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Emergence of Complex Functionality in Physically Evolving Networks

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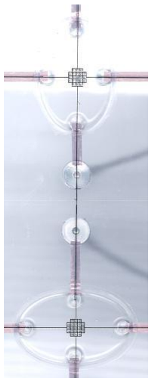
What patterns and functions can arbortron base units understand?

How do the design parameters influence performance?

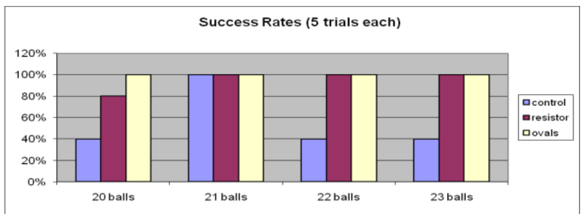
Are there overarching principles?

How is the performance affected by thermal noise?

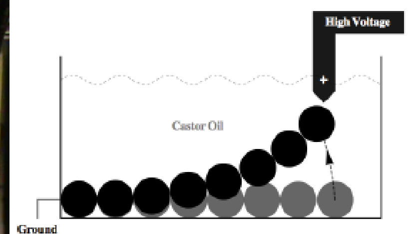
Arbortron = self-assembling branched wire network



Networks with non-identical base units process input faster and more reliable.



3D arbortrons can process complicated functions.



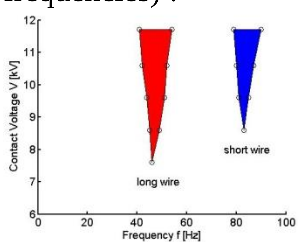
Thresholds enable arbortrons to learn nonlinear Boolean

A=1mA, B=1mA

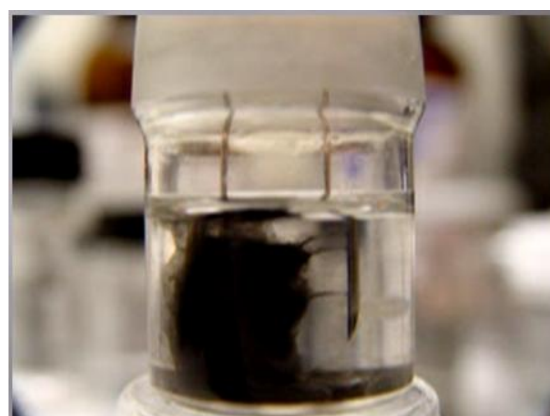
large output current

Thermal noise helps to unlearn and to break symmetries .

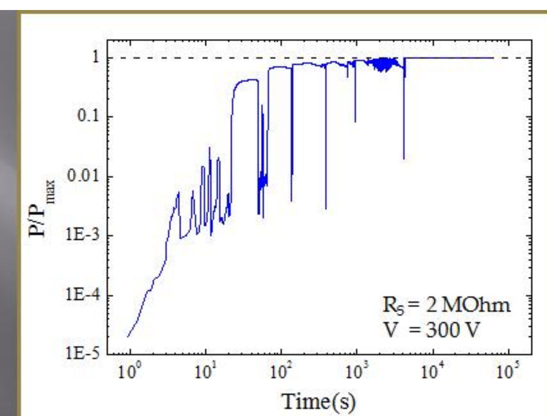
Arbortrons learn to recognize patterns (and frequencies) .



Nano implemenations require less voltage.



Entropy production is maximized if the voltage and temperature are kept constant



Sponsors: DARPA, Air Force

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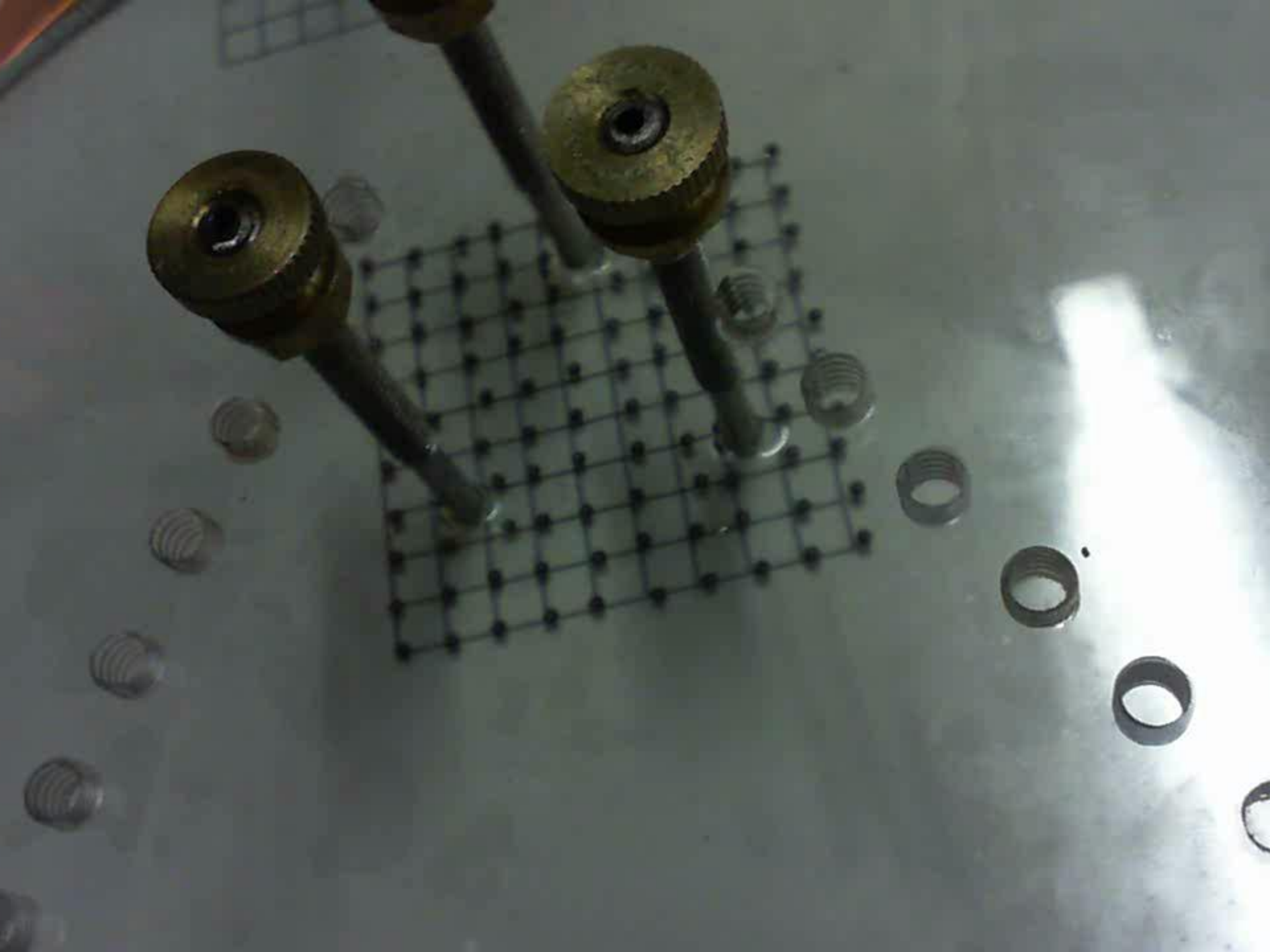
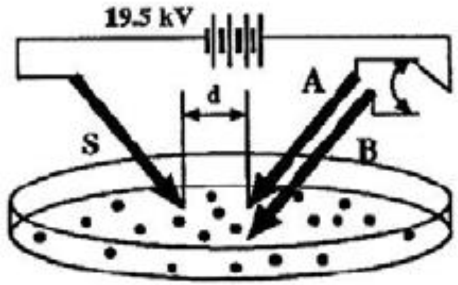
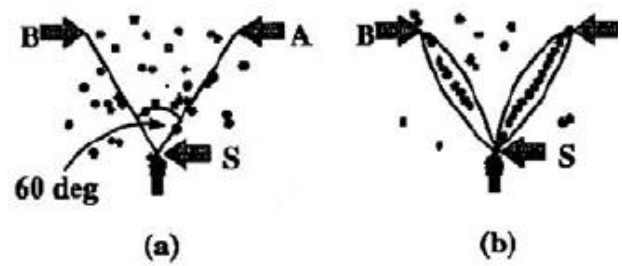


