

# Artificial Life, Evolutionary Robotics, Real World Applications

## EXTRA READING:

### Papers:

Manos, S. and Bentley, P. J. (2007) Evolving Microstructured Optical Fibres. Chapter in *Evolutionary Computation in Practice*. Springer Pub. Doi: 10.1007/978-3-540-75771-9.

Schlessinger, E., Bentley, P. J., and Lotto, R. B. (2005) Evolving Visually Guided Agents in an Ambiguous Virtual World. In Proc. of *Genetic and Evolutionary Computation Conference (GECCO 2005)*

Schlessinger, E., Bentley, P. J., and Lotto, R. B. (2006) Modular Thinking: Evolving Modular Neural Networks for Visual Guidance of Agents. In Proc. of *Genetic and Evolutionary Computation Conference (GECCO 2006)*

Dyer, J. and Bentley, P. J. (2002) PLANTWORLD: Population Dynamics in Contrasting Environments. In Proc. of the *Genetic and Evolutionary Computation Conference (GECCO 2002)*.

Ficici, Watson, Pollack.(1999) *Embodied Evolution: A Response to Challenges in Evolutionary Robotics*

Jordan B. Pollack, Hod Lipson, Sevan Ficci, Pablo Funes, Greg Hornby, Richard A. Watson (2000) Evolutionary Techniques in Physical Robotics CES '00 Proceedings of the Third International Conference on Evolvable Systems.

- The field of ALife overlaps with the field of Evolutionary Computation.
- ALife researchers investigate the use of evolution to solve problems, but they also investigate other things too.
- More specifically, they are interested in modelling natural systems, to learn more about nature and to use that knowledge in our technology (and sometimes to create novel biology).
- Typical ALife research topics include:
  - *Adaptive behaviour* – the construction of software able to adapt, change and learn in new environments. For example, evolving neural networks to control robots.
  - *Social Behaviour* – the study of interacting agents, for example an ant colony or Axelrod's Iterated Prisoner's Dilemma.

- *Evolutionary Biology* – the use of computers to model natural evolutionary systems, for example the Baldwin Effect in the Immune System, or even the origin of life itself.
- *Morphogenesis and Development* – the use of computers to model natural developmental systems, for example evolving genes that define the growth of a shape.
- *Complexity* – the study of how complexity can arise from interactions between simpler entities, for example cellular automata.
- *Learning* – the study of how evolution and neural networks can produce artificial brains capable of learning.
- *Robotics* – the study of how evolution, neural networks and other biologically-inspired techniques can define the shape and behaviour of physical robots.
- *Philosophy* – the study of what artificial intelligence actually means, and what natural intelligence, complexity, emergence and embodiment means.

- Computer models can be used to help biologists analyse understand natural behaviour.
- One example of this is PLANTWORLD by ecologist Jacqui Dyer and Peter Bentley at UCL.
- Jacqui is an ecologist interested in the evolution of life in disturbed environments.
- She believed that traditional numerical models used by ecologists do not capture the behaviour of evolution with respect to environments prone to disasters such as earthquakes or fires.

- Such models predict that population dynamics in disturbed environments will fluctuate more strongly than those in stable environments, resulting in higher extinction rates, lower biodiversity and more simple community structures in disturbed, compared to stable environments.
- But these models ignore empirical data that show that many ecosystems evolve to overcome or even make use of such disasters for their survival.
- Frustrated by the assumptions and inaccuracies of numerical models, she approached Peter with the idea of developing a more realistic computational model.
- Early on, they decided to simplify things: they would model the evolution and responses of plants only.

- The PLANTWORLD model was initially developed in order to examine the effects that the evolution of a functional response - in this case, dormancy - might have on the population dynamics of PLANTS.
- Each PLANT requires a single resource, *moisture*, which varies in availability both spatially and temporally.
- In addition, this implementation allows us to study the effects of two further strategies that can influence dynamics:
  - the effects of PLANT *Storage Capacity*
  - the effects of an alternative source of moisture, in the form of a *Water Table*.

- One of the advantages of agent-based models over numerical models of population dynamics is that our agents can exhibit *behaviours*.
- Combined with evolutionary computation, such behaviours can evolve.
- Thus, we can examine how the evolution of traits in different environments affects the population dynamics in these environments.
- The objective for building PLANTWORLD was to examine the evolution and effects of plant dormancy on population dynamics in different spatially and temporally variable environments.
- Note that the simulation is not intended to capture realistic behaviour of any specific flora but rather to test the veracity of predictions about population dynamics that arise from numerical models.

- The evolutionary algorithm used in this system is a little different from any other you will see in this course.
- Instead of populations of a few tens or hundreds of individuals, PLANTWORLD supports hundreds of thousands, even millions of individuals.
- Also, there are no fitness functions describing what is, and what is not, fit. A PLANT merely begins as a seed, which germinates given sufficient resources.
- It then grows until it reaches a mature size defined by a gene, and will be fertilised by a nearby mature PLANT, producing its own seeds (with sufficient resources).
- At all times it follows the strategies defined in its genes, going dormant or growing during certain months. If its genes help it to survive and propagate in the environment, then those genes will be passed onto its offspring.

- From an evolutionary computing perspective, the model provides fascinating evidence of the evolution of different solutions to a dynamically changing and unpredictable problem.
- Stable niches of different types of plants evolve and coexist, from tiny, short lived “grasses” to large, long-lived “trees” that can make use of the water table below.
- From an ecology perspective, the model shows realistic population dynamics: interdependent cycles of population sizes emerging, or the evolution of more dynamic strategies of survival for disturbed environments.

- **PLANTWORLD has three layers:**
- **Rainfall**

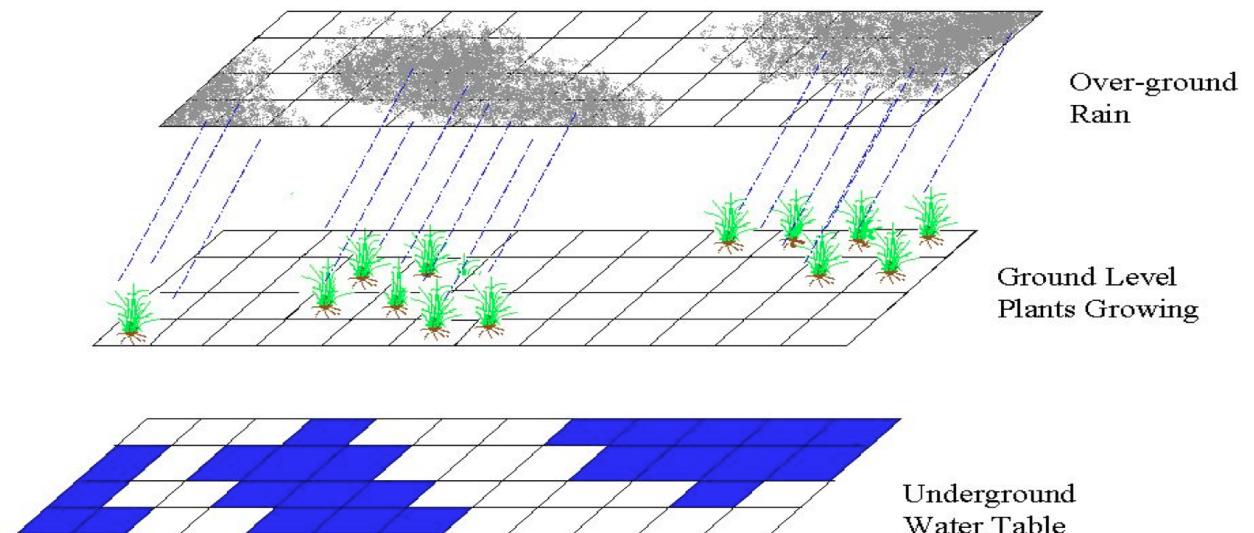
*Monthly spatial patterns of rain scaled using real-world rainfall data (e.g. Botswana, Kenya, or even UK rainfall data).*

- **Ground**

*Flat terrain, supports PLANTS and SEEDS, evaporates rainfall*

- **Water table**

*Static binary spatial pattern of underground water.*



- PLANTWORLD has two main objects / agents:

## 1 PLANTS

*Each having a yearly dormancy strategy determined by its genes:*

1	2	3	4	5	6	7	8	9	10	11	12
Kpon	Kpon	Kpoff	Kpoff	Ks	Ks	Ks	Kpon	Kpon	Kpon	Kpoff	Kpoff

- where Kpon means plant is active and requires  $m$  resources for maintenance
- Kpoff means PLANT is dormant and does not require (and cannot access) resources for maintenance, and
- Ks means plant can be active or dormant depending on resource availability.

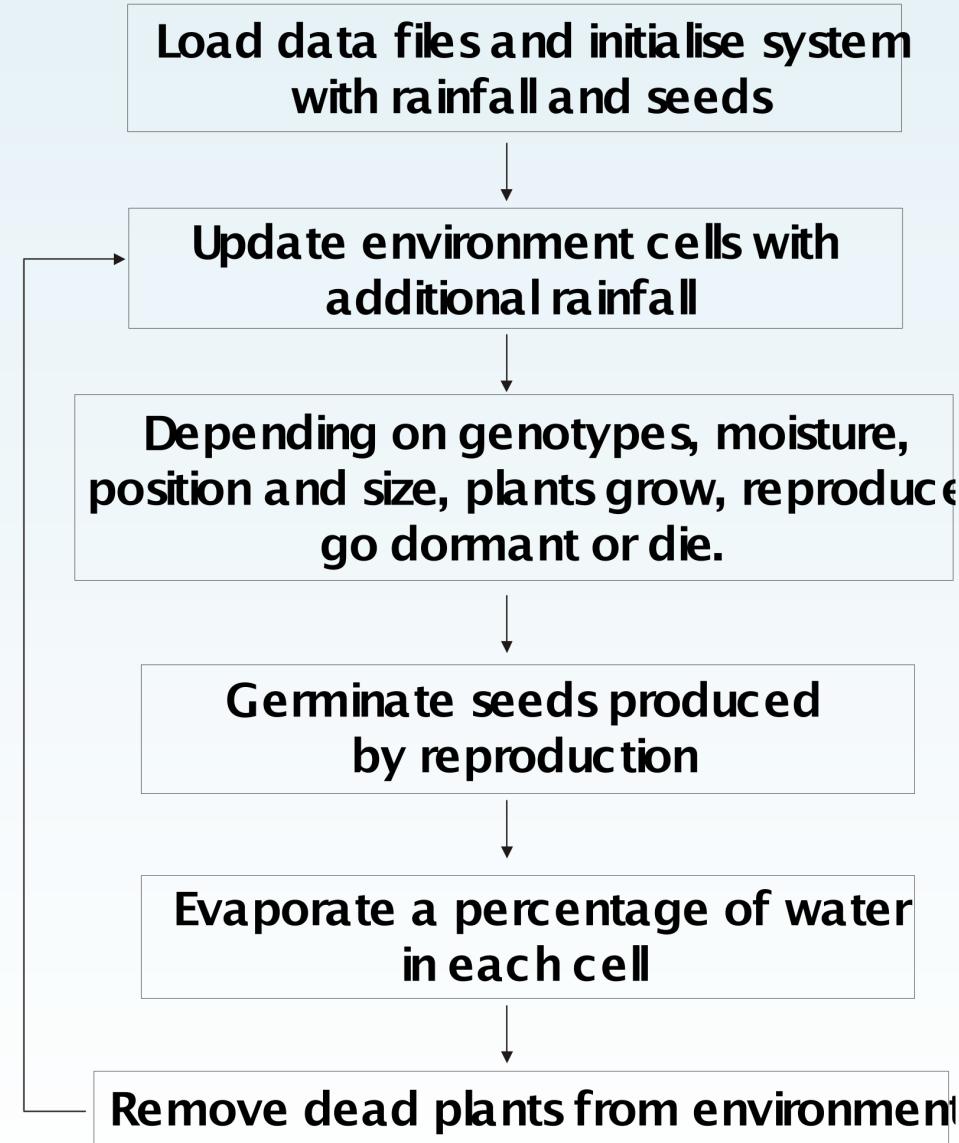
- PLANTS also have an *Adult Size* determined by their genes:

