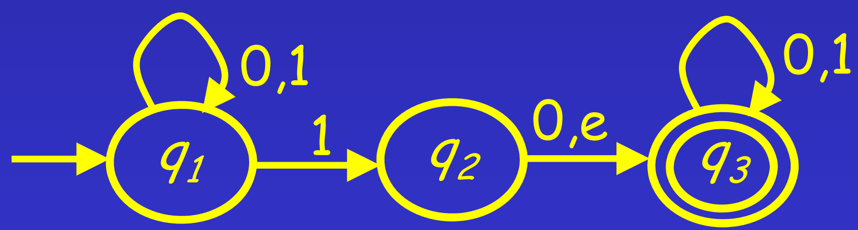
Actions can occur also – eg output set

Eg to see if odd/even
number of 0/1s



Deterministic FA:
Exactly one transition for
each combination of ins

Non Deterministic FA:
Can be 0, 1 or more transitions
for each combination of ins



Can convert NDFA to DFA

Often used in Machine Learning

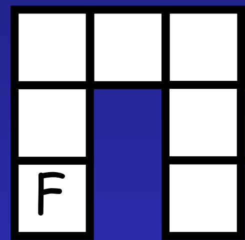
Markovian Domains

Markov chain : process for moving through set of states

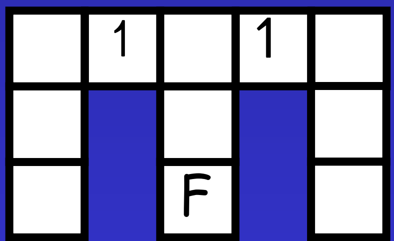
A Markov process : model for random evolution of a memoryless system : future state depends only on its present state.

Maze – unique s-a (state-action) pairs - know where you are.

Mazes often used in machine learning



Non-Markovian Domain



needs memory to optimise

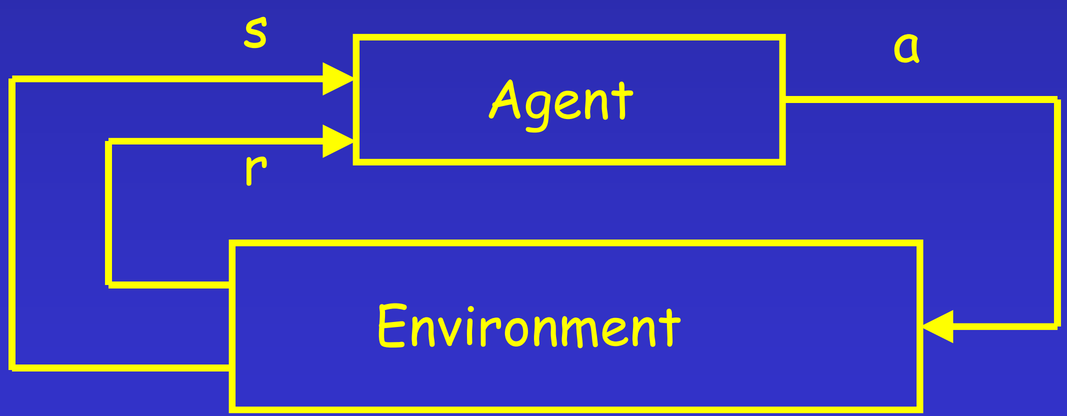
Machine Learning

Various Machine Learning methods exist

These are briefly outlined …

Reinforcement Learning (RL)

Reinforcement Learning: an Introduction
Richard S. Sutton and Andrew G. Barto MIT Press, 98



states
actions
rewards

(Book is on-line)

eg Fuzzy Automata – used in Cyb

Have series of actions: each wheel Forward / Off / Backward

Probability associated with 9 possible combinations

Choose one action probabilistically; test if success

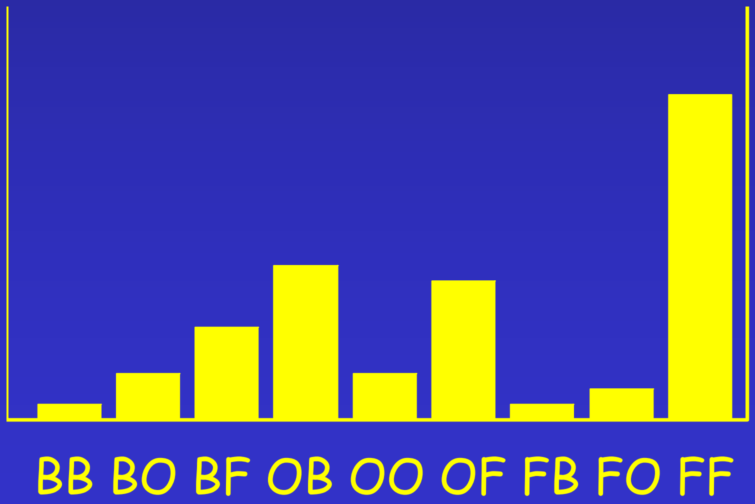
In open– how well moved; - or if moved away from object