Introduction

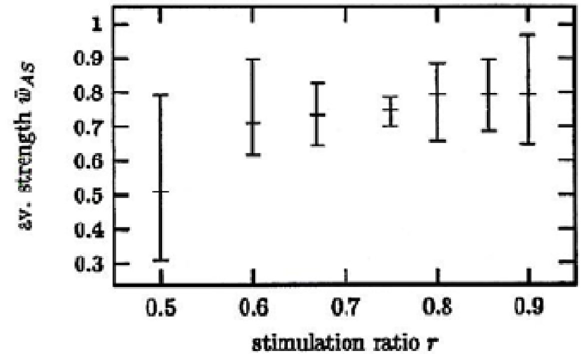
A three-electrode system is a simple perceptron:
Fixed number of accessible particles => competition for particles
Therefore, more usage => larger conductance (neural plasticity, Hebb)

$$w_{AS}=\frac{N_A}{N_A+N_B},$$





(a) (b)



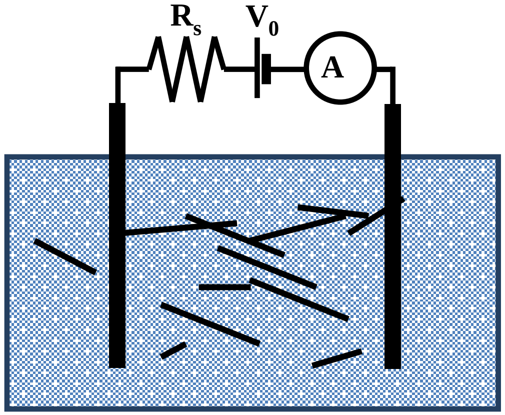
M. Sperl, A Chang, N. Weber, A. Hubler, *Hebbian Learning in the Agglomeration of Conducting Particles*, Phys.Rev.E. **59**, 3165 (1999)

Hypothesis: Self-assembling nano-particle networks can process information like biological neural networks and have several advantages:
- Nano-particle wires are a factor 1000 thinner, therefore 1000x1000x1000=1billion nano particle wires fit in the volume occupied by one biological neuron (human: 100billion neurons,
- Pulses on nano-particle wires move with the speed of light ($3x10^8$m/s), whereas biological conduction velocities 1m/s – 100m/s
- Networks of super conducting nano-particle wires have a very low power consumption, because the resistance of conducting particles is small in comparison to biological tissue

Problem: How does such a thermodynamic nano particle system learn, become intelligent?

Experiment: Arbortrons

Figure on the left: Consecutive snapshots of the sample illustrating the formation of carbon nanotube chains under the influence of the electric field without electro-convection. The wires grow continuously until they connect. Then they gradually become thicker. The distance between electrodes is 1cm, applied voltage is V_0=400 V, and the series resistor is R_s=100 MOhm. The top photograph demonstrates the fluid with nanotubes before the voltage is applied. The following photographs show the process of pattern formation and they are taken after the voltage is applied at t=45 s, t=90 s and t=1800 s.



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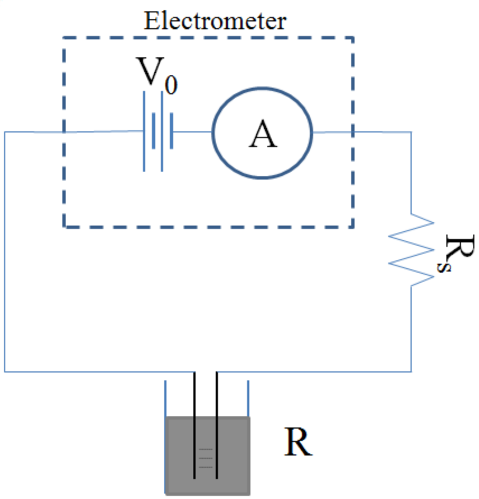
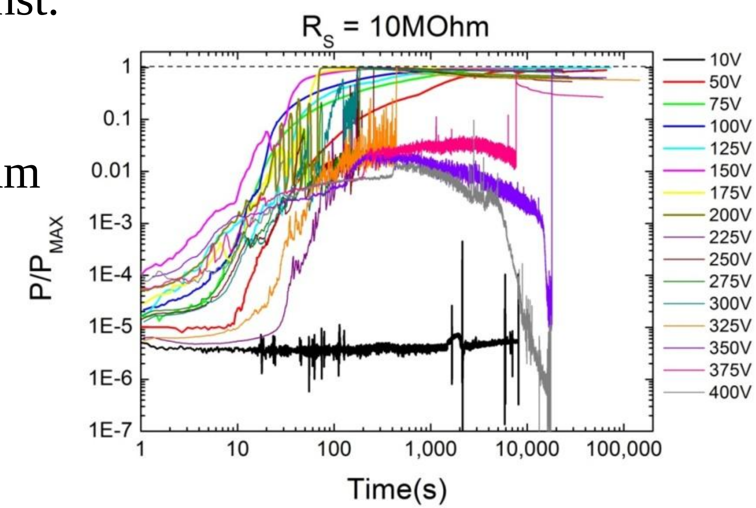
Experiment
Growth of Carbon Nano Tube (CNT) Synapses



Voltage V= 10V - 500 V = const.
Current $I = V / (R + R_s)$
R resistant of oil + CNTs
R_s resistor in series 160 M Ohm
Power dissipated in oil/CNTs:
$P = R I^2 = R V^2 / (R + Rs)^2$