0	0	1	1	0	0	0	1	0	0	0	1
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- in this case, Adult Size is 785, meaning that this PLANT will stop growing and begin producing seeds after 785 months.
- *PLANTS may be active, dormant or dead.*
- *If active, PLANTS may grow or reproduce.*

## 2 SEEDS

- *produced by an active PLANT that has reached its Adult Size and has been fertilised by a nearby active and adult PLANT.*
- *scattered in a random Gaussian distribution around the PLANT.*
- *a random quantity between 50 and 100 generated.*
- *genes are crossed over and mutated from parents' chromosomes.*
- *may go dormant (determined by their genes).*
- *will germinate and become a PLANT given sufficient resources.*



*Hypothesis:*

*that the evolution of behavioural responses to environmental variability will mitigate variability in population dynamics.*

Experiments 1 - 8 are initiated with 100% of the PLANTS carrying the following genome, referred to as the *full kpon* strategy:

1	2	3	4	5	6	7	8	9	10	11	12
<i>kpon</i>											

Experiment 9 is initiated with 100% of the PLANTS carrying the following genome, which is referred to as the *mixed strategy*:

1	2	3	4	5	6	7	8	9	10	11	12
<i>kpon</i>	<i>kpoff</i>	<i>ks</i>									

Experiment 10 is initiated with 100% of the PLANTS carrying the following genome, which is referred to as the *matched strategy*:

1	2	3	4	5	6	7	8	9	10	11	12
<i>kpon</i>	<i>kpon</i>	<i>ks</i>	<i>ks</i>	<i>kpoff</i>	<i>kpoff</i>	<i>kpoff</i>	<i>kpoff</i>	<i>ks</i>	<i>ks</i>	<i>kpon</i>	<i>kpon</i>

***Initiated with 100% full kpon strategy:***

1.	HH1000	homogeneous landscape, constant timeseries of 1000 units per cell per timestep
2.	HVUK880	homogeneous landscape, UK rainfall data (average 880 units per cell per timestep)
3.	HVIRE965	homogeneous landscape, IRELAND rainfall data (average 965 units per cell per timestep)
4.	HVCOL1216	homogeneous landscape, COLUMBIA rainfall data (average 1216 units per cell per timestep)
5.	HVZIM1025	homogeneous landscape, ZIMBABWE rainfall data (average 1025 units per cell per timestep)
6.	HVBOT593	homogeneous landscape, BOTSWANA rainfall data (average 593 units per cell per timestep)
7.	HETZIM1025	heterogeneous landscape, ZIMBABWE rainfall data (average 1025 units per cell per timestep)
8.	HETBOT593	heterogeneous landscape BOTSWANA rainfall data (average 593 units per cell per timestep)

***Initiated with 100% mixed strategy:***

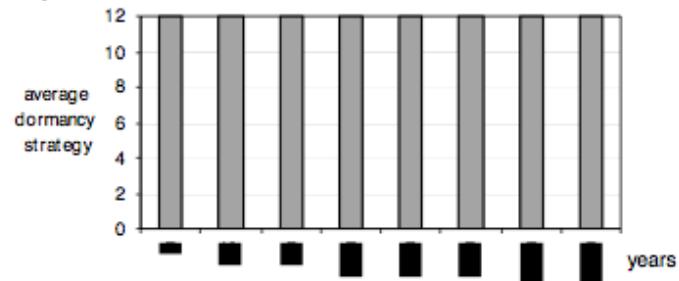
9.	HETZIM1025	heterogeneous landscape, ZIMBABWE rainfall data (average 1025 units per cell per timestep)
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***Initiated with 100% matched strategy:***

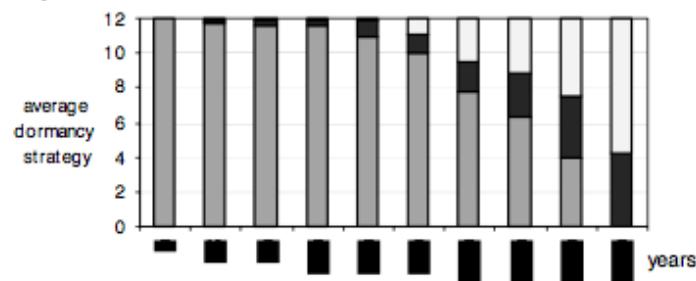
10.	HETBOT593	heterogeneous landscape, BOTSWANA rainfall data (average 593 units per cell per timestep)
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# Plantworld experiments

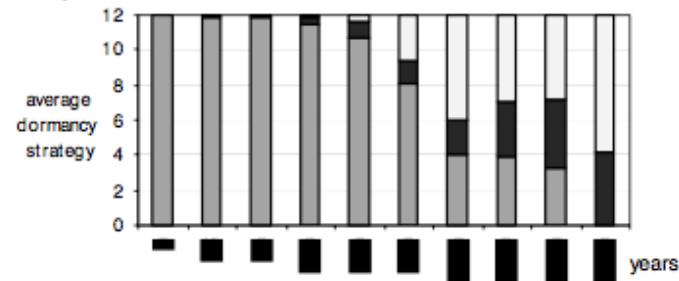
*Expt1. HH1000*



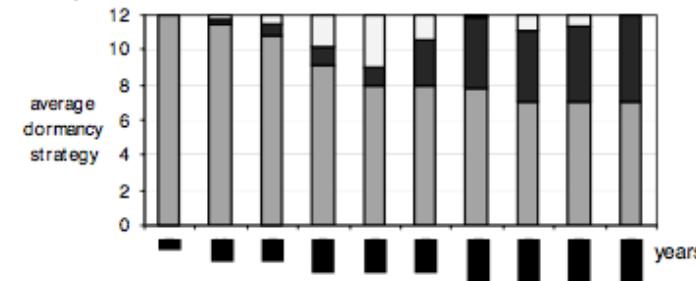
*Expt2. HVUK880*



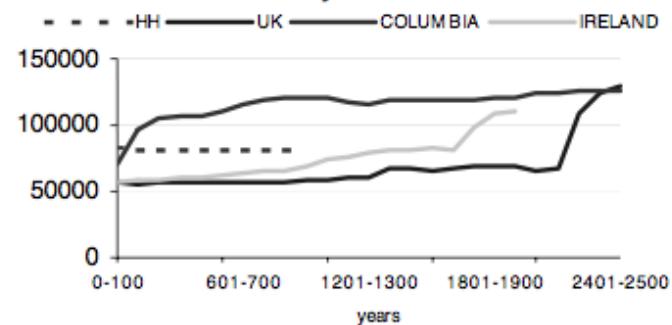
*Expt3: HVIRE965*



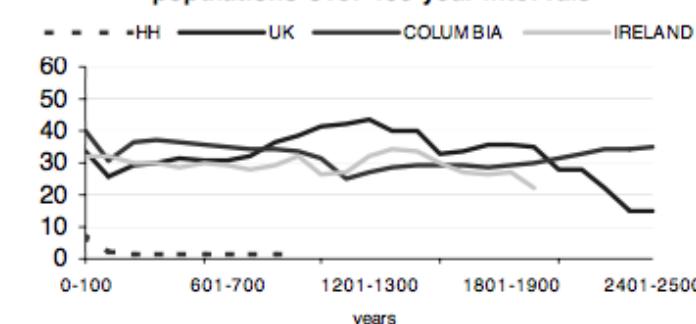
*Expt4: HVCOL1216*



**Average PLANT populations  
over 100-year intervals**



**Coefficient of variation in PLANT  
populations over 100-year intervals**



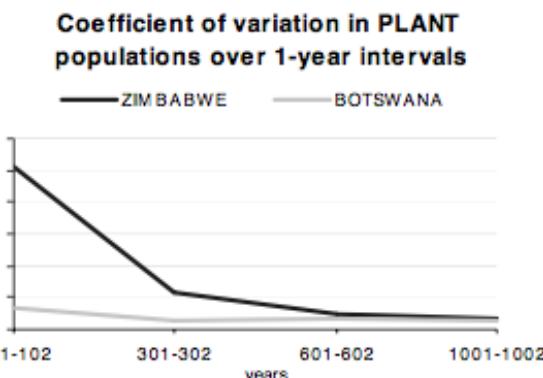
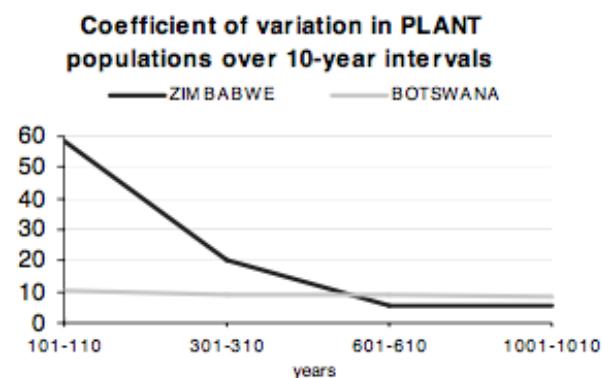
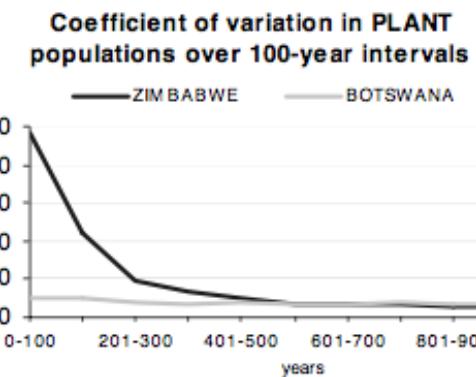
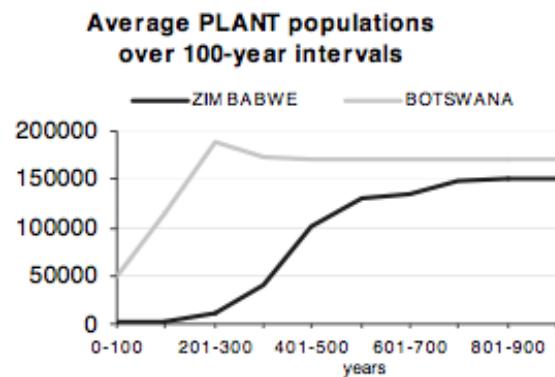
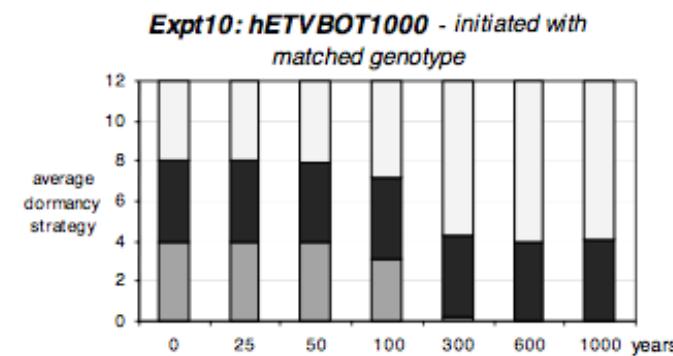
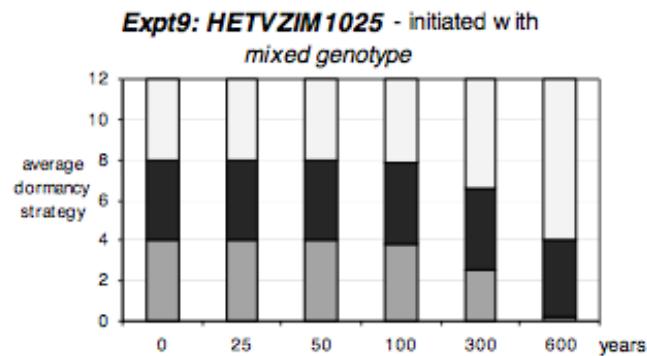