If so, increased prob of that action, else decrease

BUT, need set of such automata for different conditions

Chose 5 automata –

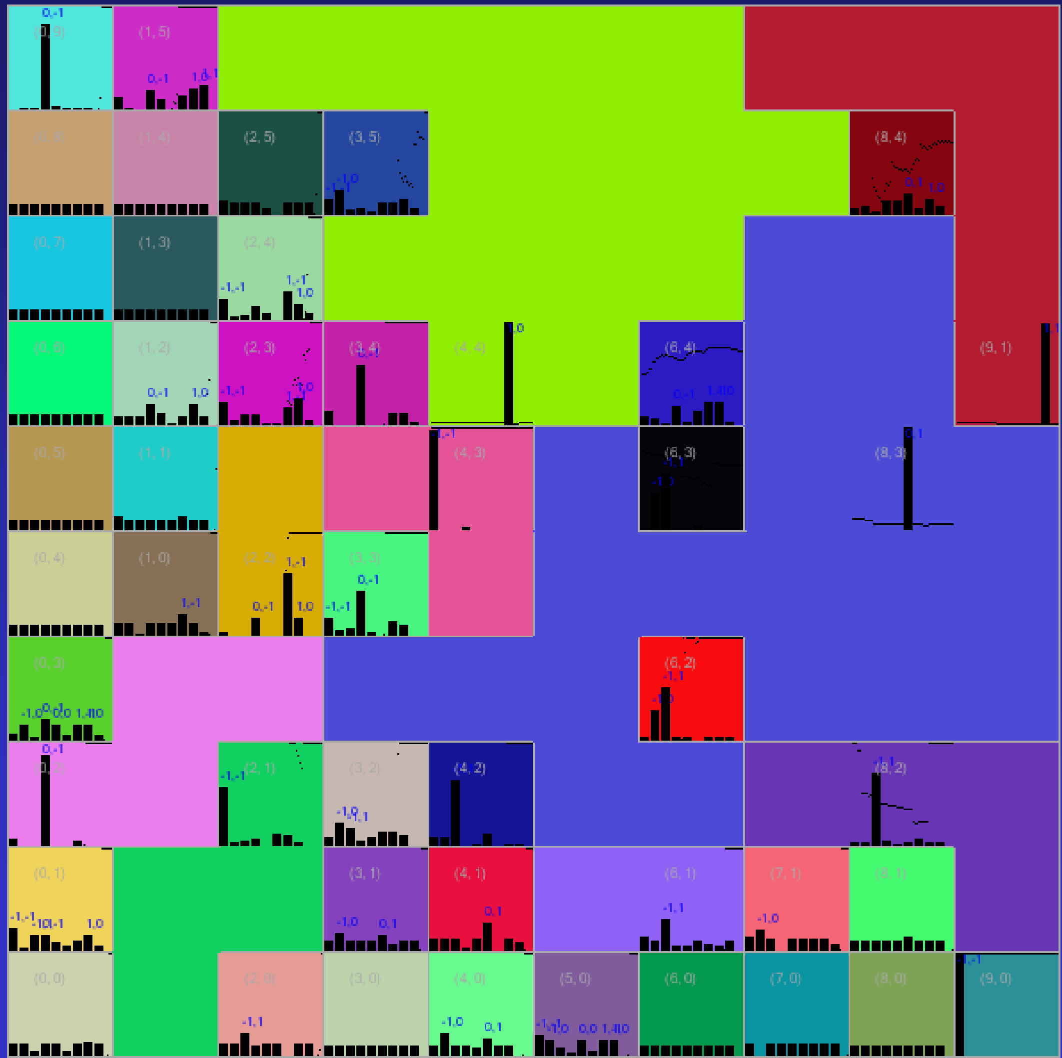
Open; Near on R; on L; Close on R; on L



Cybernetics

Automatic Selection of Automata

L

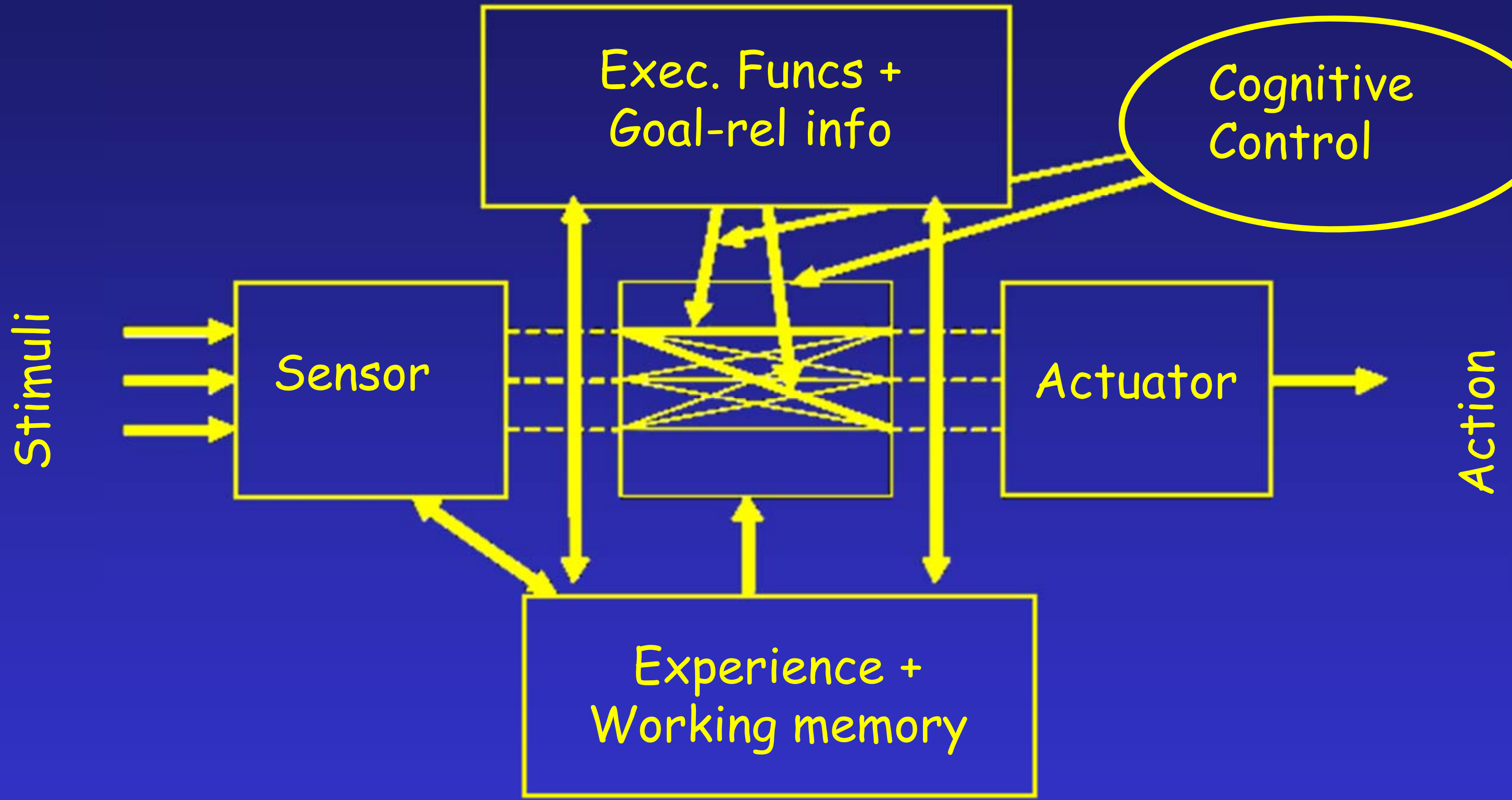


R

Have more automata ; Detect when similar, so merge them. To speed up, when adjust probabilities in chosen automaton, adjust adjacent ones also

Ashdown and Mitchell (2005) IASTED CI Conf

Cognitive Learning



K Kawamura, W Browne, "Cognitive Robotics", Chapter in *Encyclopedia of Complexity and System Science*. 2008

Mental Acting

Mental acting uses an evolved generalised environmental model to propagate reinforcement internally

In cognitive terms:

- Mental acting is comparable to a thought process
- Occurs independently of the current (outside) environment, e.g.
  - Planning
  - Mental problem solving
  - Imagination of certain events
  - Dreaming

Used in anticipatory control / learning classifier systems

Temporal Difference (TD) Learning

Combines Monte Carlo & Dynamic Programming Ideas:

Learn directly from raw experience

No model of an environment's dynamics

Update estimates due to other learnt estimates

- without waiting for outcome (bootstrap)

Used for solving Reinforcement Learning problem

Witten, I. H., 1977, An Adaptive Optimal Controller for Discrete-time Markov Environments, *Information and Control*, 34, pp. 286-295

Sutton, R.S., 1988, Learning to Predict by the Method of Temporal Differences, *Machine Learning*, 3, pp. 9-44

Q-Learning

Chris Watkins 1989, PhD Thesis Cambridge

Paul Werbos, 1977-1987

A R-L technique: learn expected utility of taking a given action in a given state then following a fixed policy

Simple way for agents to learn optimally in controlled Markovian environment

Convergence of trial-and-error learning & dynamic prog

Q : function of quality of action A in state S

Simplifies TD analysis and has convergence proofs

But Q-learning can require excessive memory and often contains non-optimum paths

For interest : Algorithm

Initialise $Q(s,a)$ and $Model(s,a)$ for all $s \in \mathcal{S}$ and $a \in \mathcal{A}(s)$

Do forever:

$s \leftarrow$ current (non terminal) state

$a \leftarrow \varepsilon$- greedy(s,Q)

Execute action a; observe resultant state s' and reward r

$Q(s,a) \leftarrow Q(s,a) + \alpha\ [r + \gamma \max_{a'} Q(s',a') - Q(s,a)\ ]$

$Model(s,a) \leftarrow s',r$ (assuming deterministic environment)