<u>Power P has a maximum at $R = R_s$</u>



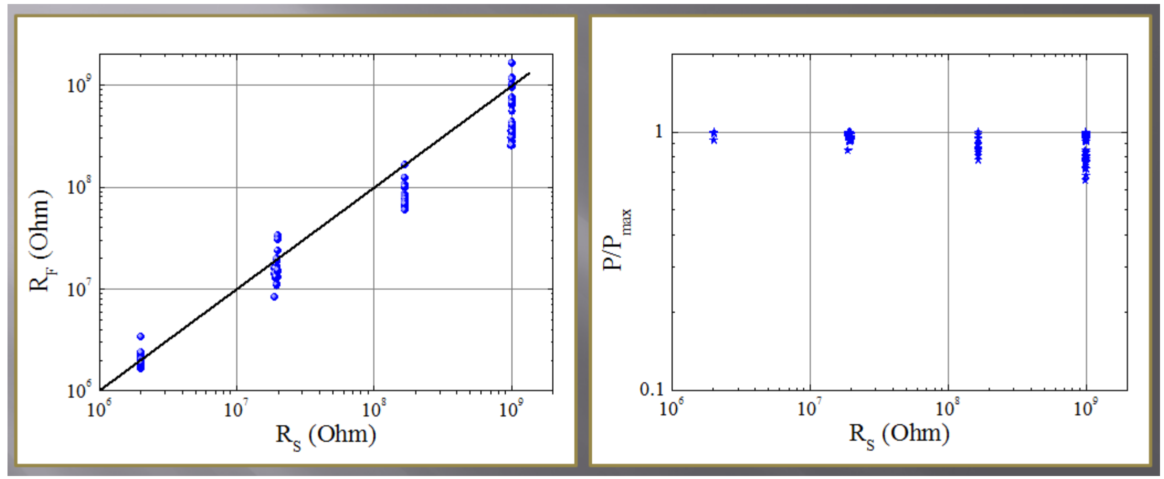
Two regimes of self-assembly:
- <u>Convection regime</u> (0s < time < 900s): Creation of chains and their annihilation due to electro convection.
- <u>Stable regime</u> (time > 900s) : The maximum possible dissipated power is reached (maximum for the fluid with nano particles only). Slow formation of additional chains stabilizes the system.

<u>In the stable regime the resistance of the electo-rheological fluid is of the same order of magnitude as the resistance of the series resistor R_s, i.e. $R = R_s$.</u>
<u>If the temperature is kept constant, the limiting state has maximum entropy production in the oil/CNT system.</u>

Experimental Results: CNT Synapses

Preliminary results:

- Electro convection destroys CNT Synapses.
- The limiting wire resistance R_F is equal to the series resistance R_S
- Ohmic heating in the wires is maximized.
- Maximum power wires have the largest tensile strength.

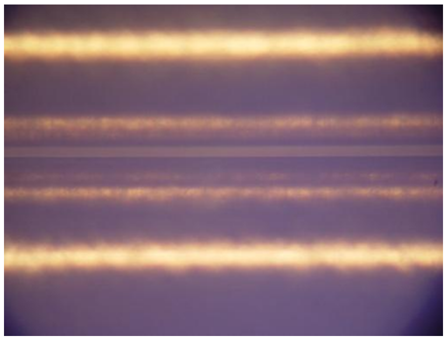


Figures: Limiting resistance and limiting power versus series resistance

Arbortrons: Grounded graphite nano particles – Self-assembling micro wires at **10V** in a 50µm gap with R_s= 20MOhm