Figure 2: Evolution of dormancy and population dynamics in Experiments 7 – 10.

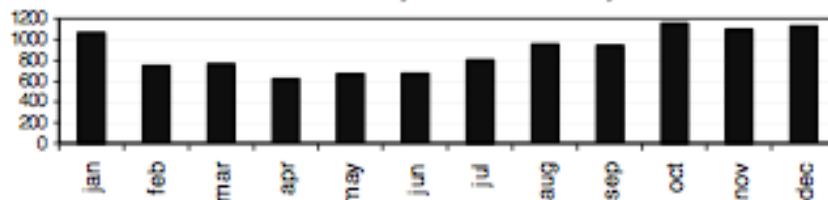
## Expt2: HVUK880

Most common genotype in population over time

*Allele position:*

year	1	2	3	4	5	6	7	8	9	10	11	12
0	129	kron										
100	129	kron										
300	129	kron	ks	off	kron							
600	128	kron	ks	off	kron	kron	ks	kron	kron	kron	kron	kron
1000	127	kron	ks	off	kron	off	ks	ks	kron	kron	kron	kron
1300	127	kron	ks	off	off	ks	ks	kron	kron	kron	kron	kron
1800	126	kron	ks	off	off	off	ks	ks	ks	kron	kron	kron
2500	126	ks	off	off	off	off	off	ks	ks	ks	ks	ks

UK880 - mean monthly rainfall over 100 years



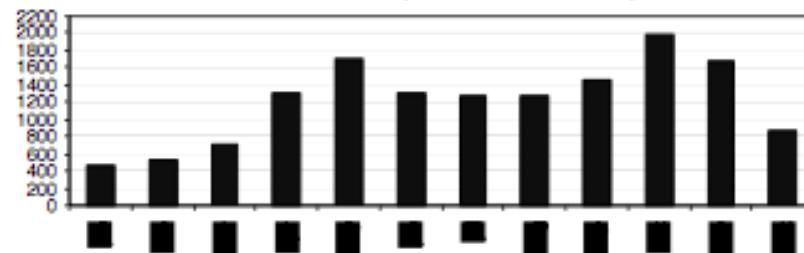
## Expt4: HVCOL1216

Most common genotype in population over time

*Allele position:*

year	1	2	3	4	5	6	7	8	9	10	11	12
0	129	kron										
100	129	ks	off	kron	ks							
300	129	ks	off	ks	kron	kron	kron	kron	kron	kron	ks	
600	128	ks	off	ks	kron	kron	kron	kron	kron	kron	ks	
1000	128	off	off	off	kron	kron	kron	kron	kron	kron	off	
1300	127	off	off	off	ks	kron	kron	kron	kron	kron	off	
1800	127	off	off	off	ks	kron	kron	kron	kron	kron	off	
2500	126	off	off	off	off	kron	kron	kron	kron	kron	off	

COL1216 - mean monthly rainfall over 100 years



- **Plantworld** showed that plants would evolve strategies of dormancy during periods of draught
- Like many Alife models, Plantworld was driven by real-world data, and was designed to test a clear hypothesis.
- It has no explicit fitness function; only an implicit notion of survival. Given a limited resource that must be consumed in order to survive, if the agents evolve appropriate strategies to make use of that resource then they will live, otherwise the species will become extinct.
- Plantworld allows experiments at a scale not possible outside a simulation, and analysis at greater depth than is possible in biology.

- Mosaic world is another example Alife model.
- In Mosaic world, vision is the important feature to be modelled – we want to investigate the evolution of colour vision (both the light receptors and the neural structures necessary to process the light)
- The hypothesis in this work is that in order for colour vision to evolve, the agent must be embodied in a sufficiently challenging world that forces that agent population to evolve to process colour.
- Senses do not evolve without reason, and while monochrome vision should be good enough for many situations, if the world contains significant features relating to survival that have ambiguous colour caused by unpredictable lighting changes, then colour vision should become necessary.

- As in natural environments, each stimulus arising from each surface in Mosaic World is determined by the relative contribution of its reflectance and its illumination:
- $Stimulus (S) = Reflectance (R) \cdot Illumination (I)$
- It is this ambiguous stimulus that is presented to the virtual agents, with the consequence that there is no direct way for the agent's sensors to estimate a given surface's type from the stimulus alone

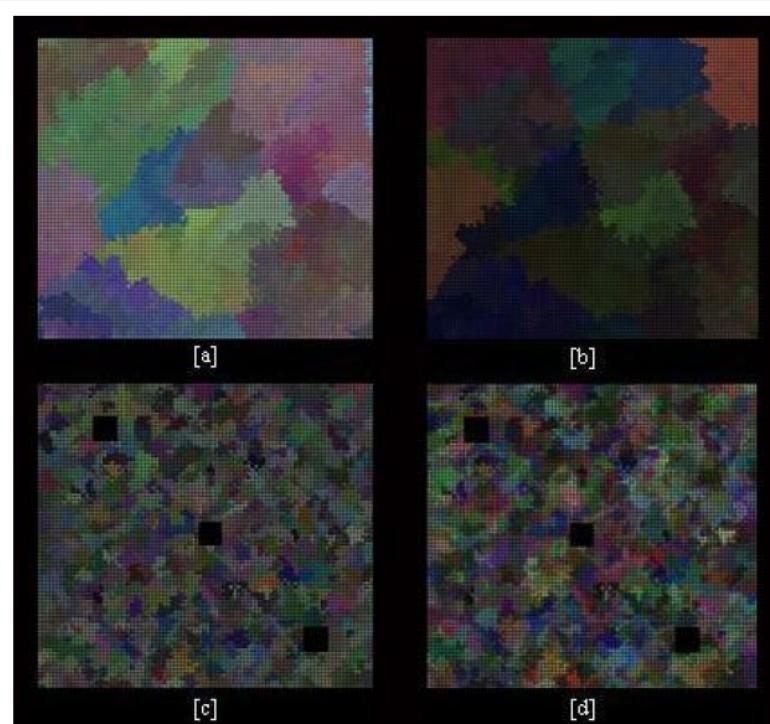


Figure 2: A few sample worlds. [a] Large clusters, uniform 'white' illumination. [b] Same world as [a] with multiple illuminants. [c] Many small clusters, uniform 'white' illumination, 3 holes. [d] Same world as [c] with multiple illuminants

# Mosaic World – the critter

Size: 1x1

*Transmittance wave function:* 0.33, 0.35, 0.37, 0.40, 0.42, 0.44, 0.45, 0.46, 0.46, 0.47, 0.48, 0.50, 0.52, 0.54, 0.56, 0.58, 0.57, 0.5, 0.53, 0.51, 0.49, 0.51, 0.52, 0.54, 0.55, 0.57, 0.58, 0.58, 0.59, 0.60, 0.61

*3D Neural network* (partially connected):

*Visual layer:* 3 units:

- Health unit
- Receptor 1: coordinate: [0,-1], peak: 680nm, tuning: 0.01226, active.
- Receptor 2: coordinate: [0,0], peak: 400nm, tuning: 0.02868, active.

*Hidden layer:* 4 units:

- Hidden unit 1: coordinate [-1,-1]
- Hidden unit 2: coordinate [0,0]
- Hidden unit 3: coordinate [2,0]
- Hidden unit 4: coordinate [-1,1]