Repeat N times

$s \leftarrow$ random previously

$a \leftarrow$ random action previously taken in s

$s',r \leftarrow Model(s,a)$

$Q(s,a) \leftarrow Q(s,a) + \alpha\ [r + \gamma \max_{a'} Q(s',a') - Q(s,a)\ ]$

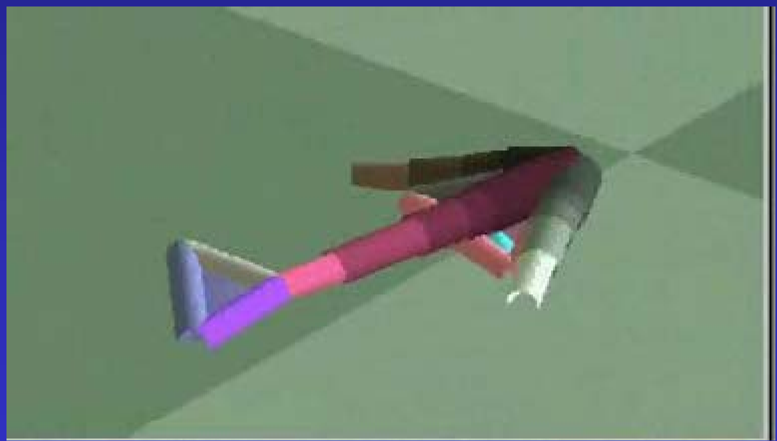
Can utilise models in Q-learning

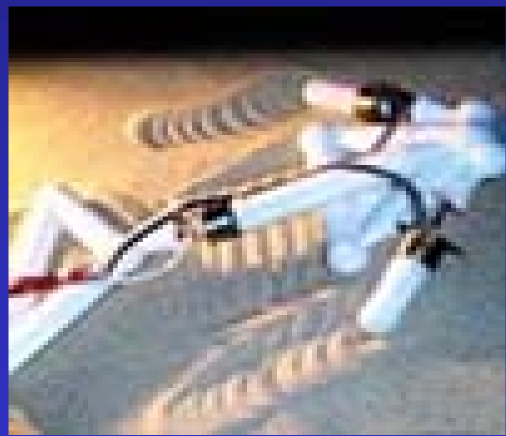
Evolutionary Design and E.. Robotics

The Golem project   http://www.demo.cs.brandeis.edu/golem/

Genetically Organized Lifelike Electro Mechanics

Simple electro-mechanical machines evolve from scratch

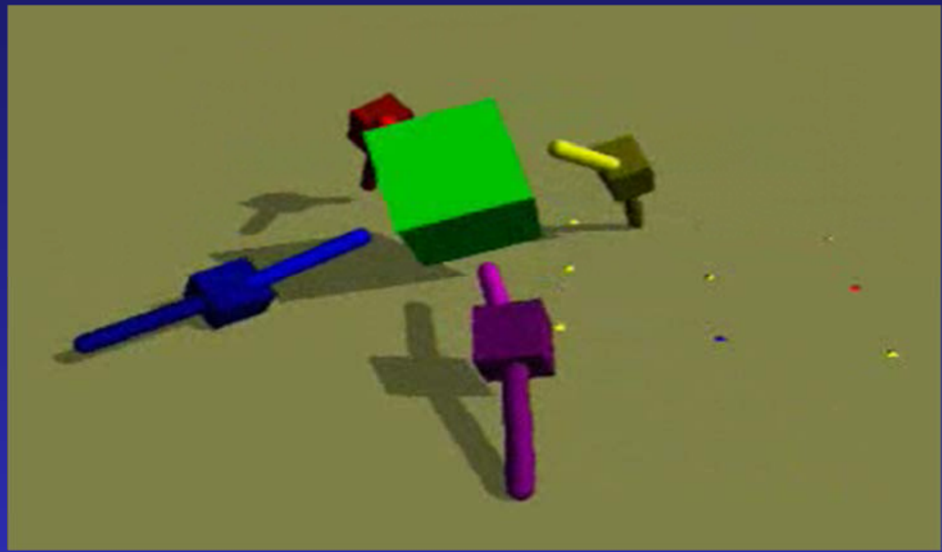




Lipson H. "Evolutionary Design and Evolutionary Robotics", ***Biomimetics***, CRC Press (Bar Cohen, Ed.) pp. 129-155, 2005

Robots that are "self-aware"

'real robot'



Software version

http://www.ted.com/index.php/talks/hod_lipson_builds_self _aware_robots.html in own time watch this

Concluded progress not limited by computational power – rather need better approach

Machine Consciousness

http://cswww.essex.ac.uk/staff/owen/machine/mchome.html

CRONOS Project

Hardware robot CRONOS, a virtual copy SIMNOS,

visual system closely based on the human brain,

the SpikeStream neural simulator,

systematic methods for identifying and describing the conscious states of the system.

David Gamez investigates : might a machine be conscious

Owen Holland : intelligent agent needs own world model: SIMNOS provides basis CRONOS' model

'Anthropomimetic' robot

http://cswww.essex.ac.uk/staff/owen/machine/videos.html

Videos from the development of CRONOS and SIMNOS
http://www.youtube.com/watch?v=3_0ig6g46Jw

Holland's view

http://cswww.essex.ac.uk/staff/owen/adventure.ppt

Want robot that is conscious like humans –

really conscious and feelings – not mimicking them

Consider agent with mission in hostile changing world

Cant be programmed with all eventualities

Cant learn consequences of all actions in all situations

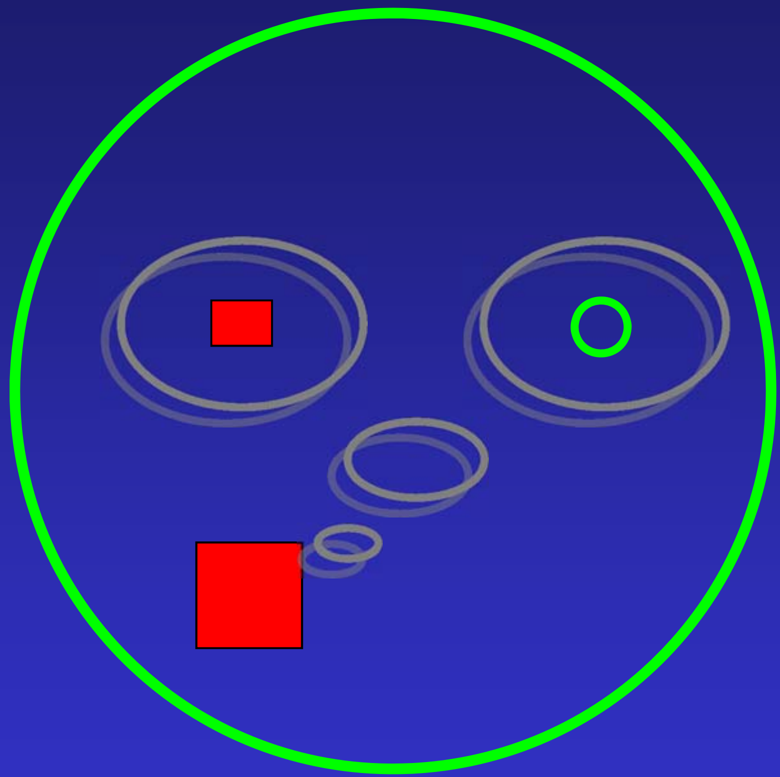
Could succeed if learned enough so can predict consequences for mission of tried and untried actions, and by selecting suitable actions

Proposes IAM …

IAM Internal Agent Model

We're trying to build a robot that has an internal model of itself and an internal model of the world, and that uses them to predict the outcomes of novel or untried actions.

And maybe the IAM will be conscious…



Is this The Future of Embodied Artificial Intelligence?
See Owen Holland : *www.machineconsciousness.org*

Other Web Sites

http://www.idsia.ch/~juergen/rl.html

http://ccsl.mae.cornell.edu/

http://www.mae.cornell.edu/Lipson/

http://ccsl.mae.cornell.edu/papers/Science06_Bongard.pdf

Resilient Machines Through Continuous Self-Modeling

« a robot that can recover from change through self modelling »

Next lecture – looking at Wet Life and Biological Aspects

5 : Wet and Biological Alife

Wet alife is artificial life created in chemical substrates based on water or another solvent.

It is created in vitro (in glass) as opposed to the normal in silico

Generally involves expts with chemical substrate in water/solvent

hence "wet" in "wet alife".

The holy grail of wet artificial life is to create an artificial cell in the laboratory out of materials found in a chemical supply room.

If we let "soft" artificial life refer to computer simulations or other purely digital constructions that exhibit life-like behavior, we should also recognize "hard" artificial life which produces hardware implementations of life-like systems, and **"wet" artificial life which involves the creation of life-like systems from biochemical substances in the laboratory.** Mark Bedau

Belousov-Zhabotinsky reaction

The BZ reaction is an auto-catalytic reduction-oxidation (redox) process. Each step of multi-step reaction sequence generates a catalyst that speeds up the counter reaction:

http://www.meta-synthesis.com/webbook/24_complexity/complexity.html

Standard:

http://uk.youtube.com/watch?v=SzncgG8dPVI&NR=1

Spirals:

http://uk.youtube.com/watch?v=GEF_NtTNeMc

http://online.redwoods.cc.ca.us/instruct/darnold/DEProj/Sp98/Gabe/bzreact.htm where can see chemisty/maths …

Animats

Artificial animals, a contraction of anima-materials.

The term includes physical robots and virtual simulations.

Animat research became popular since Rodney Brooks' seminal paper "Intelligence without representation".

Word coined by S.W. Wilson in 1991, in first proceedings of the Simulation of Adaptive Behaviour, or “From Animals to Animats”

An example using the Animat model as proposed by Wilson is discussed in chapter 9 of Stan Franklin's book, Artificial Minds.

Here, the animat learns independently about its environment by application and evolution of pattern-matching rules called "taxons".

In 2001 Thomas DeMarse performed studies on 'Neurally controlled Animat'.

Society of Adaptive Behaviour meets every two years - journal

Anti-Animats : Alan H Goldstein

Based on the Animat Test (reference "I, Nanobot.") any nonbiological material or entity that exhibits the minimum set of behaviors that define a life form is, de facto, an Animat.

Goldstein's basic premise : in age of nanobiotechnology must follow the chemistry and molecular engineering rather than watching for emergence of some pre-conceived minimum level of 'intelligence'.

He cautions: serious disconnect between nanobiotechnology and A-life based on profound differences in scientific training, experimental systems, and the different sets of terminology (jargon)

Nanobiotechnologists (really molecular engineers who work with both biological and nonbiological molecules) are generally not concerned with complex systems per se.