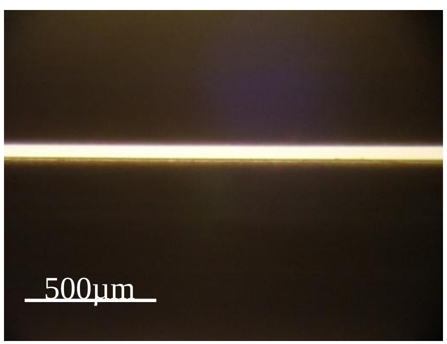
Bright Field View

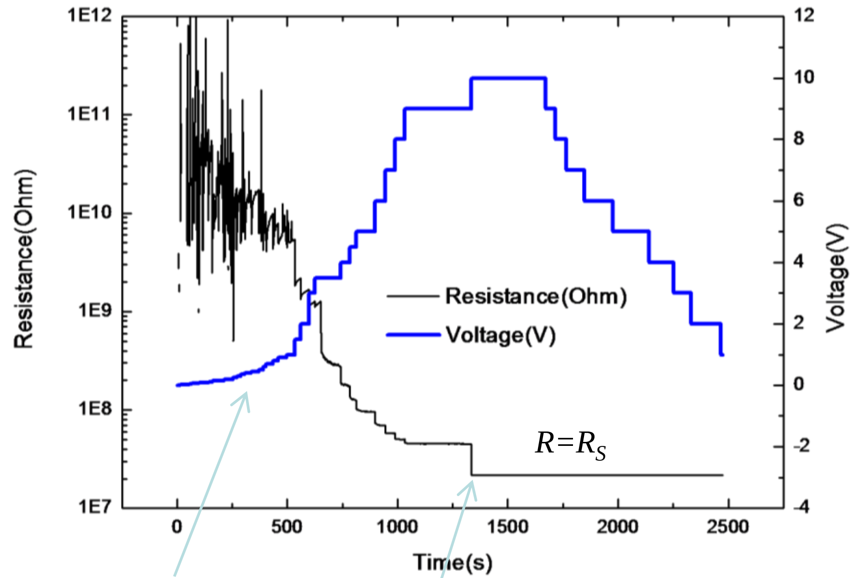
50 µm Gap



Dark Field View

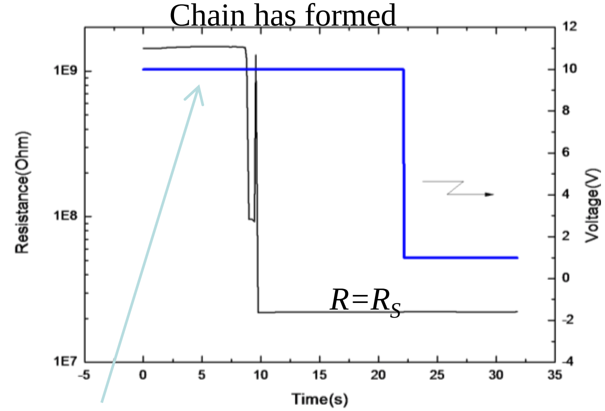
500µm Gap





Slow voltage ramp

Chain has formed



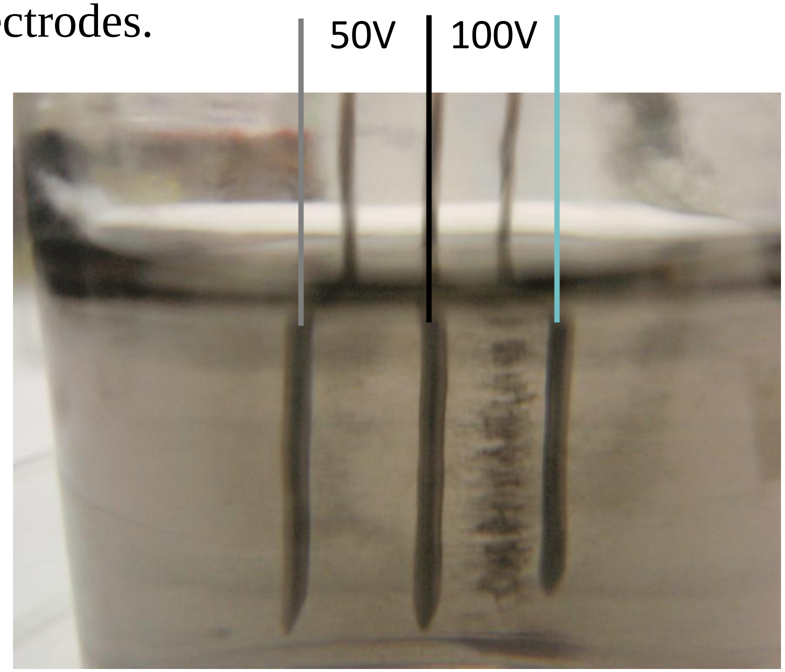
Fast voltage ramp

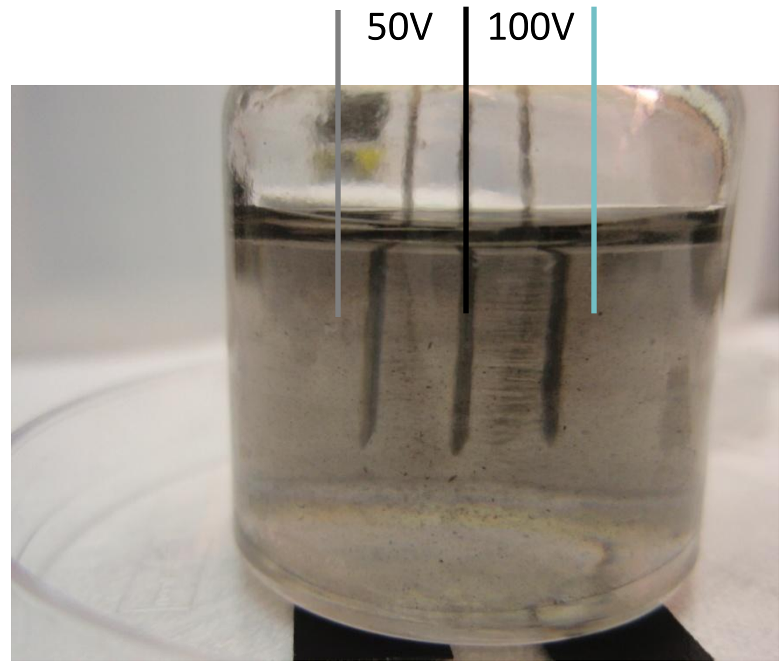
Self-assembling wires persist for hours and days and can be created with small voltages.

Experiment

Competing Carbon Nano Tube (CNT) Synapses

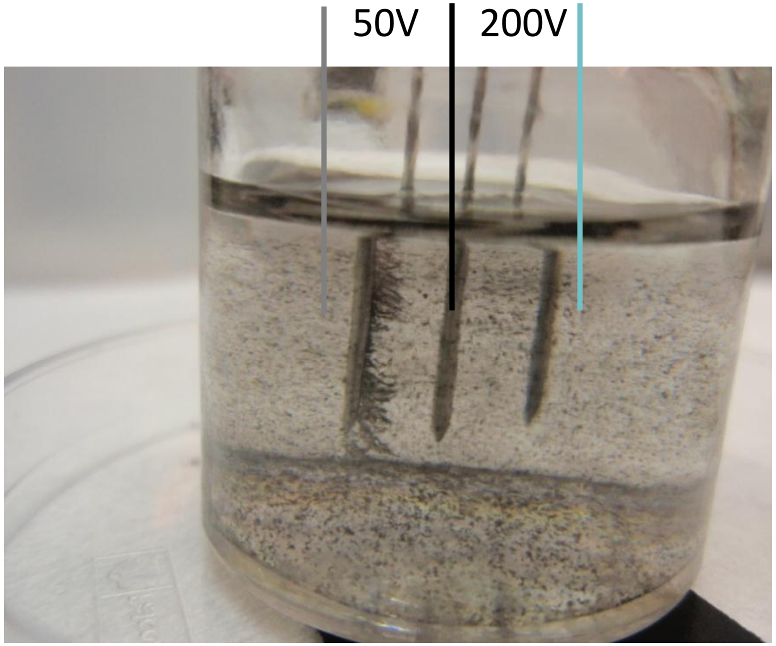
Setup consists of 3 stainless-steel cylindrical electrodes, 0.7 mm in diameter, separated by 5 mm and immersed over 15 mm into an electro-rheological fluid. The fluid consists of a dielectric solvent (toluene) with ultrasonically dispersed conducting multiwall carbon nano tubes. Central electrode is grounded and the positive voltage is applied to the side electrodes.

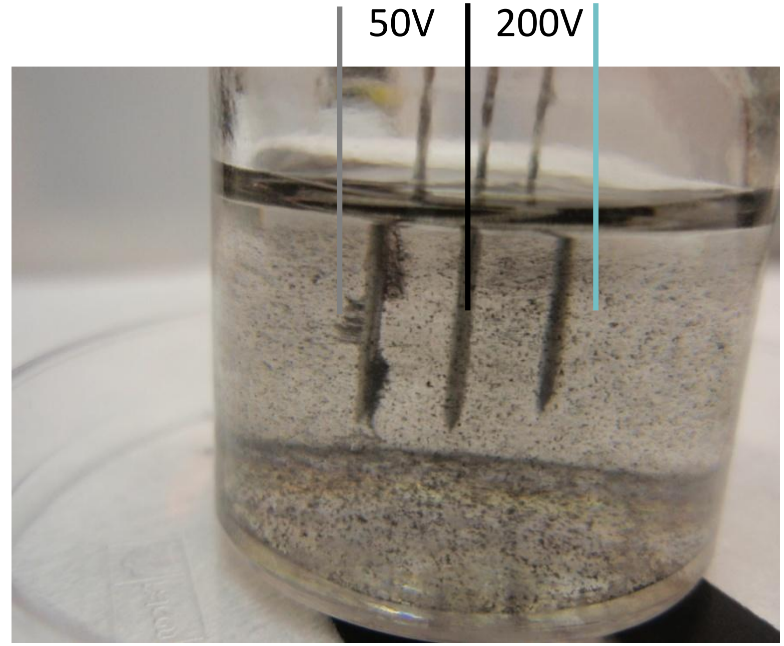


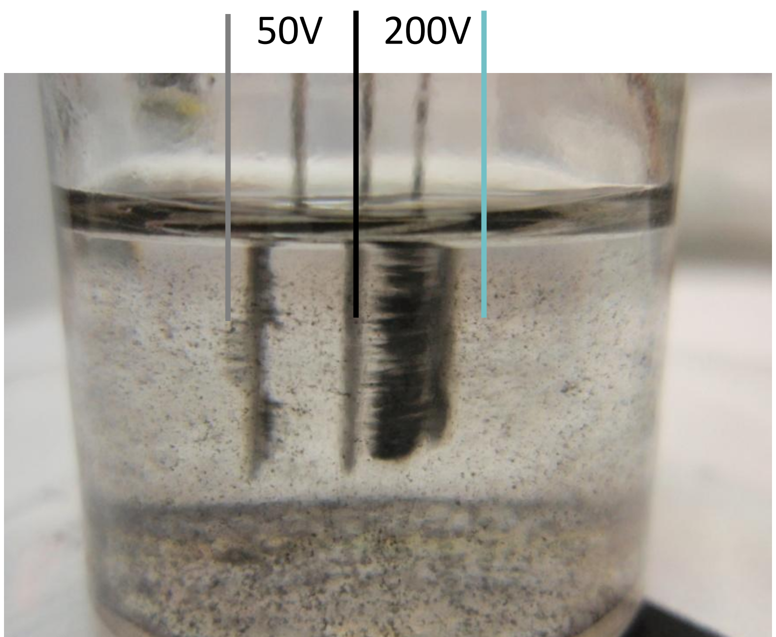


$\Rightarrow$ Self-assembling wires between the electrodes: **higher voltage = more wires**

- What is the growth dynamics?
- How many wires grow as a function of the applied voltage, history,…?