*Output layer:* 7 units

*Active Connections:* 33

*Unconnected connections:* 1

Figure 3: Sample summarised critter genome

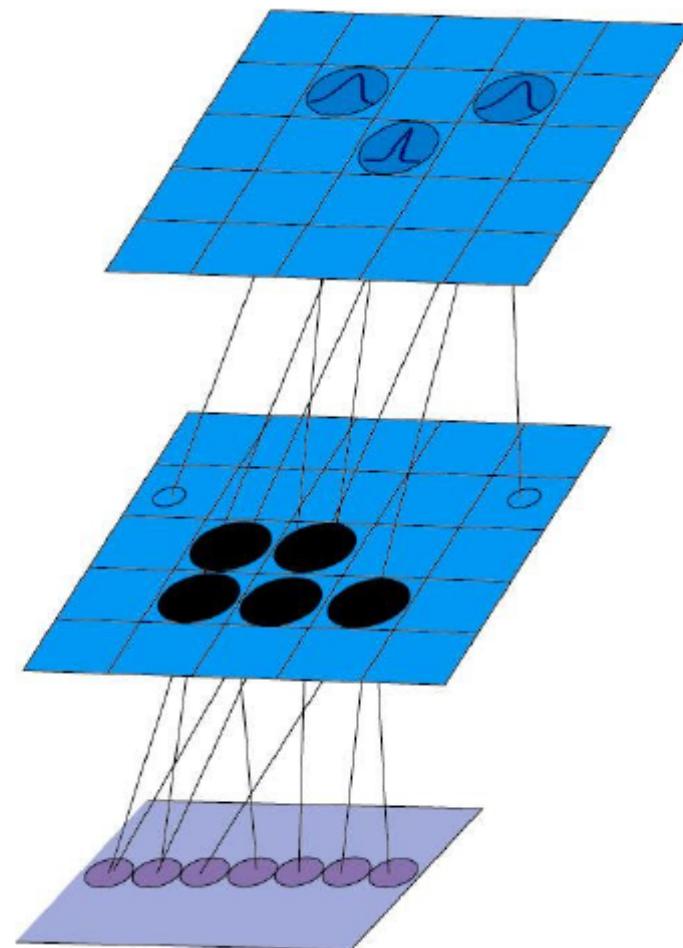
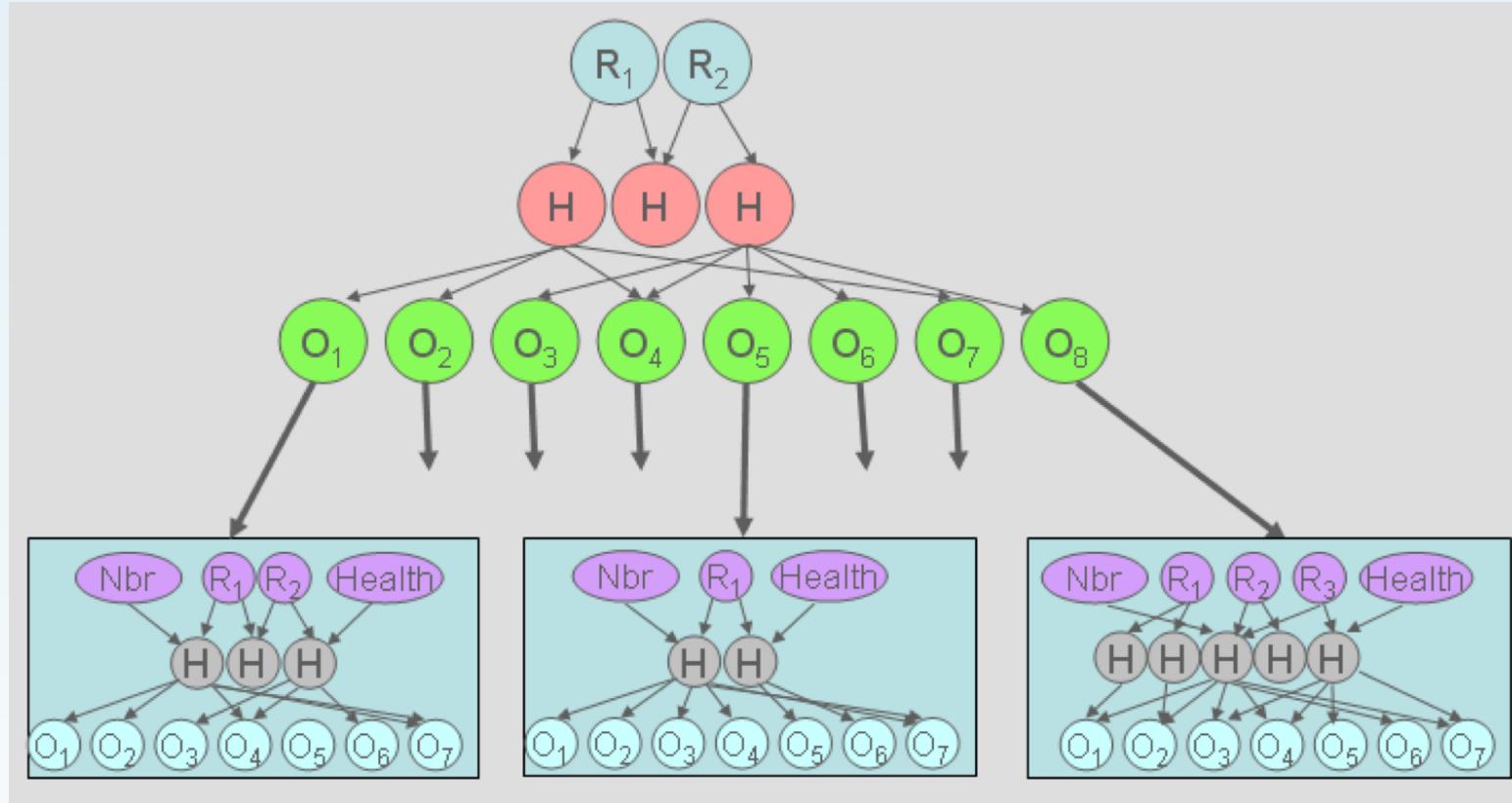
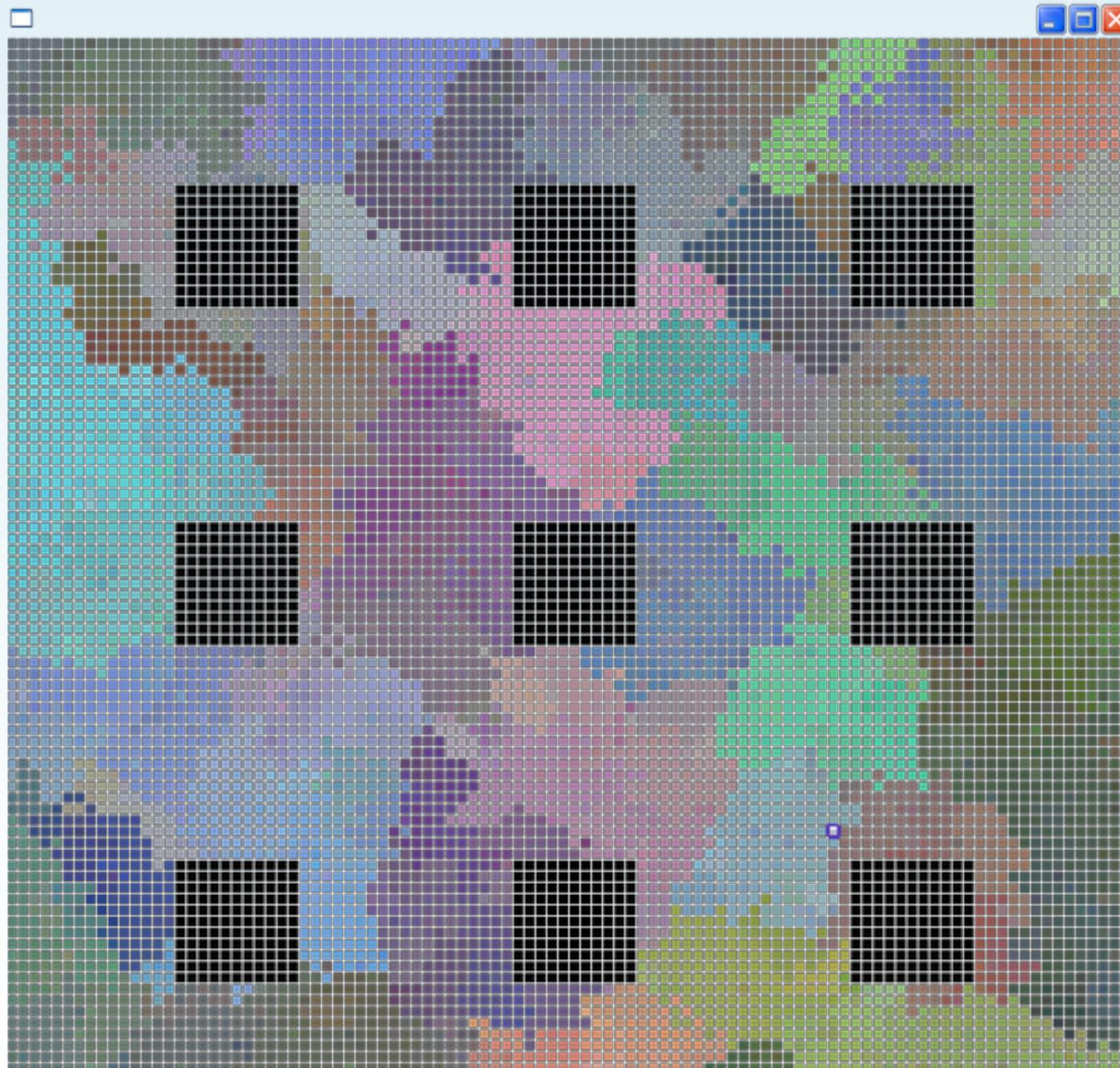


Figure 4: ‘Visual Brain’ - 3D neural network. This brain has three layers (one hidden layer). The visual layer contains three receptors (one highly tuned, the other two possess lower tuning values). The visual layer is connected to the hidden layer, specifically to five hidden units and two empty coordinates (partial connections). The hidden layer is connected to the output layer

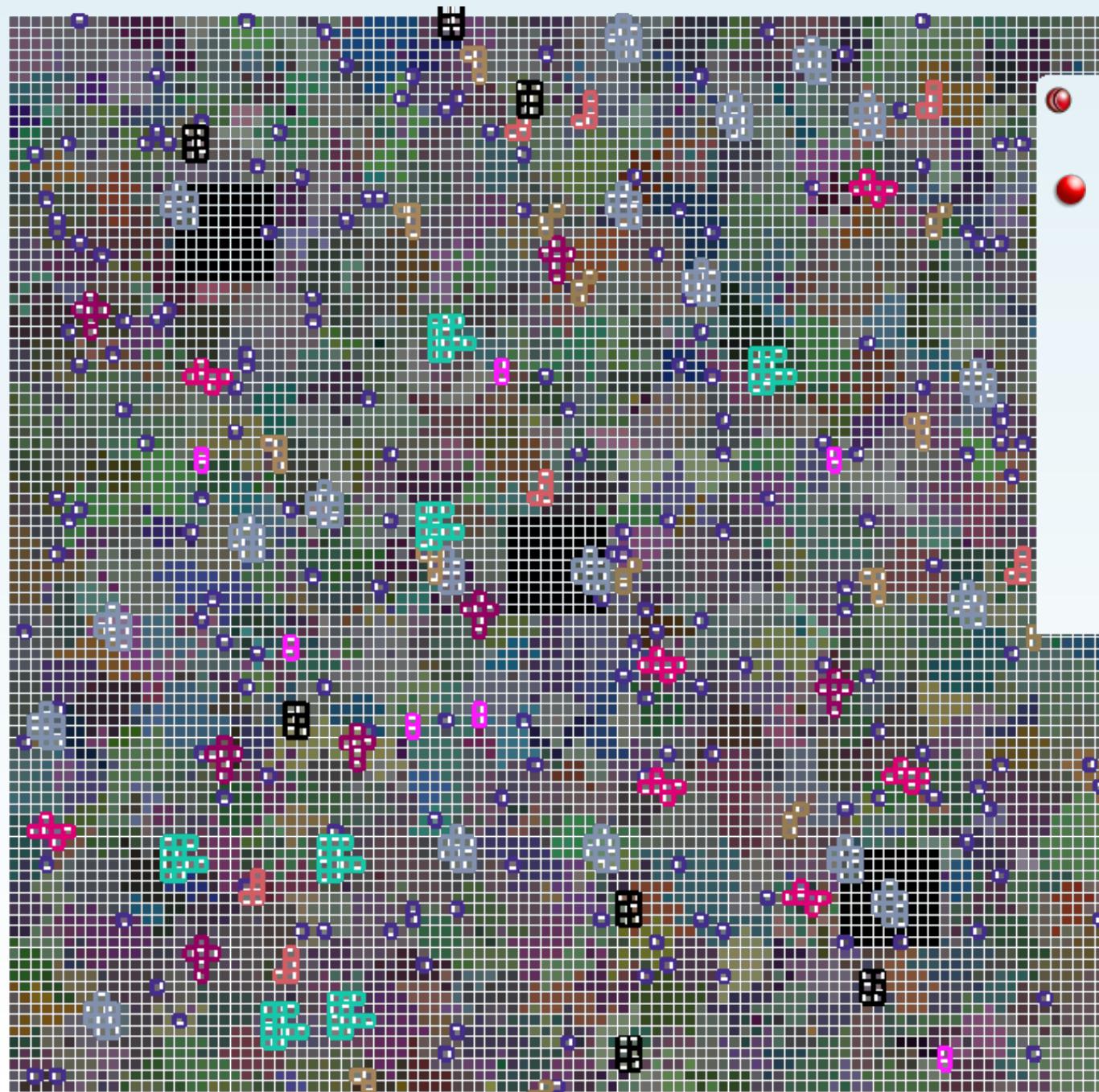


- A modular critter brain comprised of a gating network (2 receptors, 3 hidden units), that connects to 3 modules. (3D coordinate scheme not shown).
- Later model Critters also gained the ability to glue themselves together and become “multicellular”