A-Life researchers mainly take a systems-level approach

Nanotechnology could produce animats that don't fit A-Life paradigms

In Vitro Neuronal Networks

A hybrot (short for "hybrid robot"): cybernetic organism : robot controlled by a computer with both electronic and biological elements (rat neurons connected to a computer chip).

First accomplished by Dr. Steve Potter, Prof of biomedical engineering at the Georgia Institute of Technology:

Droplet of solution with 1000s rat neurons onto Si chip with 60 electrodes. Signals from firing cells picked up by electrodes, amplified into computer, which wirelessly relays to robot.

Robot manifests neuronal activity with physical motion.

Robot sends info back to cells. Knows environment via light sensors.

Not a cyborg as is not a human augmented by computer…

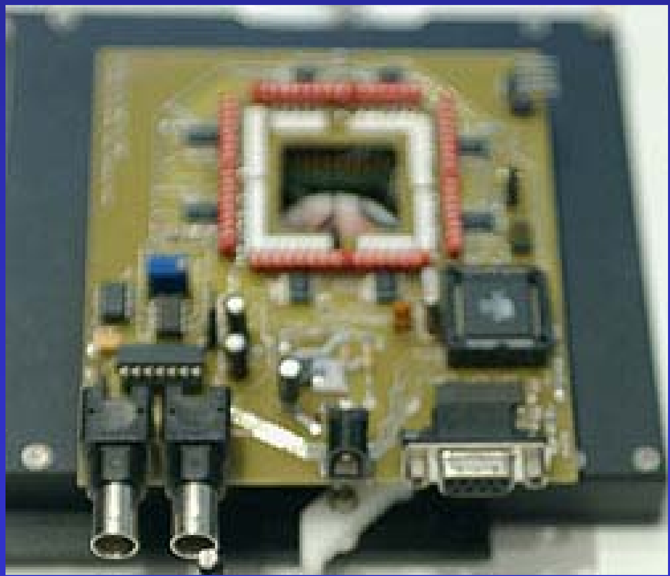
In Vitro Neuronal Networks

Another interesting feature of the hybrot is its longevity. Neurons separated from a living brain usually die after a short period of time; however, due to a specially designed incubator utilizing a new sealed-dish culture system, a hybrot may live as long as two years.

wiki

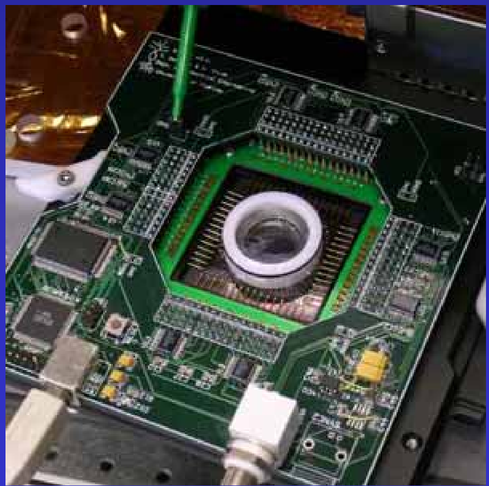
http://www.neuro.gatech.edu/groups/potter/

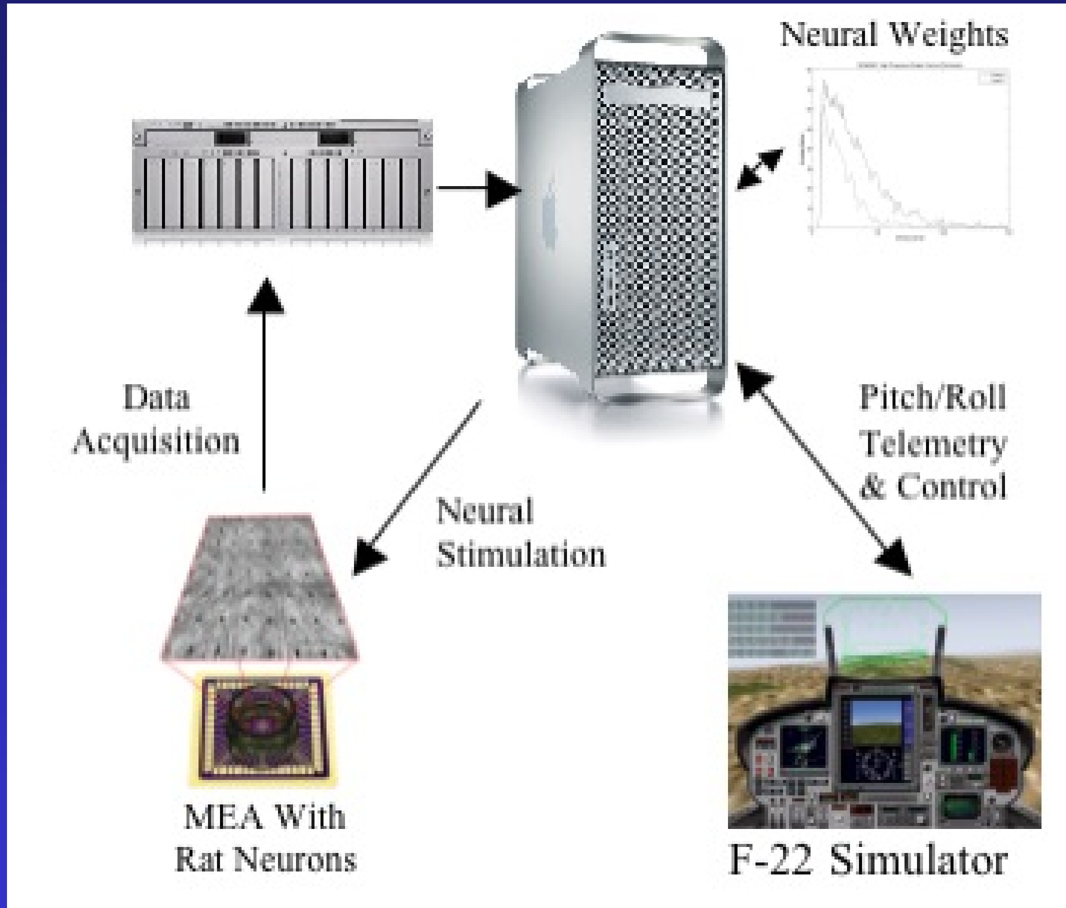
http://neuro.gatech.edu/groups/potter/articles/TechReviewArticle.htm



Thomas DeMarse: Neuronal Networks

http://neural.bme.ufl.edu/





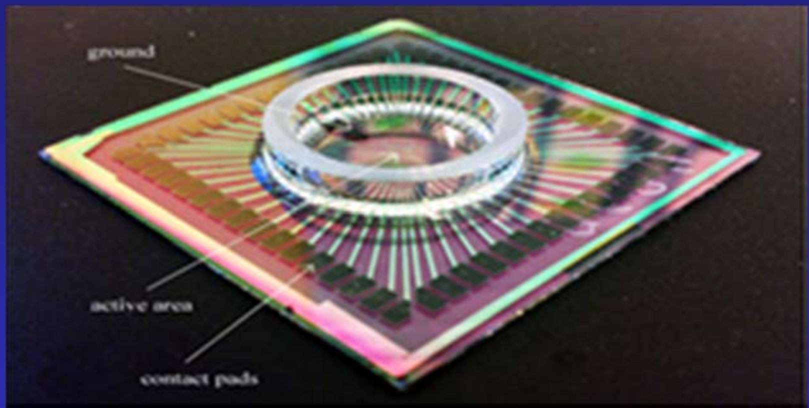
In Vitro Neuronal Networks

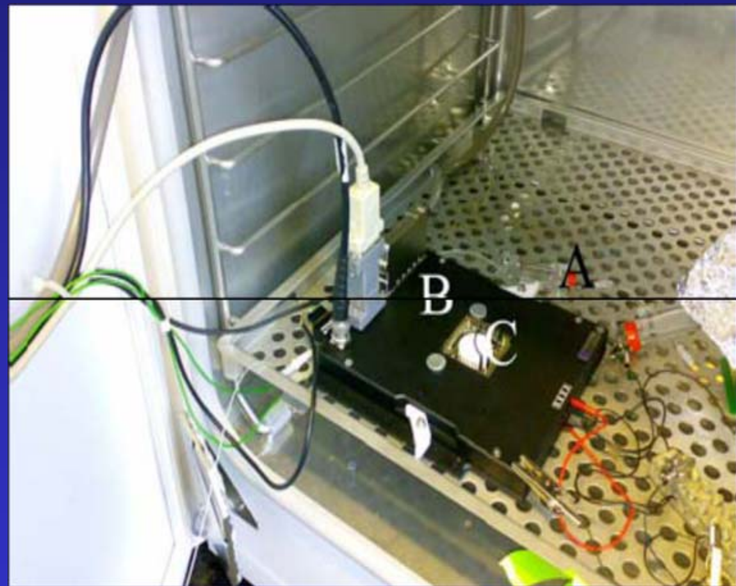
Initial results from the use of learning classifier systems to control *in vitro* neuronal networks, Larry Bull Ivan S. Uroukov, Proc 9th annual conference on Genetic and Evolutionary computation : pp 369 - 376: 2007

In this paper we describe the use of a learning classifier system to control the electrical stimulation of cultured neuronal networks. The aim is to manipulate the environment of the cells such that they display elementary learning, i.e., so that they respond to a given input signal in a pre-specified way. Results indicate that this is possible and that the learned stimulation protocols identify seemingly fundamental properties of in vitro neuronal networks. Use of another learning scheme and simpler stimulation confirms these properties.