The chains formed between 50V-electrodes become destroyed when 200V are applied to other pair of electrodes. This suggests that the systems may go beyond **Hebb's learning rule (unused connections are destroyed – morphology change).**

Experiment:
Wires grow from both electrodes equally

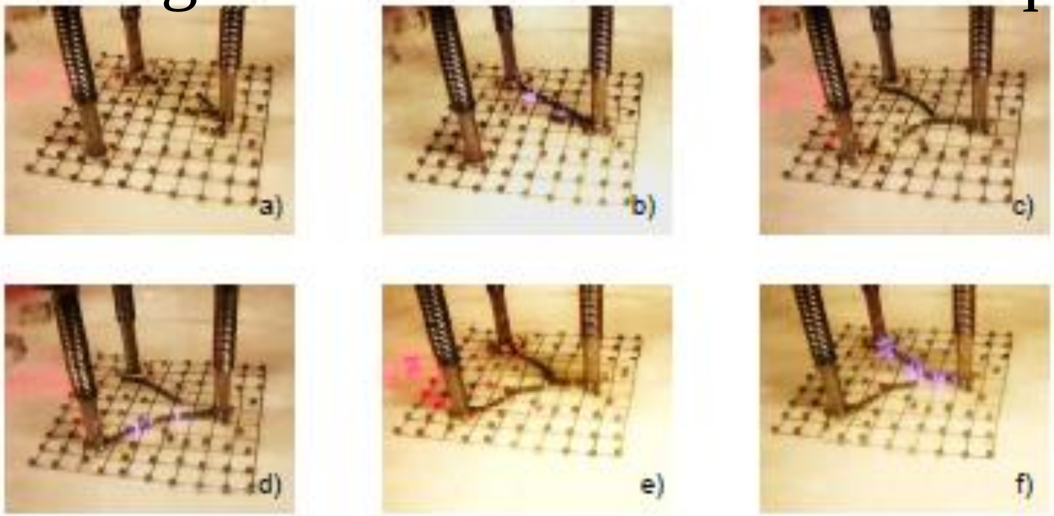


FIG. 3. The general method of connection is demonstrated in the pictures labeled a-f above: a) stems are formed around the first two electrodes b) stems elongate and finally form a wire when electric current is passed through c) wire bends and branches to accommodate the electric field formed with the new ground d) a second connection is made e) particles associate to the previous connection and repairs the broken wire f) wire is reassembled.

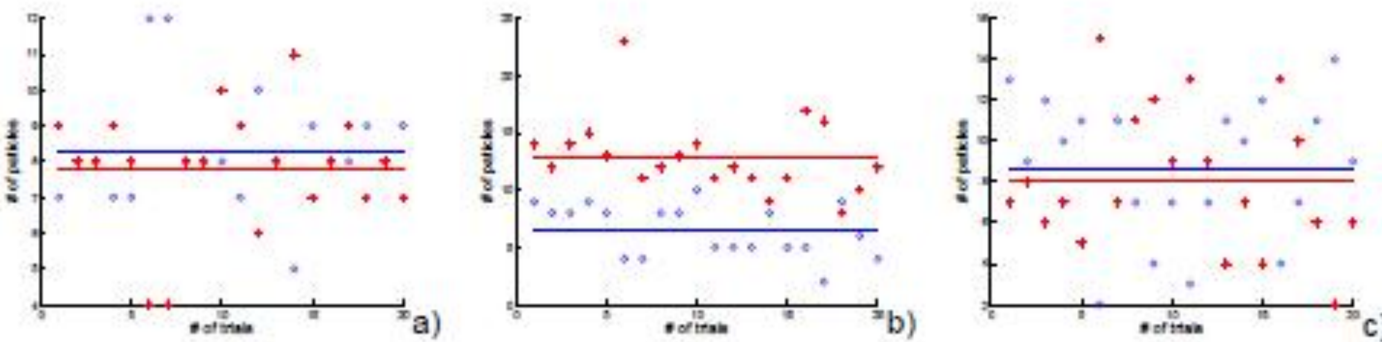
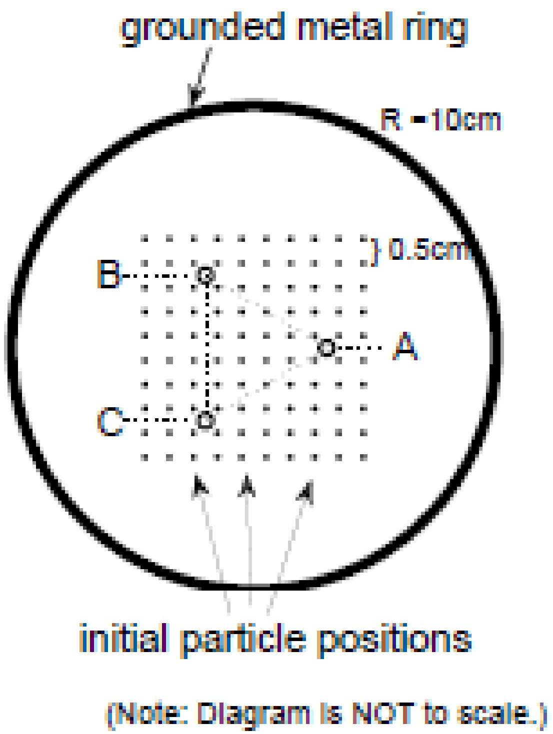


FIG. 4. These trials were done at 25 kV and show the number of particles at the grounding and the positive electrode at the time of connection. The blue represents particles from the grounding electrode while the red represents the particles from the positive electrode.

Experiment: Switching Times Shorten

- Stainless steel particles (diameter 1mm) in a 1mm layer of Castor oil
- 87 particles are set up in a 9 by 10 square grid, particle spacing 0.5 cm
- Grid area: -2cm < x < 2cm, 0 < y < 4cm, Stationary electrode (0cm, 0cm), Electrode 1 (2cm, 4cm), Electrode 2 (-2cm, 4cm)