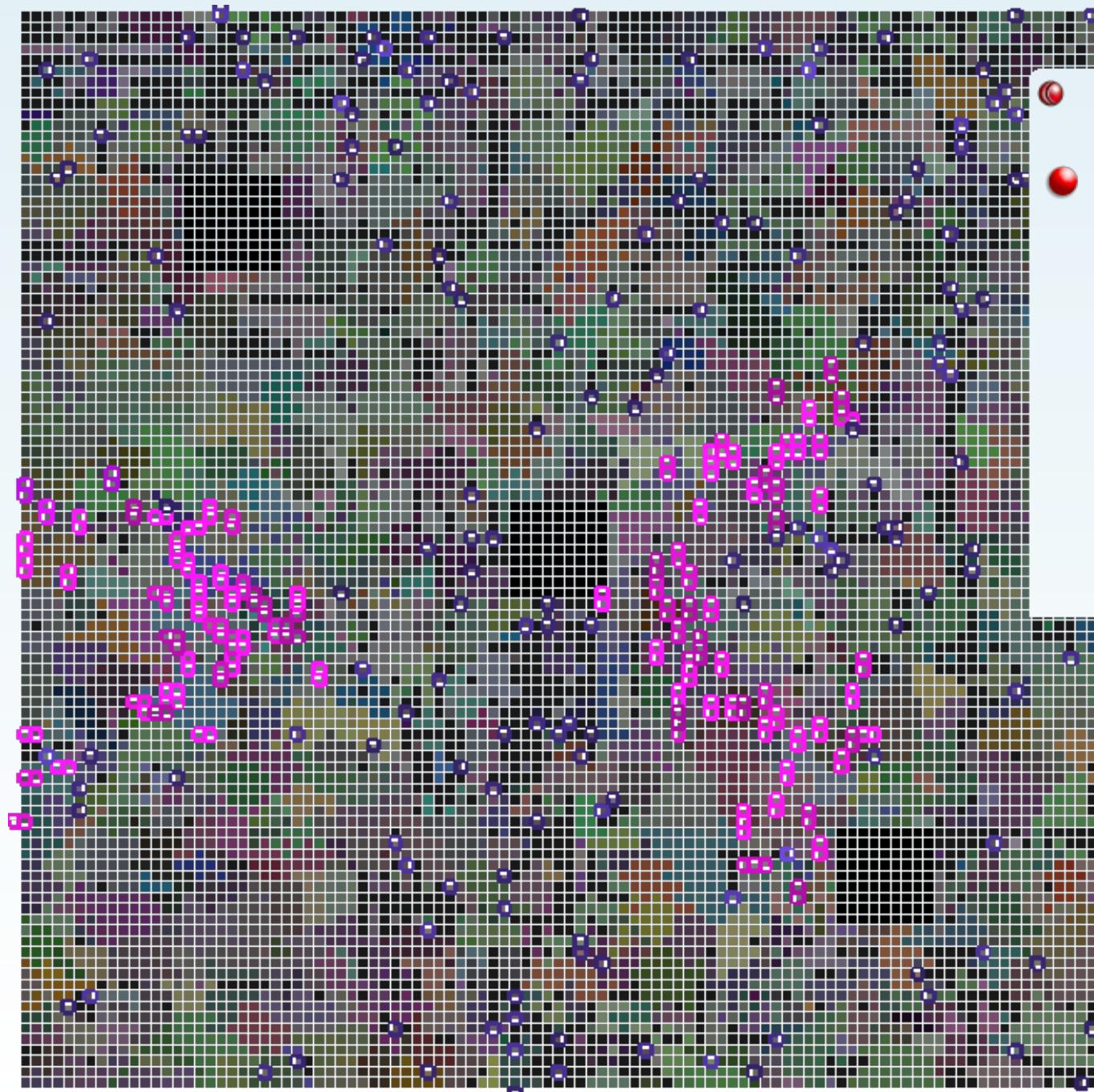
# Evolving perceptive critters



# Evolving perceptive critters

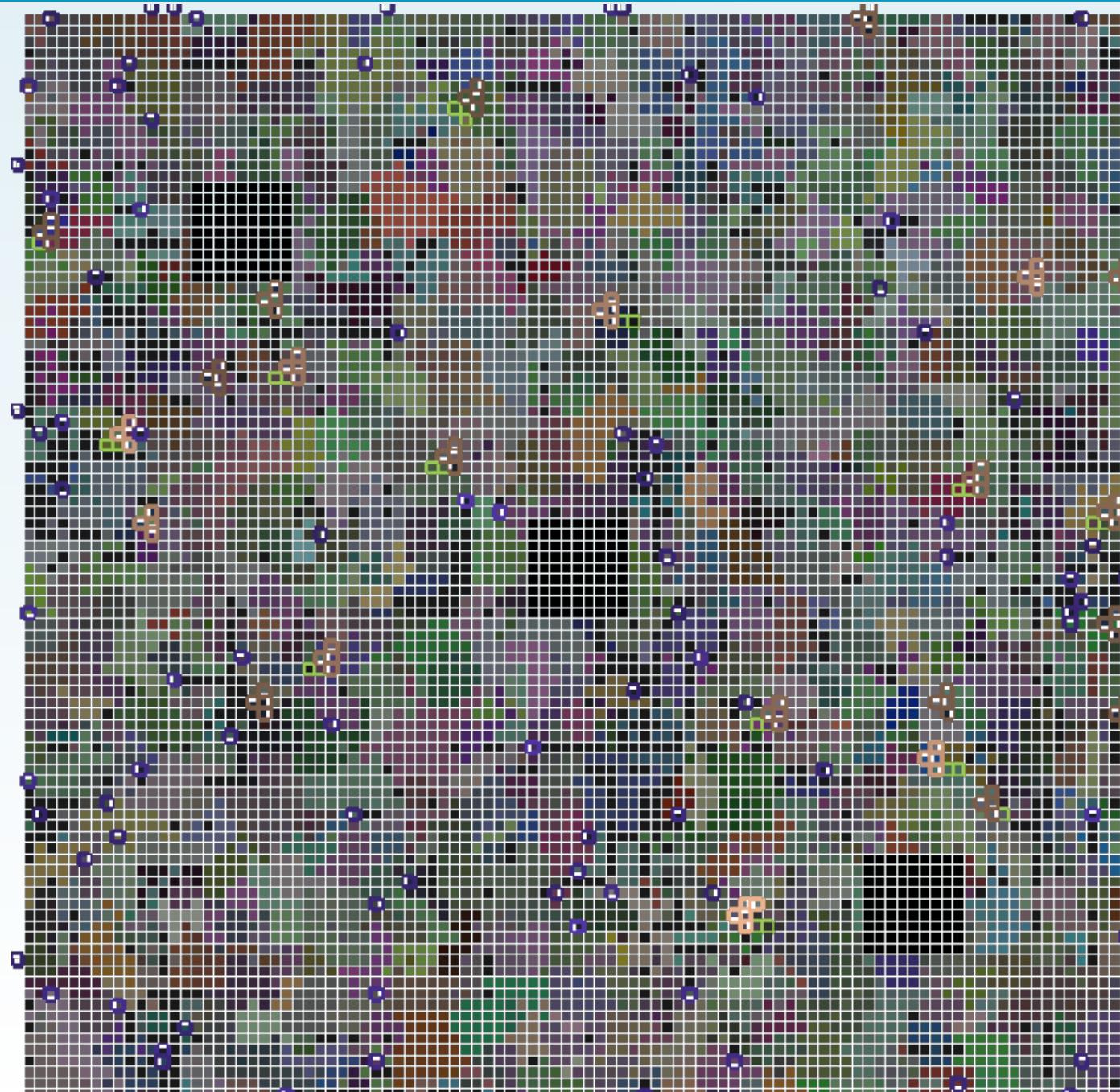


# Evolving perceptive critters



Udi Schlessinger

# Critters with shells



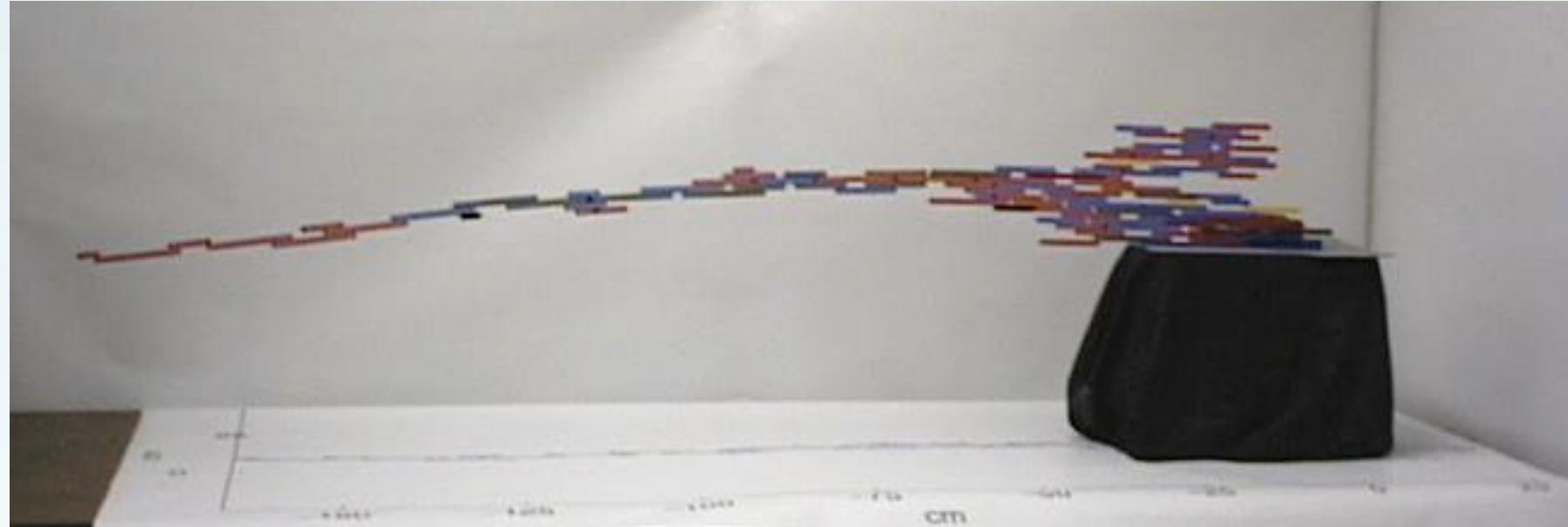
- Evolutionary robotics examines many different aspects of applied evolutionary algorithms, including morphology, control, perception and even self-\* (self-adapting, self-assembling, self-repairing, etc)
- One of the biggest problems is the **reality gap**, or the **transference problem**
- We are usually forced to evolve many or most aspects of the robots in simulation, but transferring the evolved solutions for the shape, controller or perception into the real world usually results in considerably worse performance or even failure.
- Reality is complex and our simulations are not.
- The answer is either improve the simulations, or try to evolve embodied robots – evaluate them in the real world (or both).