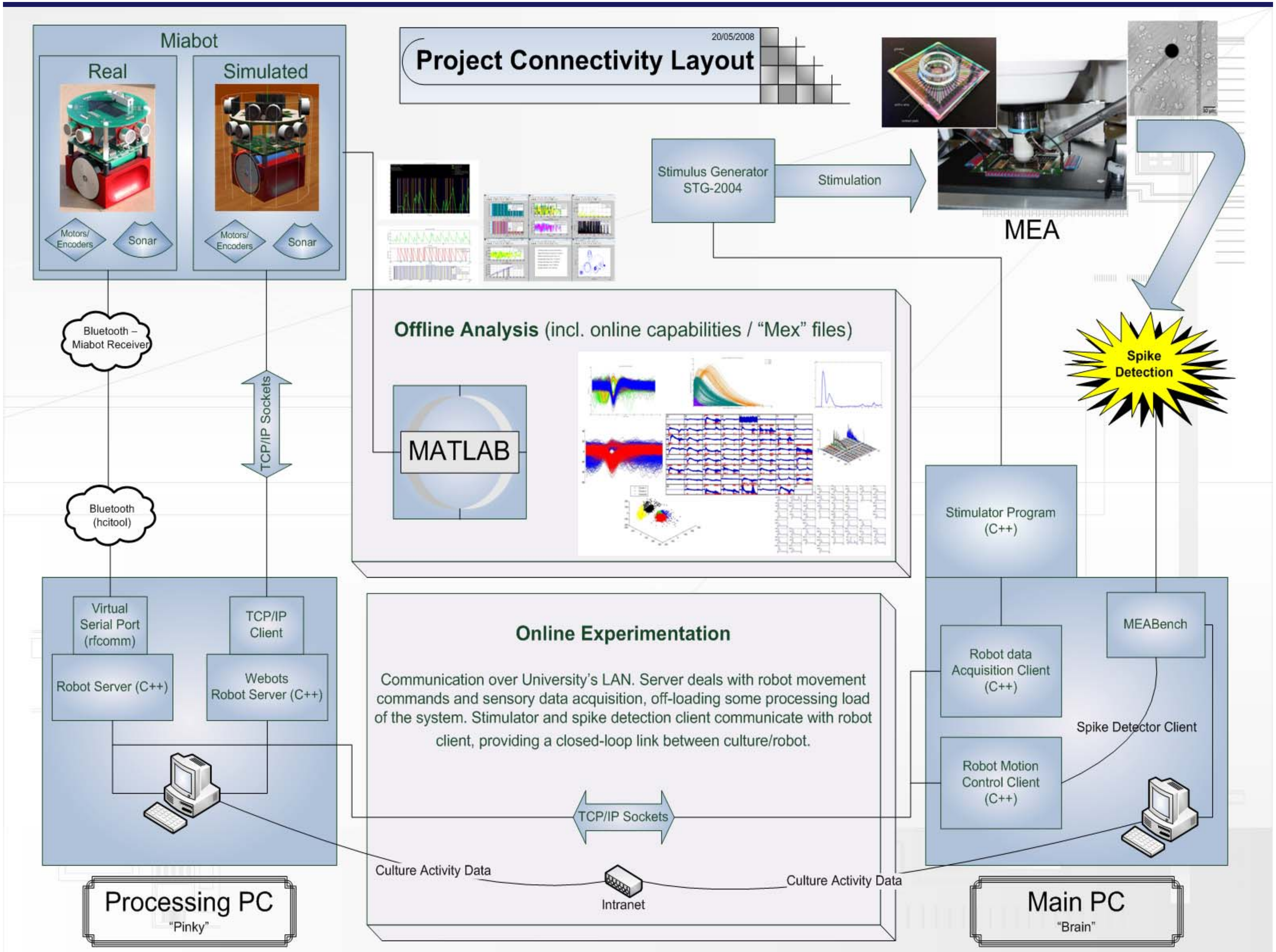
Cultured NNs and Mobile Robots

Ben Whalley, Kevin Warwick, Slawek Nasuto, Mark Hammond, Julia Downes, Dimitris Xydas: U of Reading





Used on 'Gordon', robot in Science Museum



20/05/2008
Project Connectivity Layout
Miabot
Real
Simulated
Motors/ Encoders
Sonar
Motors/ Encoders
Sonar
Bluetooth – Miabot Receiver
TCP/IP Sockets
Bluetooth (hcitool)
Stimulus Generator STG-2004
Stimulation
MEA
Spike Detection
Offline Analysis (incl. online capabilities / "Mex" files)
MATLAB
Stimulator Program (C++)
Virtual Serial Port (rfcomm)
TCP/IP Client
Robot Server (C++)
Webots Robot Server (C++)
Online Experimentation
Communication over University's LAN. Server deals with robot movement commands and sensory data acquisition, off-loading some processing load of the system. Stimulator and spike detection client communicate with robot client, providing a closed-loop link between culture/robot.
MEABench
Robot data Acquisition Client (C++)
Spike Detector Client
Robot Motion Control Client (C++)
TCP/IP Sockets
Culture Activity Data
Intranet
Culture Activity Data
Processing PC
"Pinky"
Main PC
"Brain"

Live Run

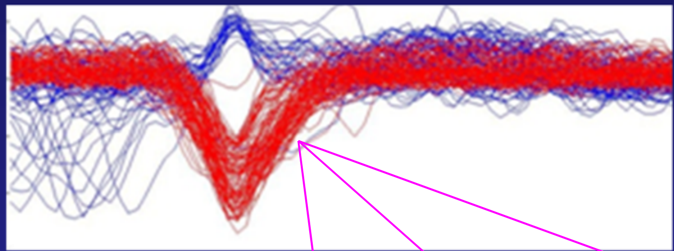
http://www.youtube.com/watch?v=1-0eZytv6Qk

Wall -> Stimulation -> Response
Wall -> Stimulation 100%
Stimulation -> Response 100%
Total closed loop time: 75 ms

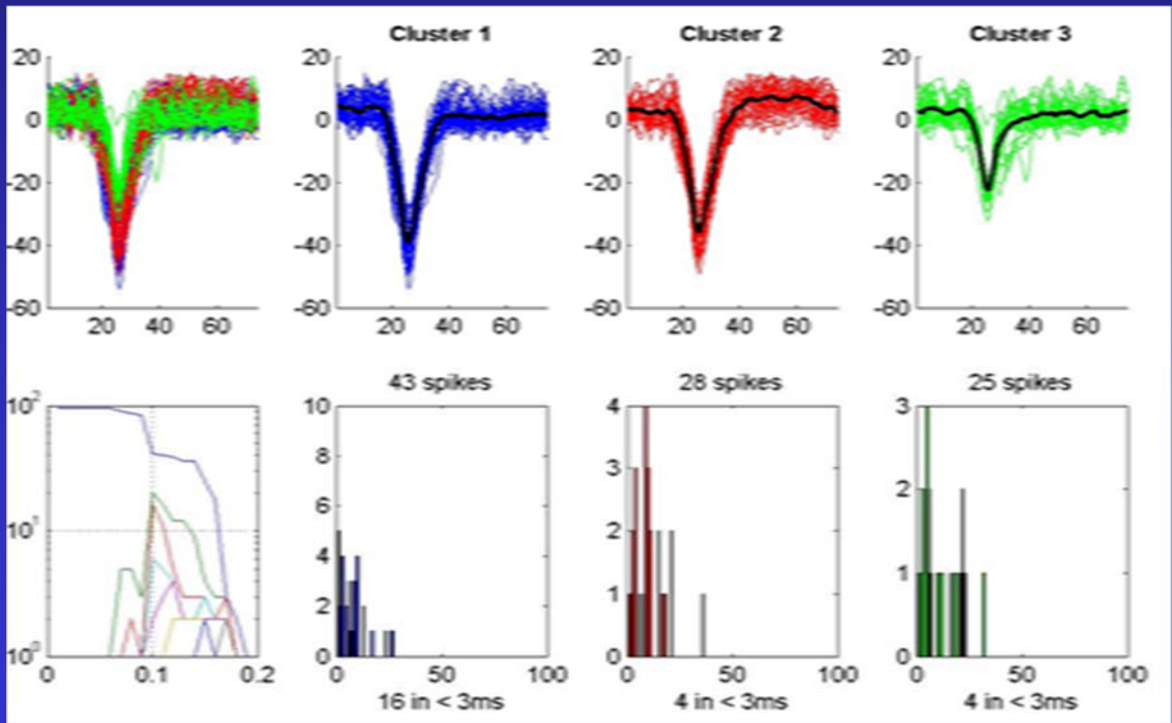
Run time: 4 min
Total Turns: 41
Meaningful turns: 41
Spontaneous turns: 0
Wall Hits: 0