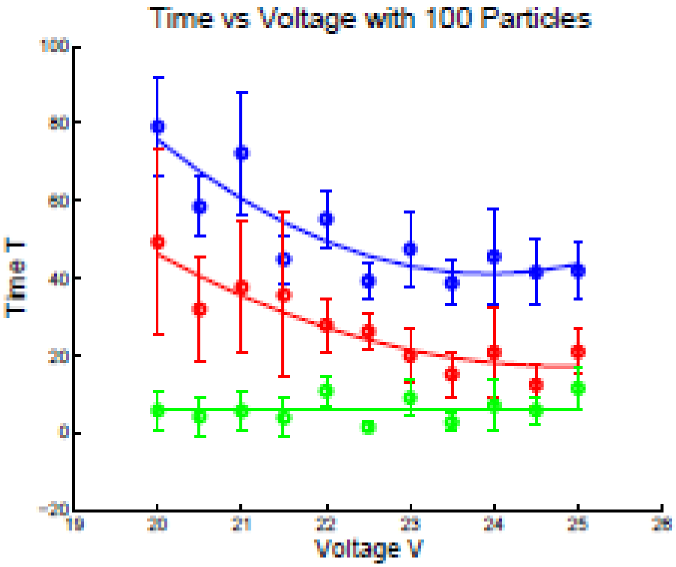


Fig.1

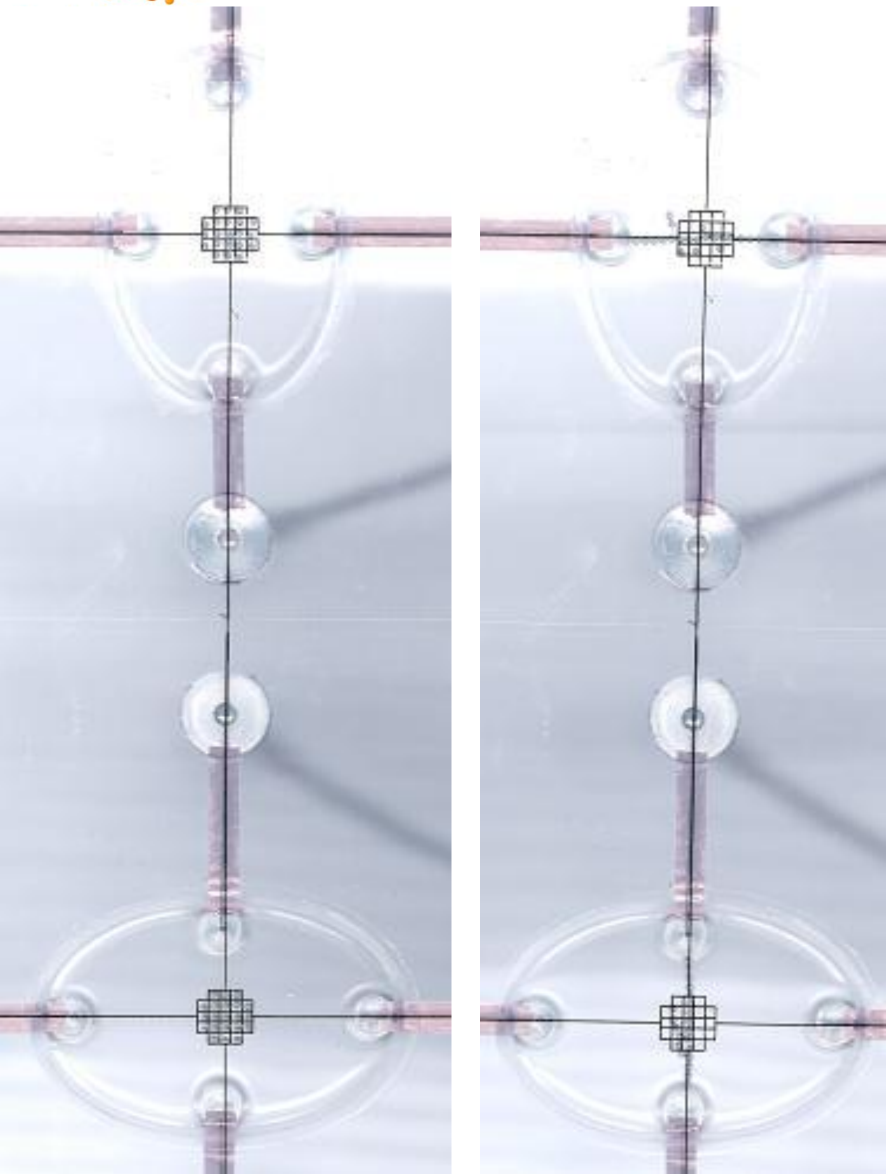
Time to connect to electrode 1

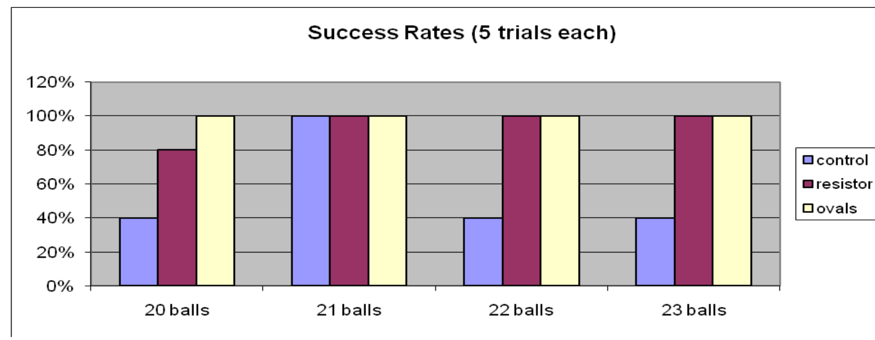
Time to switch to electrode 2

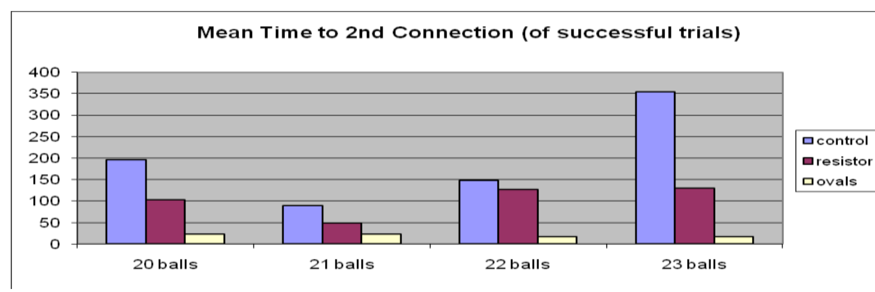
Time to switch back to electrode 1

The voltage is in kV.

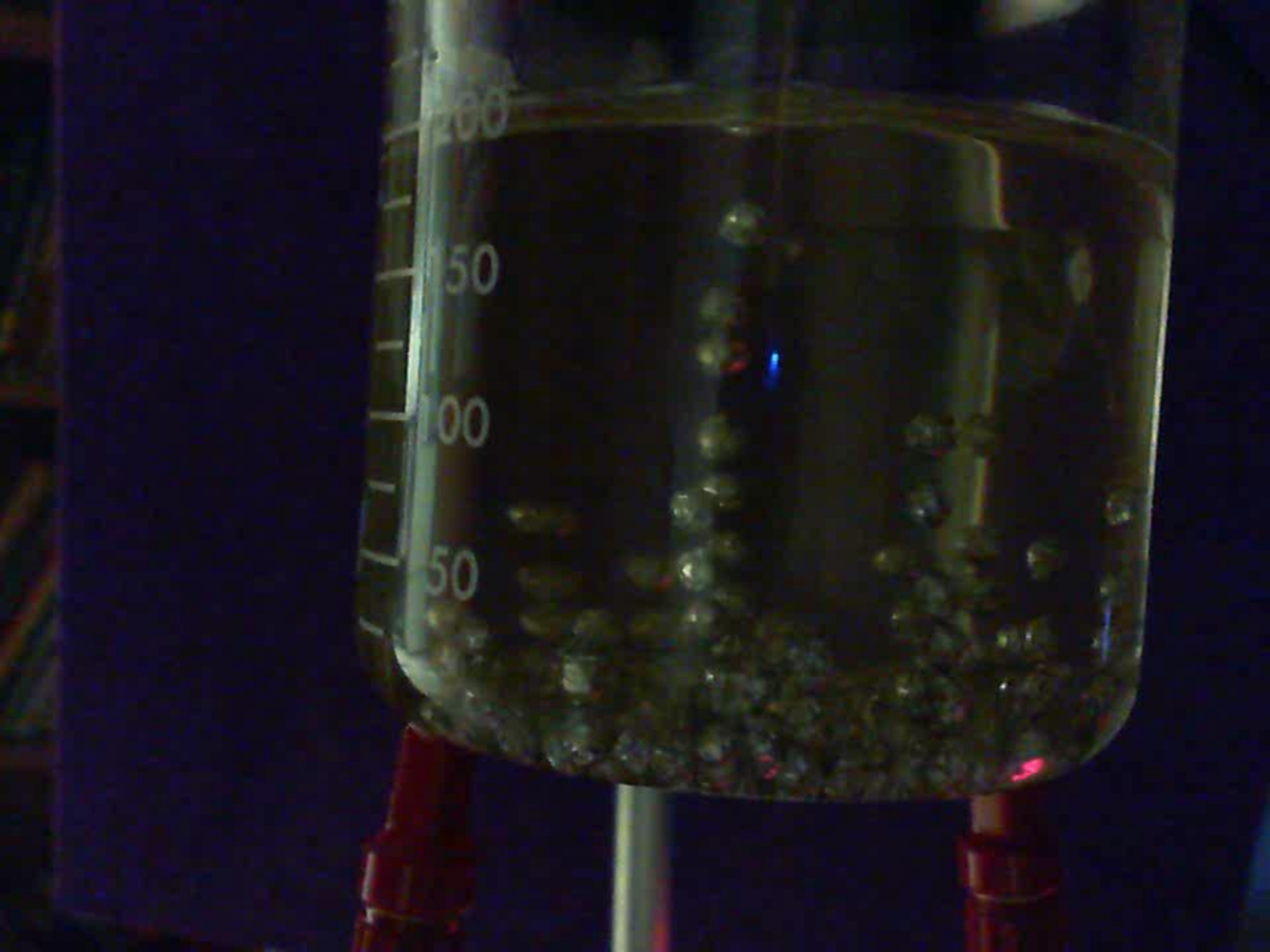
Experiment: Learning the X – pattern with two identical base units and two different base units