- **Buildable simulation**
- One way to reduce the reality gap is to constrain the possible building blocks and the environment.
- An example of this was the work by Pablo Funes on buildable LEGO structures. The physical properties of LEGO bricks are designed to be consistent, reliable and predictable, making them much easier to model.
- The requirements for their model (and indeed any model of this type) were:
  - *Representation*: it should be capable of modelling the behaviour of any possible evolved form
  - *Conservative*: recognise that the simulation will be imperfect so build in a margin of error
  - *Efficient*: the model should be quicker than reality
  - *Buildable*: it should be possible to transfer the evolved results into the real world (i.e., don't allow physically impossible solutions).

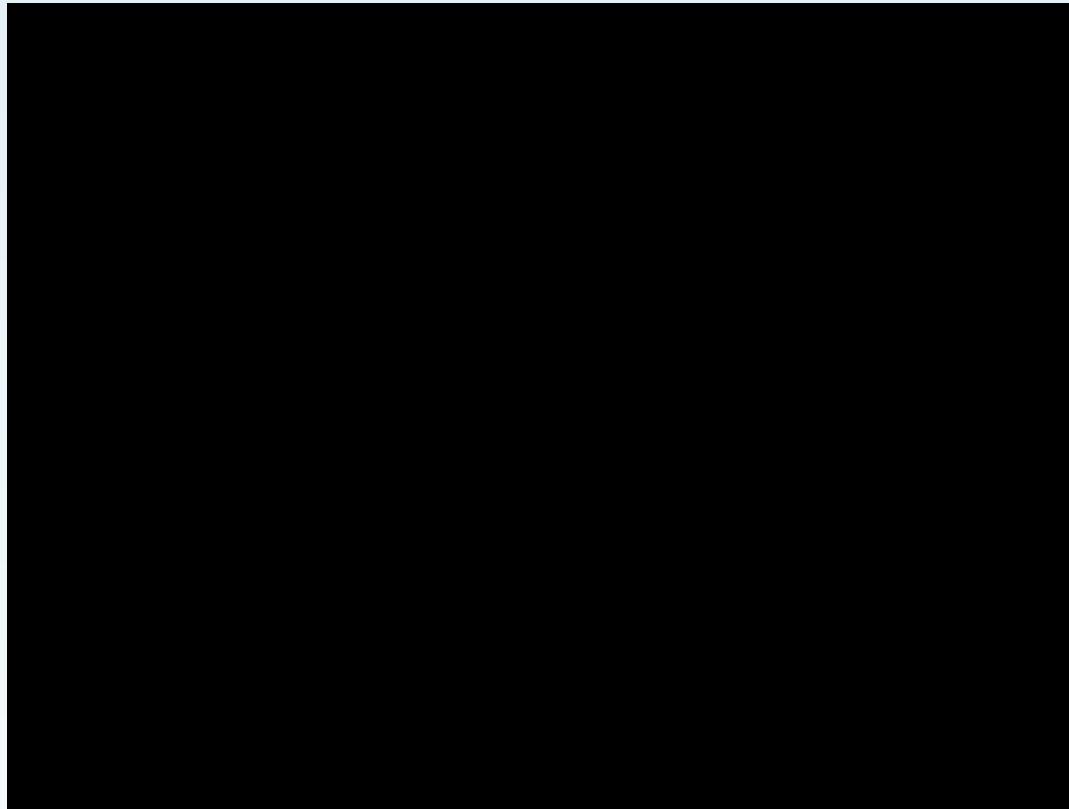
- Their model was still a simplification of reality (it considers the union of two bricks as a rigid joint between the centre of masses of each one, located at the centre of the actual area of contact between them)
- However it was good enough to enable a genetic algorithm to evolve a series of structures capable of spanning distances or carrying weights.
- To prove these were valid morphologies, the team then built those evolved structures and tested them for real.



- The problem was to construct a 'Bridge' structure fixed to one of the tables in the lab that would span the distance of 1.5m that separated it from a neighboring table. The animation follows the lineage of an individual from its humble beginnings (a single brick) all the way through the final solution. Both mutations, changes affecting only one brick, and crossovers, addition or removal of part of the structure of another individual, can be observed.

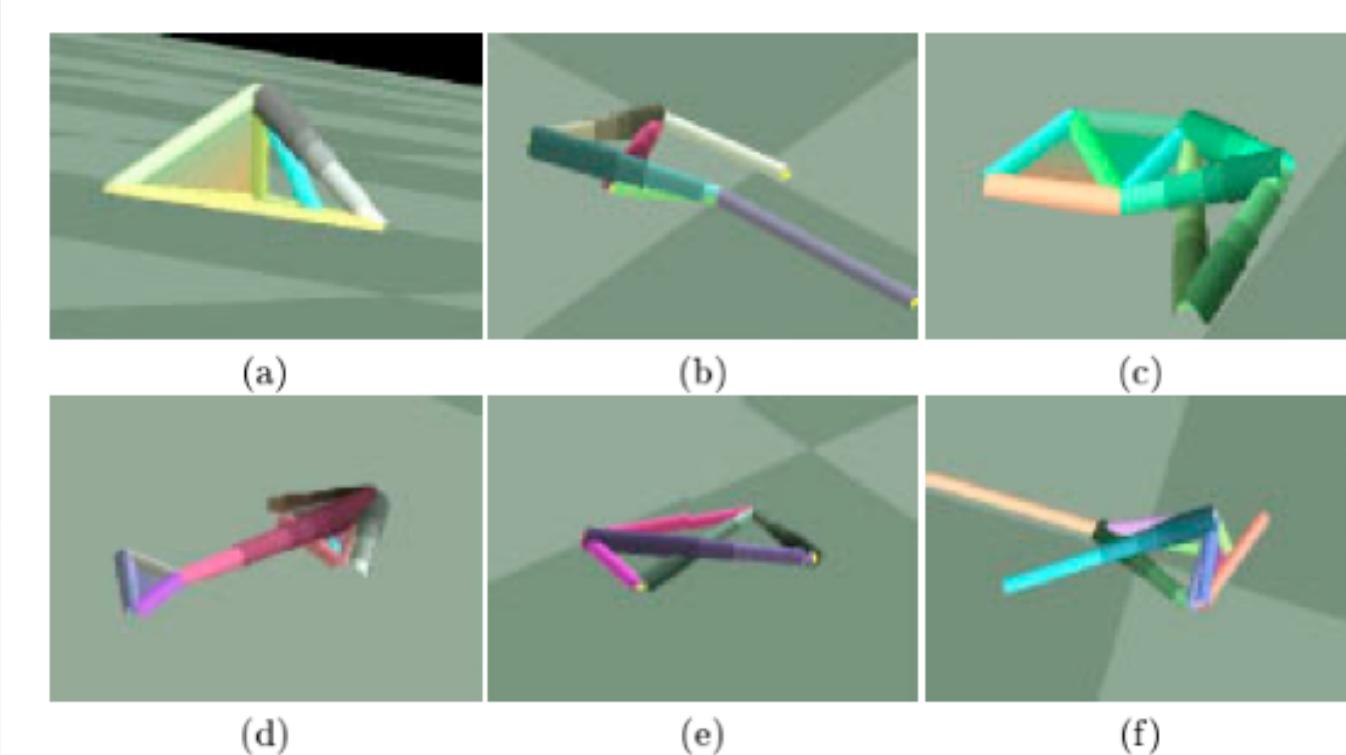


- The "Long Bridge" is really a cantilever: They just asked the computer to evolve a structure as long as possible. The result spans almost 2 meters.



- This animation shows their evolutionary LEGO crane in action. The arm of this crane was evolved by the evolutionary LEGO simulation system to lift a weight of .5 kg. They designed a rotating base for the crane and fed it into the genetic algorithm in the form of a set of constraints. After a satisfactory arm was found, the computer printed a schematic of the arm. They built it, carefully following the instructions. This video shows the crane lifting a .5 kg roll of solder.

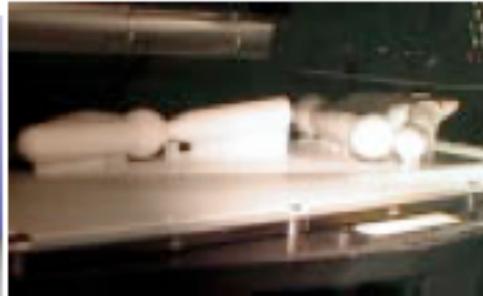
- Jordan Pollack and Hod Lipson at Brandeis were also the first to use 3D printer technology as a way of transferring evolved robot morphologies into the real world.
- Their physical simulator (not unlike that used by Karl Sims) enabled only linear actuators, calibrated to exert the same forces as produced by real linear actuators.
- Robot bodies were then evolved using a representation of “bars” and linear actuators. The actuators were controlled by evolved neural networks.
- Both brain and body were evolved at the same time (like the brain and perception and bodies of the Critters we saw earlier).
- The fitness function was also like Karl Sims’ – the robots were fitter if they could move further in a given time period.



**Fig. 3.** (a) A tetrahedral mechanism that produces hinge-like motion and advances by pushing the central bar against the floor. (b) Bi-pedalism: the left and right limbs are advanced in alternating thrusts. (c) Moves its two articulated components to produce crab-like sideways motion. (d) While the upper two limbs push, the central body is retracted, and vice versa. (e) This simple mechanism uses the top bar to delicately shift balance from side to side, shifting the friction point to either side as it creates oscillatory motion and advances. (f) This mechanism has an elevated body, from which it pushes an actuator down directly onto the floor to create ratcheting motion. It has a few redundant bars dragged on the floor.



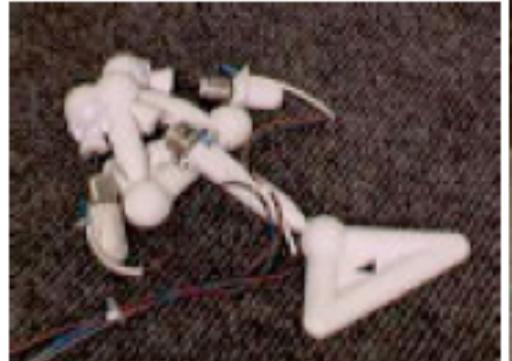
(a)



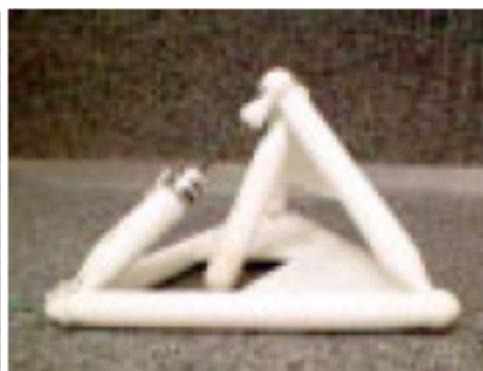
(b)



(c)



(d)



(e)



(f)

**Fig. 4.** (a) Fleshed joints, (b) replication progress, (c) pre-assembled robot (figure 3f),  
(d,e,f) final robots with assembled motors



- Even once a robot is built and running, it is possible to evolve its behaviour.
- This may be desirable in order to achieve adaptive behaviour – for example should the environment of the robot change or should the task or mission for the robot be altered, then new behaviour is needed.
- Richard Watson's work demonstrated one way to achieve this.
- He used a population of robots, first evolving their brains (neural networks) offline to get them started, then allowing them to continue to evolve while actually working.
- A little like a swarm, each robot calculated how well it performed its current task – if doing well then it broadcast its genes using infrared. Any robot receiving this transmission who was doing less well, would inherit these new genes and get a new brain as a result.