http://www.reading.ac.uk/sse/about/news/sse-newsarticle-2008-08-18b.asp

Cleaning and spike sorting data



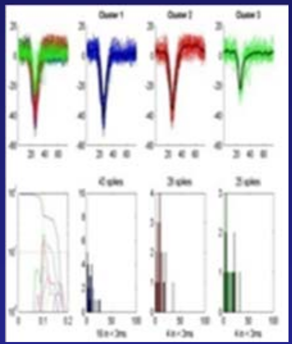
Raw data needs processing



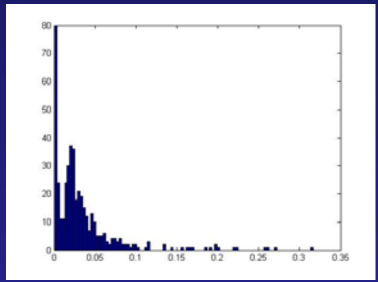
Saved spikes contain other spikes, overlaps etc which need to be removed before clustering on spike shape.

Most units successfully separated and clustered, usually between 2 and 6 per channel.

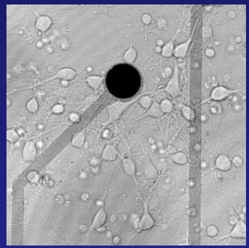
The Grand Plan



+



+



= Possibility of identifying unit type

Spike shape

Firing pattern (ISI), amplitude changes etc

Morphology

Cross correlations between unit firing times.

+

Other temporal and spatial info (e.g. distance between electrodes)

=

Identification of a set of feasible networks of specific units underlying robot behaviour.

Wet-Alife Issues

1. Ethics

   "Our goal is not to hook up primate brains to a robot," said Higgins. "There's the possibility, when you start to tap into brains, for all sorts of evil applications. There are certainly all these ethical issues when you start talking about human and primate brains."

   Creation of artificial viruses and lifeforms may have unknown effects on the ecosystem

   Sullins J; Ethics and artificial life : From modeling to moral agents

   Ethics and information technology 2005, vol. 7, no 3 pp. 139-148

2. Results too simple

   Utilising known patterns within biology is not the same as the biology learning useful patterns.

   Inserting material into the host cell and utilising the living machinery … is not the same as creating a self-replicating life.

Biological A Life

Evolutionary Biology

Epigenetics

Baldwin Effect

Unconventional computing

Wetware computing

Miscellaneous topics

- Synchronisation
- Small Word Theory

Evolutionary biology

Charles Taylor (of UCLA) recommends the following books

Evolutionary Biology, by Douglas J. Futuyma.

Evolutionary Genetics, by John Maynard Smith.

From the perspective of mathematical modelling:

Theory of population genetics and evolutionary ecology : an introduction, by Jonathan Roughgarden.

('bit old, but good')

Principles of population genetics, by Daniel L. Hartl and Andrew G. Clark. ('a class of its own; contains ref list')

http://www.faqs.org/faqs/ai-faq/alife/

Epigenetics

http://www.stanford.edu/class/cs273a/papers.spr07/10/epigenetics.pdf

Recently evolved diverse phenomena to defined field

Term coined by Waddington, 1942 – 'branch of biology which studies causal interactions between genes and their products, which bring the phenotype into being'

'Epi' may be thought of as "outside of" or "in addition to".

Now, E is 'bridge' between genotype & phenotype

- Phenomenon that changes final outcome of chromosome without changing underlying DNA sequence
- Multiple cells : same genotype, but different 'profiles'

Cellular differentiation governed by changes in Waddington's 'epigenetic landscape' not by genetic inheritance

Epigenetic Landscapes

A B C D

Cell (ball), rolls down an landscape

End represents different 'fates' of cell,

External factors, set if reach A, B, C or D

Current view of epigenetic machinery

Known phenomena shown directing pinballs (cells)

Epigenetic Landscape

Four "dimensions" in evolution—

Four inheritance systems that play a role in evolution:

- genetic,
- epigenetic (non-DNA cellular transmission of traits),
- behavioral,
- symbolic (transmission through language and other forms of symbolic communication).

These systems, they argue, can all provide variations on which natural selection can act

Baldwin Effect

The role of genetic inheritance dominates current evolutionary theory.

Learned behaviors could also affect the direction and rate of evolutionary change.

This notion was called the Baldwin effect, (after psychologist James Mark Baldwin)

In recent years, various philosophers and theorists have begun to employ the Baldwin effect in their accounts of the evolutionary emergence of mind and of how mind, through behavior, might affect evolution.

Evolution and Learning The Baldwin Effect Reconsidered

Edited by Bruce H. Weber and David J. Depew

Baldwin Effect

Assume a trait is absent from a population

(e.g. using sticks as tools)

A number of the population members **learn** this trait

The Baldwin effect allows for the trait to become innate throughout the population.

This may be considered as local learning

(as opposed to global learning through genetics)

This is different to Lamarckian learning, where the traits alter the genes.

It may help to explain innate skills where several traits are needed at once, e.g. hook making

Betty the Crow

http://www.youtube.com/watch?v=TtmLVP0HvDg
http://www.sciencemag.org/feature/data/crow/

Uses tool to get food

Unconventional Computing

Computing by a wide range of new or unusual methods (also known as alternative computing) including

optical computing,

chemical computing,

biologically-inspired computing,

DNA computing,

amorphous computing,

reversible computing,

analogue computing.

quantum computing,

natural computing,

wetware computing,

molecular computing,

nanocomputing,

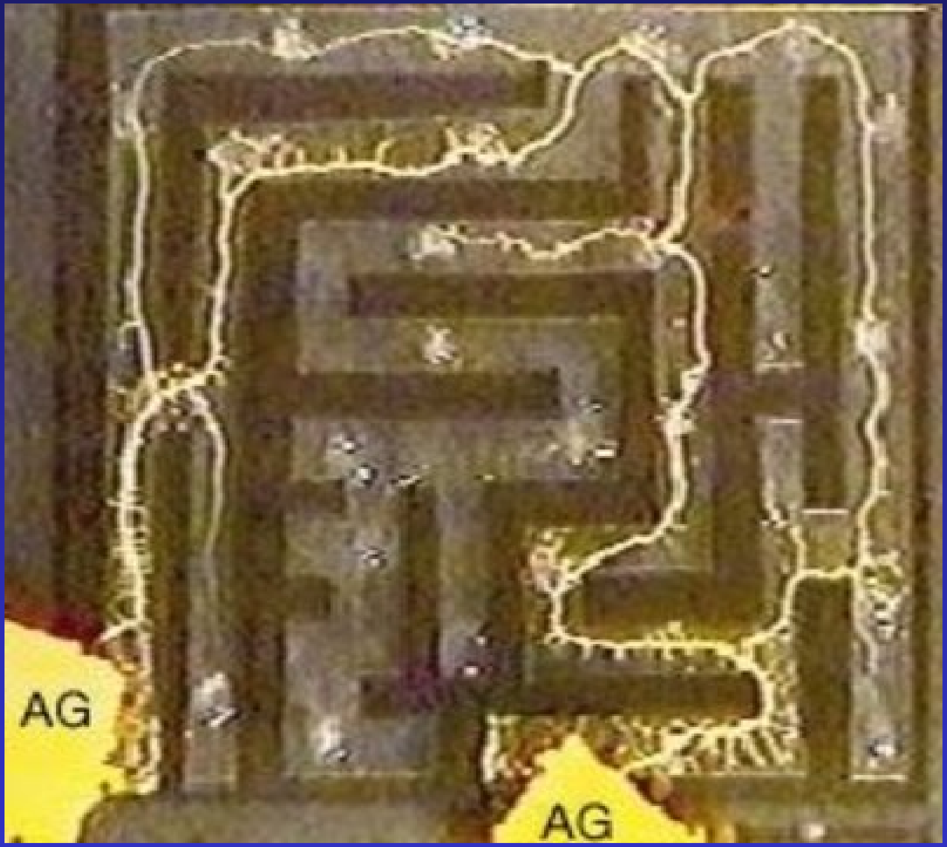
ternary computing,

Unconventional Computing

'Avoids' limitations of the von-Neumann computer architecture and the Turing machine concept,

e.g. serial processing, computability …

Slime moulds solve maze …



http://twistedphysics.typepad.com/cocktail_party_physics/2008/10/ig-nobel-dreams.html