Result: If the base units are different, the learning success is larger, and the learning is faster


200
50
00
50

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Experiment: 3D Arbortrons connection time

-Suspended conducting PVC particles,
-Electrodes vertically separated by 3cm-4cm
- 200 ml Castor oil in a glass beaker
- 200 particles, diameter 4mm
- Voltage 16kV – 25 kV

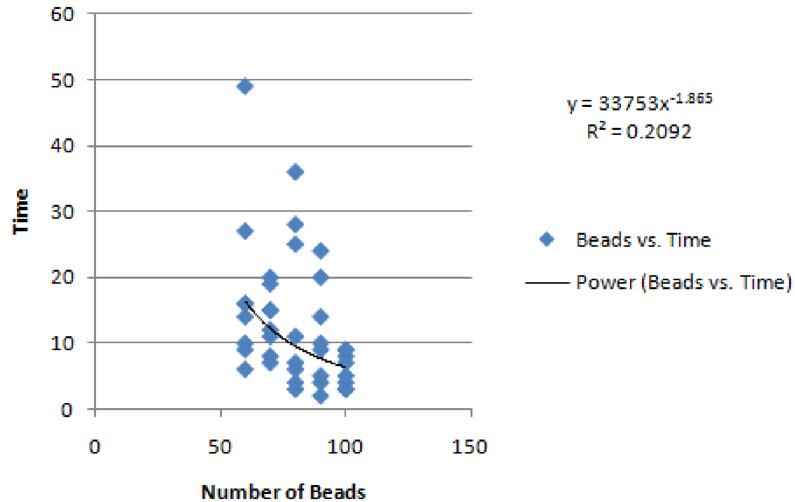


Fig. 2 Connect time versus number of particles, 125 mL Casor oil, 20 kV in glass beaker

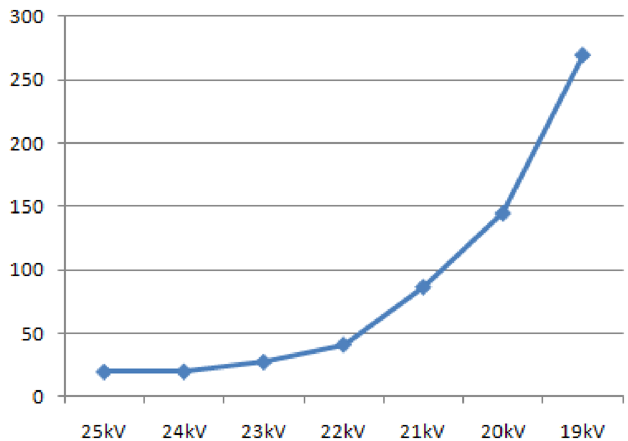
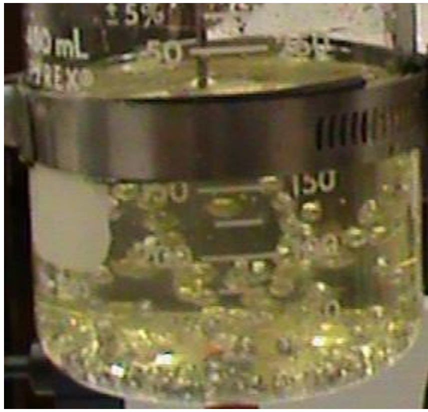
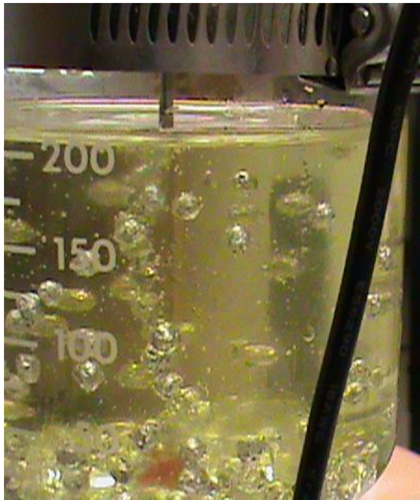


Fig. 1 Connect time versus voltage [kV], 140 mL Castor oil, 100 particles in a glass beaker





Experiment: The impact of thermal noise.

The impact of thermal noise on the time until the particle gets stuck. This experiment shows that **thermal noise** can support the formation of wires 6mm glass beads,

Fig. 1 Photograph of an experimental set-up with one super conducting disk. A heater is installed below the glass beads to amplify thermal fluctuations . The liquid nitrogen boils heavily if the power consumption of the heater is large.

Result: Thermal noise decreases static friction, but increases kinetic friction.

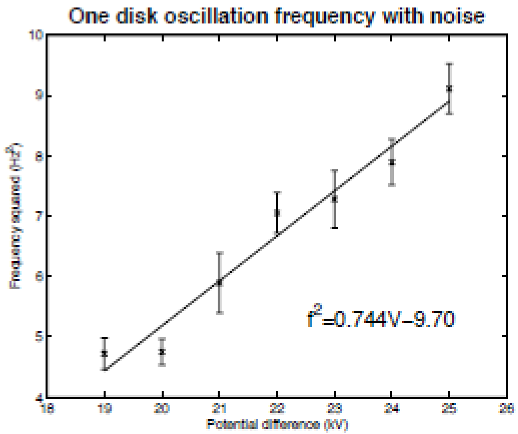
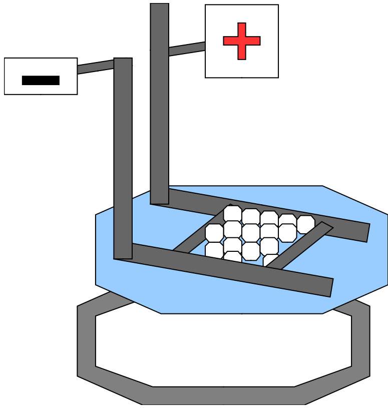