- So more successful robots influence others while attempting to resist being influenced by others.
- The robots operate on a powered floor and wireless communication, enabling long term robot evolution tests without the “reset problem” or other problems of cables and power.
- However, this solution assumes that robots do not become isolated or unable to communicate with each other...



(a)



(b)

**Fig. 5.** 4" diameter robot picks up power from its environment and learns while on-line.

- The best platforms for evolution are those that are more **embodied**
- One good definition of embodiment is:

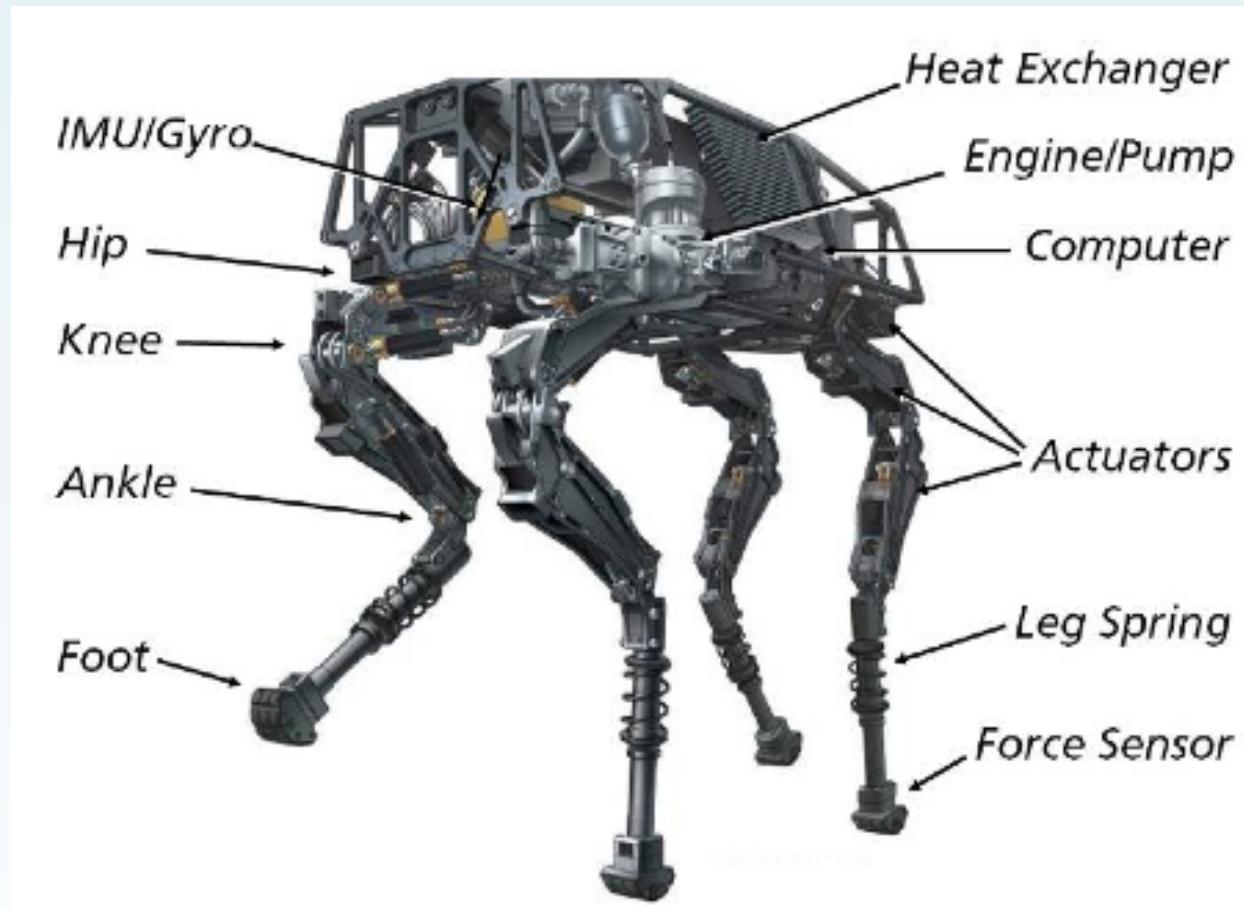
*A system is embodied if it can be affected by its environment and it can affect its environment.*

- The more *perturbatory channels* (sensors / actuators) that exist between the system and environment, the more embodied that system is.
- So a robot which has more flexibility in its actuators, and plasticity in its morphology, control and sensors, can adapt itself physically and in terms of its behaviour in response to a rich set of inputs.
- It can also modify its environment in order to make it more suitable for its needs, just as we do.



# **Embodied Cognition in a Compliantly Engineered Robot**

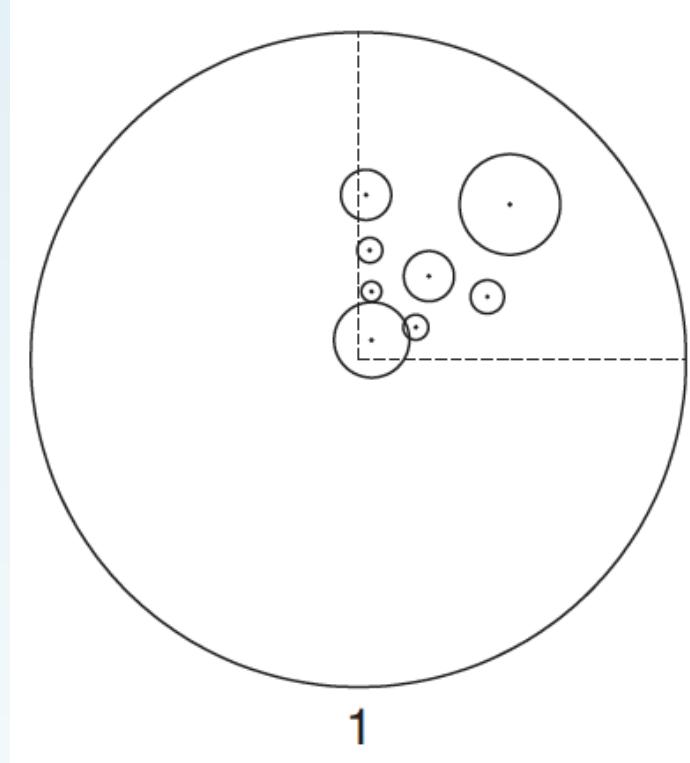
Technische Universität München  
Robotics and Embedded Systems



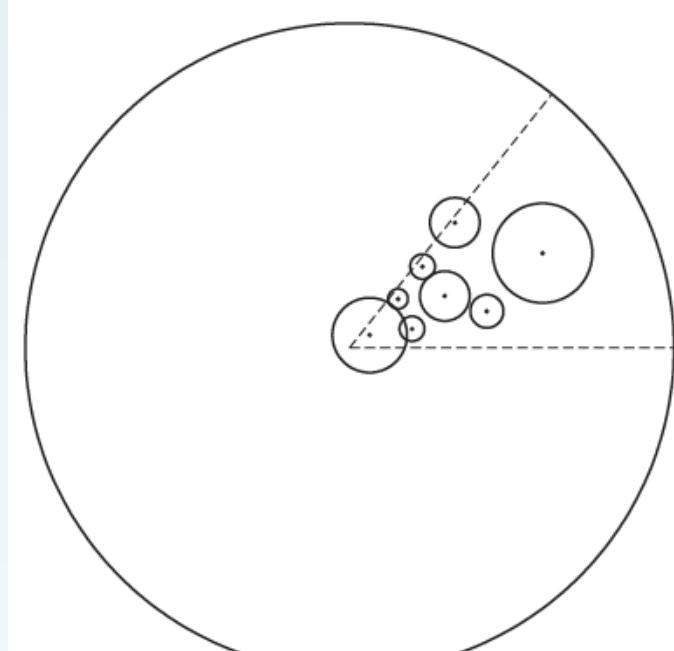


- Real world problems are usually much more messy than the simple problems researchers prefer to tackle
- It's common for there to be multiple objectives, and multiple good solutions.
- It's common for the fitness function to be noisy and unpredictable (especially in evolutionary robotics)
- Standard GAs are rarely used. More commonly:
  - Real-coded GAs are used (genes are real numbers and mutation creeps the numbers up or down by small random increments)
  - There may be variable-length chromosomes. Why do you think this is a problem?
  - Methods such as elitism and lifespans are needed to hold onto good solutions yet prevent them from becoming immortal.
  - Constraints are common. How do you think constraints should be handled in a GA?
  - Complex representations may be needed.

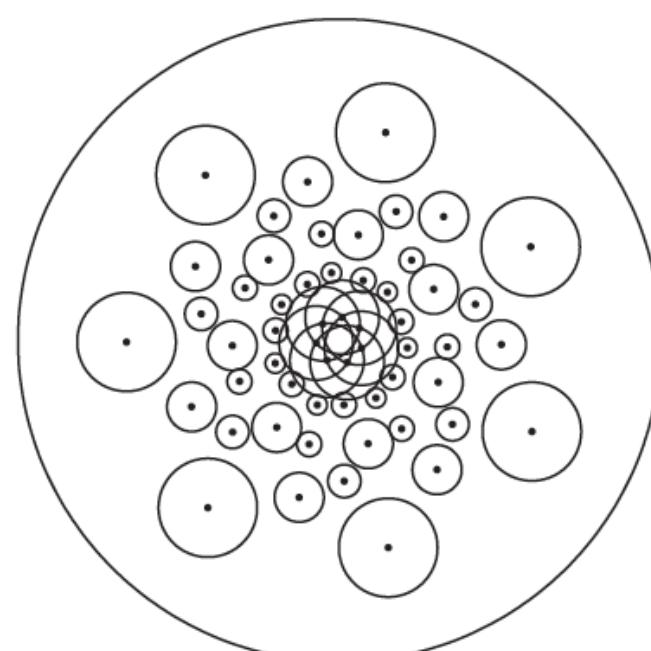
- Luckily, not all real-world problems are beyond our reach.
- One example is Steve Manos' fibre optic cables.
- In fibre optics, having holey cables can help specific frequencies of light travel further.
- The optical characteristics of a specific hole pattern can be simulated.
- However with an infinite number of possible hole patterns, and some manufacturing constraints, how to design the best holey optical cable?