Wetware computing

Prof Higgins, See http://neuromorph.ece.arizona.edu/

Project areas Higgins Lab – Arizona

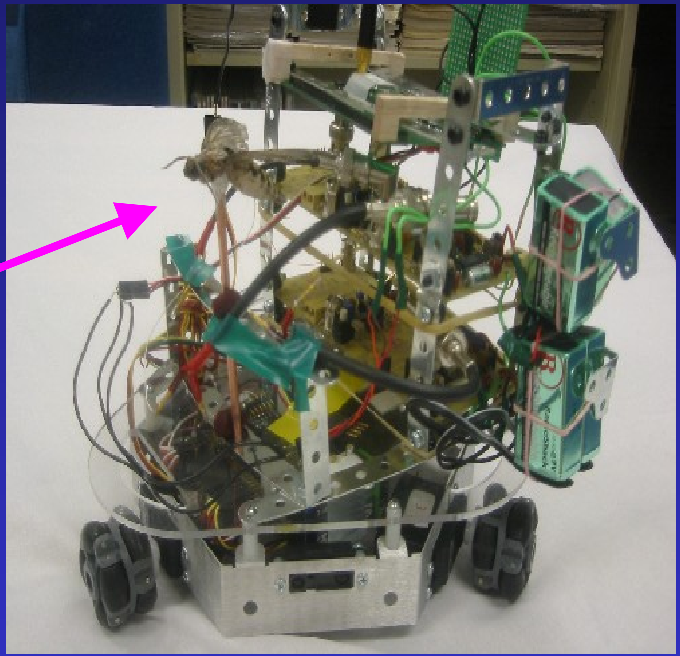
Computational neuroscience : insect visual motion proc

Biologically-inspired engineering systems : inc robots

Hybrid bio-robotics : robots with insects as sensors

Visual electrophysiology : in flies, moths and dragonflies

Behavioral experiments : in honeybees and bumblebees.



Robotic electrophysiology instrument : velocity set by bioelectrical signals from hawk moth

Small World Networks (of real life?)

Networks of coupled dynamic systems often studied

Connection topology usually either regular or random

Many biological/social networks in-between

Can 'rewire' dynamic systems to this middle ground

to be highly clustered with small characteristic path lengths

These are called small world networks

Eg Neural Network of a worm, Power Grid; film actors

"Small-world phenomenon" – we are linked by few acquaintances –

Pioneering academic work of Stanley Milgram in the 1960's.

http://www.cs.cornell.edu/home/kleinber/swn.d/swn.html

'Bacon' Number

Studies of movie stars: find number of steps necessary to link just about anybody who has ever been in a movie to, say, Kevin Bacon

http://oracleofbacon.org/center.php

$$Av = \frac{\sum Step*NumPeople}{\sum NumPeople}$$

Bacon : 2.95

Connery 2:828 better

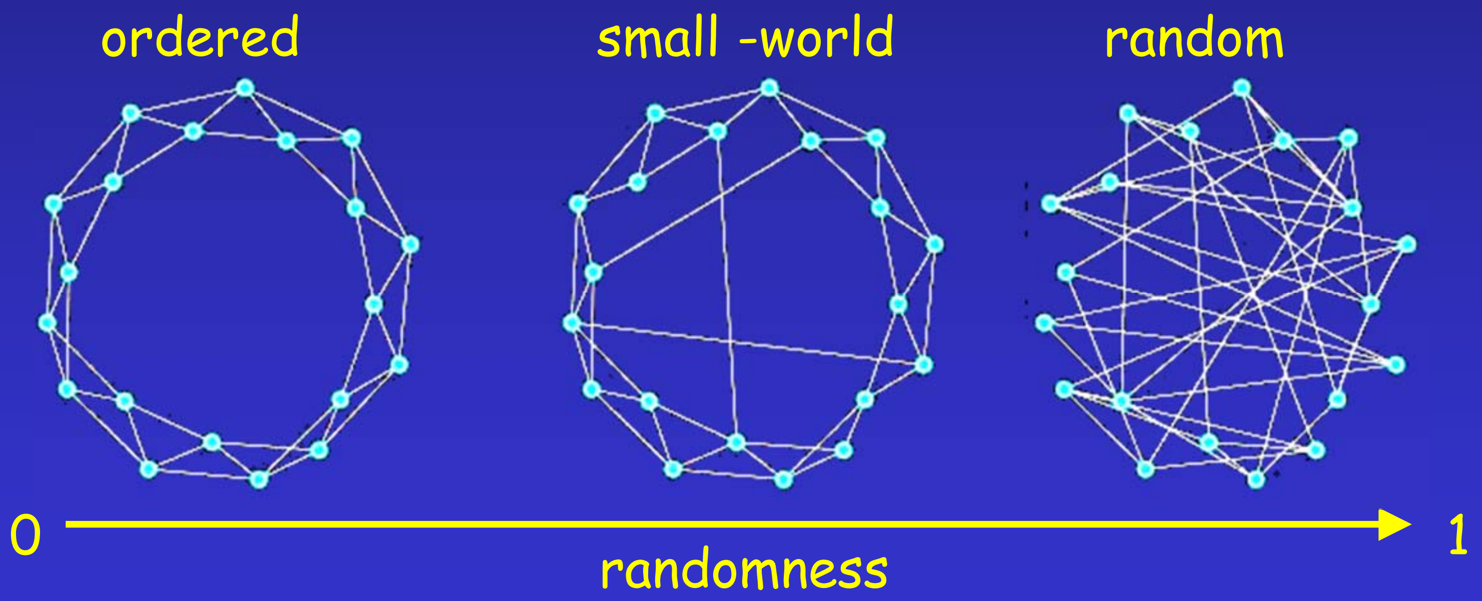
Steps	# of people
0	1
1	1806
2	145024
3	395126
4	95497
5	7451
6	933
7	106
8	13

Small World Phenomenon

Connected graph or network with a high graph diameter

Add a few edges randomly, the diameter tends to drop drastically.

A random generation model that produces graphs with small-world properties, including short average path lengths and high clustering



Application – Spread of Infection

Watts and Strogatz use simple model of infection in pop.

Pop. Modelled by family of graphs.

- At t = 0, one 'bod' infected.
- Infected bods die after a time.
- But infect healthy neighbours with probability r

Disease spreads along edges of graphs

- Whole pop infected, or disease dies – having infected only some

Critical infectiousness decreases rapidly for small p

Watts, D. J. Strogatz, S. H. "Collective Dynamics of Small-World Networks." *Nature* **393**, 440-442, 1998.
www.tam.cornell.edu/tam/cms/manage/upload/SS_nature_smallworld.pdf

Synchronisation – and Biology

Synchronization of chaos is a phenomenon that may occur when

two, or more, chaotic oscillators are coupled,

or when a chaotic oscillator drives another chaotic oscillator.

When a male cricket wants to attract the ladies, he serenades : one wing on other, opens and closes wings : finely tuned tone …

Henry Bennet-Clark : in theory, wings vibrate in opposite directions, disrupting the sound's constant and even tone.

Crickets must have found a way … so both wings vibrate in sync

http://jeb.biologists.org/cgi/content/full/212/2/i-a

1967 Winfree proposed a model for spontaneous synchronization in large pops of biological oscillators such as flashing fireflies or cardiac pacemaker cells

Synchronisation

In 1967, Winfree proposed a model for spontaneous synchronization in large pops of biological oscillators such as flashing fireflies or cardiac pacemaker cells.

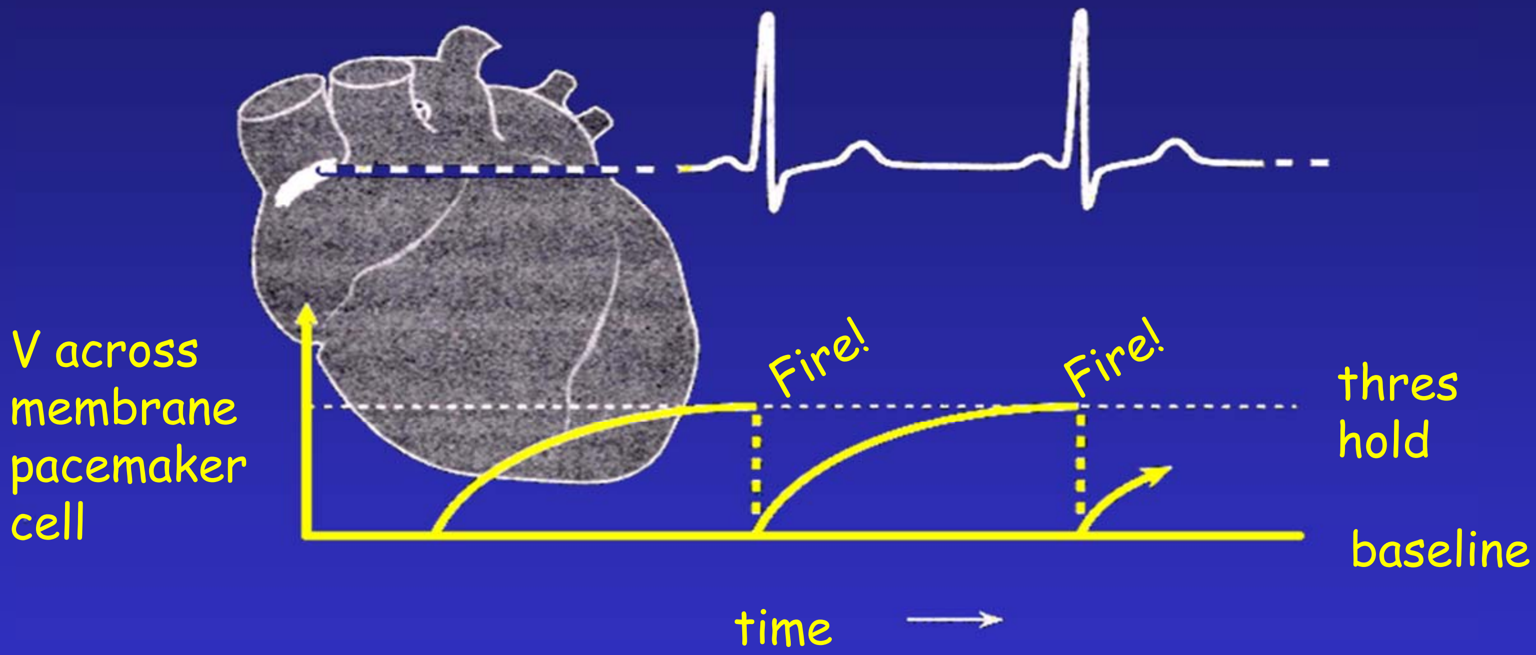
In system of weakly coupled, nearly identical oscillators, more coupling strength → temporal analogue of a phase transition and, beyond a threshold value, the oscillators synchronize, with finally locked amplitudes and phases.

Ariaratnam and Strogatz take special case of Winfree model and identify (using phase plane) conditions for locking, etc. See

http://www.nature.com/physics/highlights/6834-3.html

Synchronisation

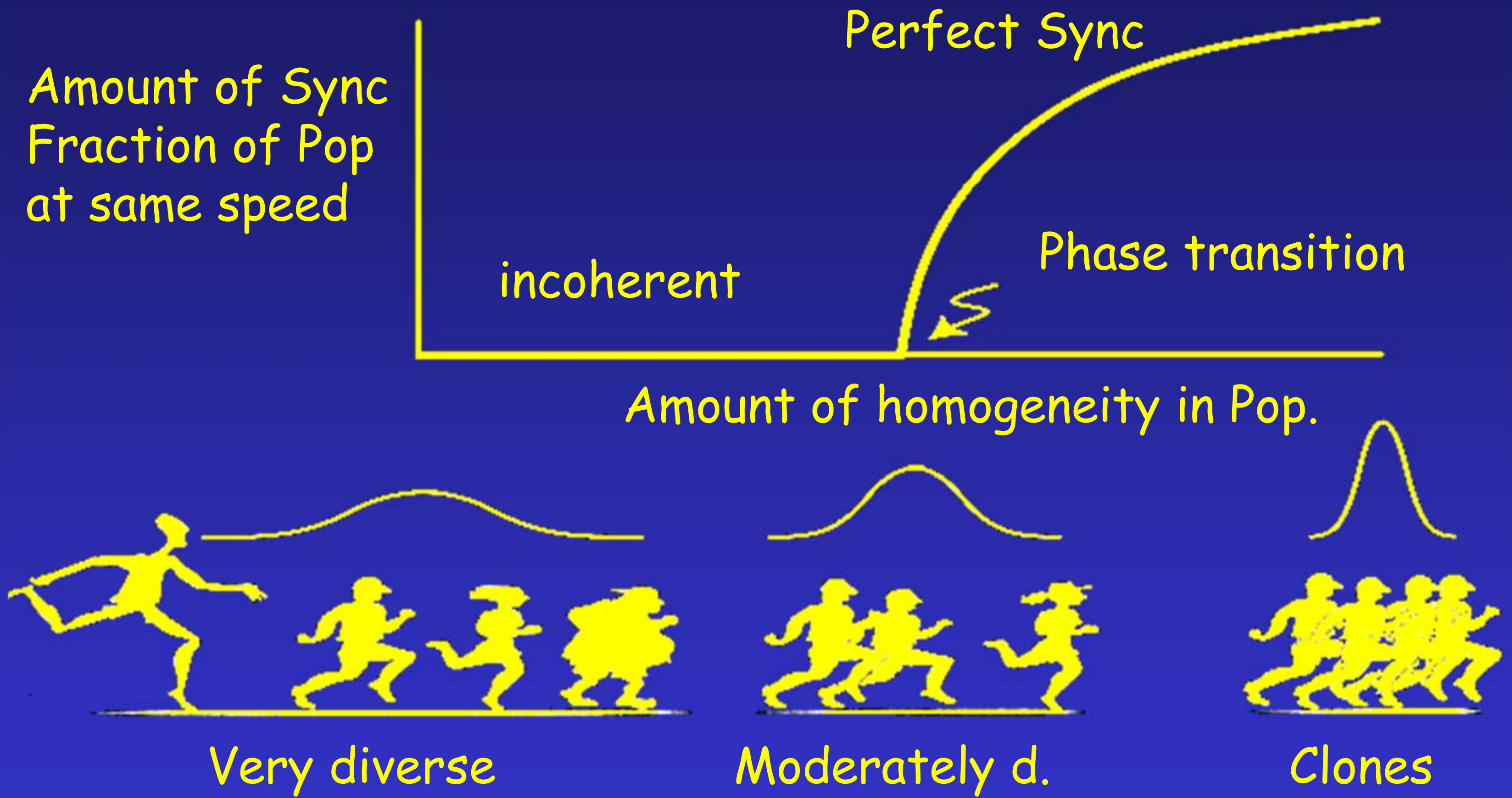
Example: pacemaker and heart autosynchronise ..



Ariaratnam and Strogatz take special case of Winfree model and identify (using phase plane) conditions for locking, etc. See

http://www.nature.com/physics/highlights/6834-3.html

Synchronisation



Sync: The Emerging Science of Spontaneous Order, Steven Strogatz

More Websites

http://www.kcl.ac.uk/ip/davidpapineau/Staff/Papineau/OnlinePapers/SocLearnBald.htm

http://www.cems.uwe.ac.uk/~lbull/

http://users.ox.ac.uk/~kgroup/tools/introduction.shtml

http://www.youtube.com/watch?v=8HN86pEfNc8

http://www.youtube.com/watch?v=tLO2n3YMcXw

(4 – 6.30mins)

http://tinkerlog.com/2007/05/11/synchronizing-fireflies/

http://en.wikipedia.org/wiki/Brainwave_synchronization

Here endeth Lectures