- Step 1. The binary genotype is decoded into the symmetry  $n_{symm}$ , and  $N_h$  triplets of  $xi$ ,  $yi$ ,  $ri$  values. The triplets describe the placement of holes in the first sector of the  $x$ ,  $y$  plane, forming the raw structure with  $n_{symm} = 4$ . The binary versions of  $xi$ ,  $yi$  are decoded to the real valued position of the hole.  $ri$  is decoded to an integer value: each possible value refers to a user defined list of available hole sizes, which reflect the available drills used to produce the initial MPOF preform.

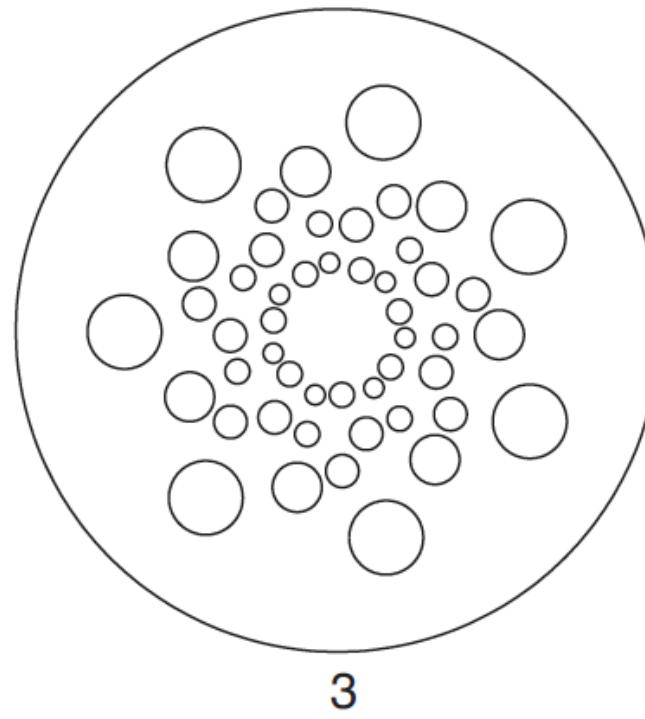


2a



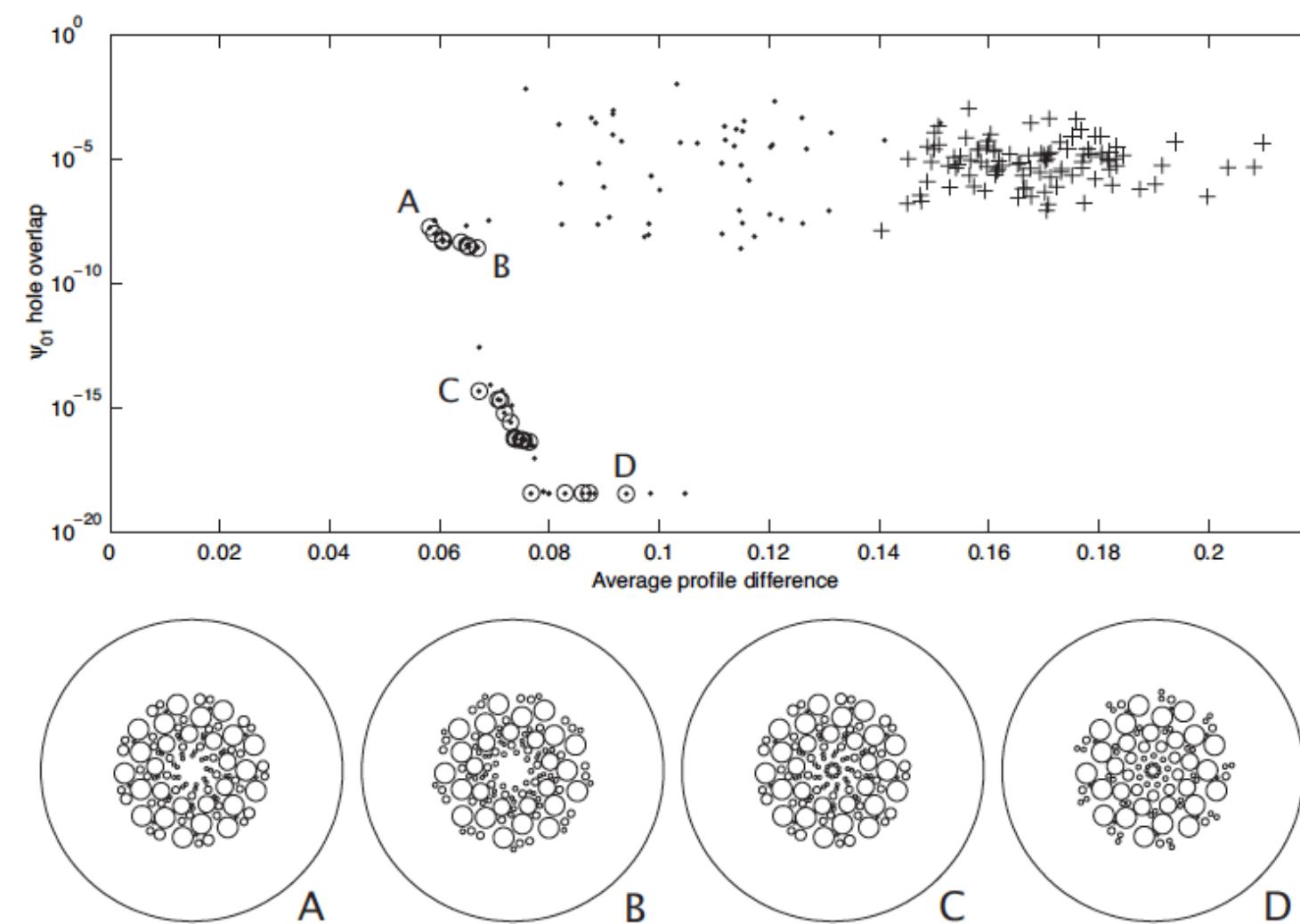
2b

- Step 2. The  $N_h$  hole positions  $x_i, y_i$  are reflected into the new symmetry  $n_{symm}$  (a symmetry of 7 is used in the above example).
- 2a. The holes are converted to polar coordinates  $(ri, i)$ , where  $i$  values are scaled by  $n_{symm}/4$ .
- 2b.  $(n_{symm} - 1)$  copies of the holes are made to complete the fibre.



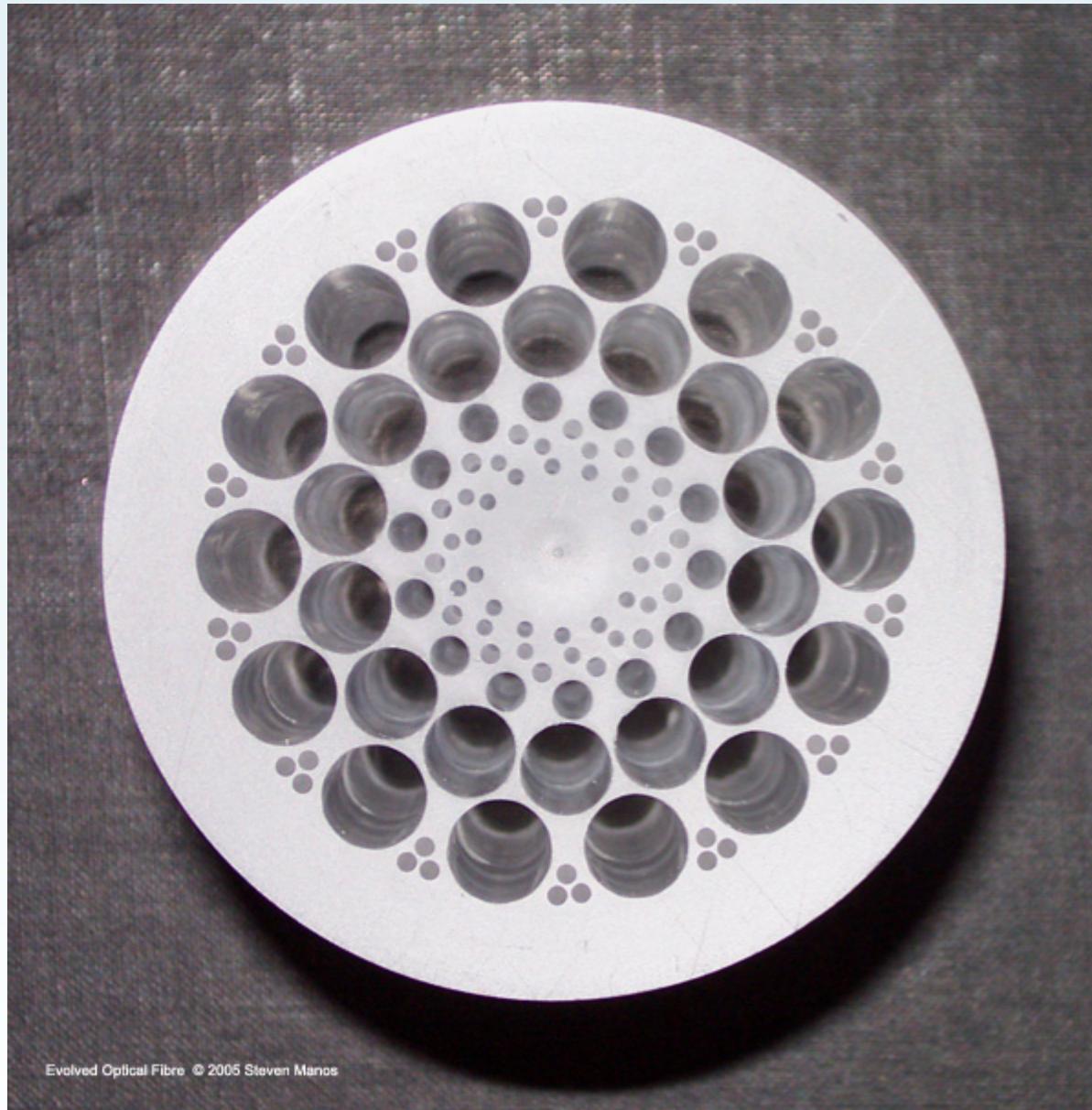
- Step 3. The holes are grown until manufacturing constraints prohibit further growth. The holes are grown in a step wise manner through the list of available hole sizes, and stop growing when they too close to a neighbouring hole or exceed their own maximum radius  $r_i$ . Growth states are updated in parallel at the end of every hole growth cycle, and the cycle is terminated when the growth state of every hole is false.

- In this work there are two key objectives:
- Bandwidth
- Transmission loss
- So a multiobjective GA was used.



**Fig. 8. Top:** Population evolution with respect to the 2 design objectives. Crosses indicate the initial population, black dots the final population after 5000 generations and circles the final non-dominated set. **Bottom:** Four designs from the final non-dominated set, A,B,C and D are shown.

# Steven Manos and his holey fibre optics



Evolved Optical Fibre © 2005 Steven Manos

- The work was very successful, winning awards for human-competitive results.
- Many of the designs were better than human designers could create and have been patented.
- Steve created a company to exploit this technology.

**End of Lecture!**