Fig. 2 Oscillation frequency versus voltage



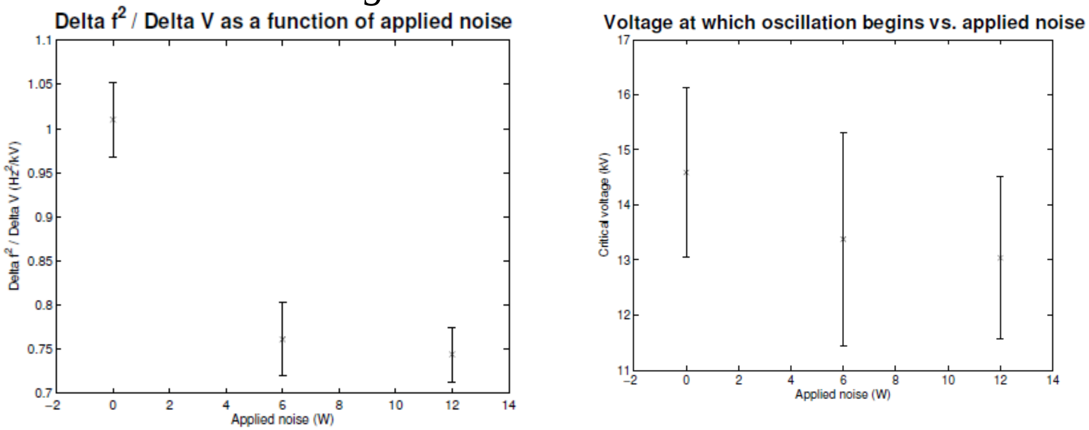


Fig. 3 Rate of change of oscillation frequency and minimum voltage versus noise level

Experiment: Arbortrons learn to recognize sound and learn to differentiate between different frequencies (Pask's ear)

-2 vibrated grounded electrodes of different length

Fig.1 10V electr & 0.5 molar H_2SO_4 with saturated iron salt

Fig. 2 11kV perimeter electrode & steel balls in castor oil

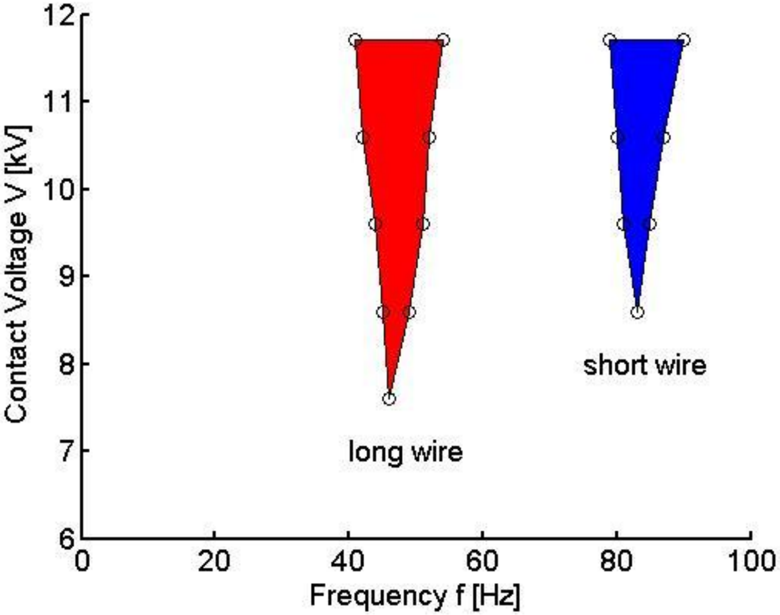


Fig.3 The onset of arcing versus the driving frequency after a training period. Within the red region there is arcing between the long vibrated wire and the particles. The blue region indicates arcing between the short wire and the particles.

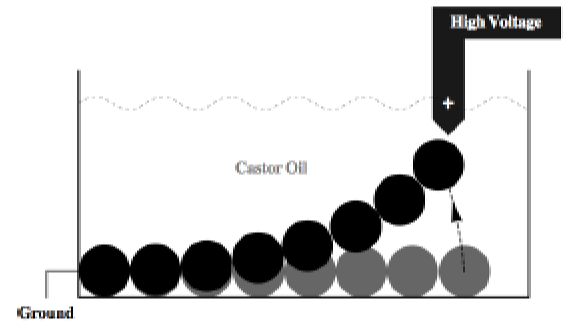
Experiment: Thresholds and short term memory of branches connected to an elevated electrode

Preliminary Results:

- In systems with elevated electrodes there is a threshold voltage for forming wires which depends on the elevation height

-Wires disconnect at a lower voltage

- Wires do not disconnect instantly



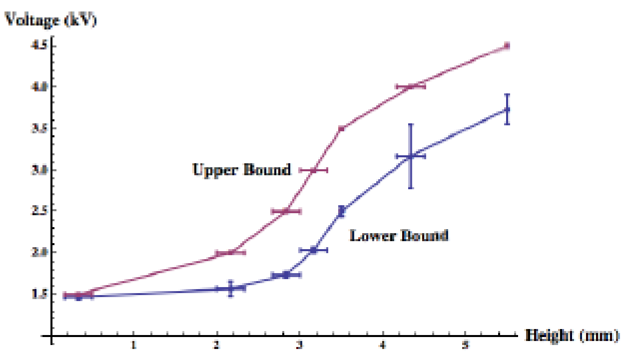


Fig.1 The minimum voltage to connect (blue) and the minimum voltage to stay connected (red)

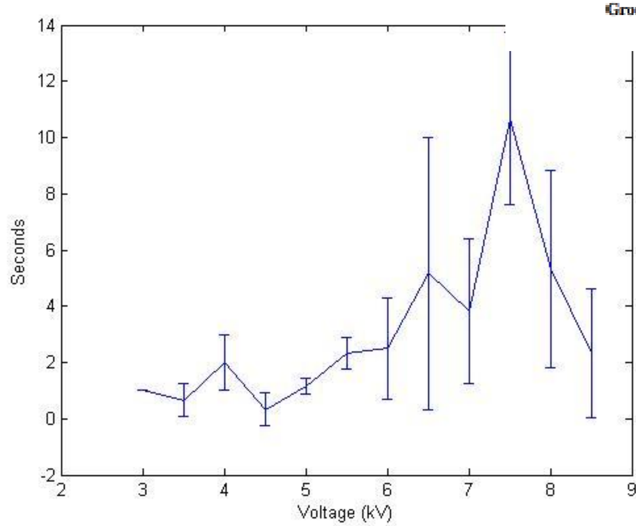
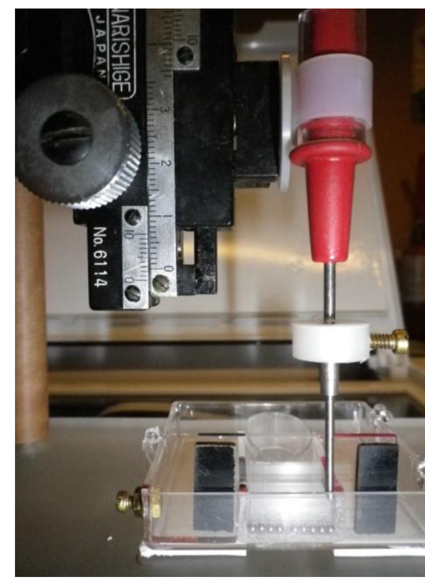
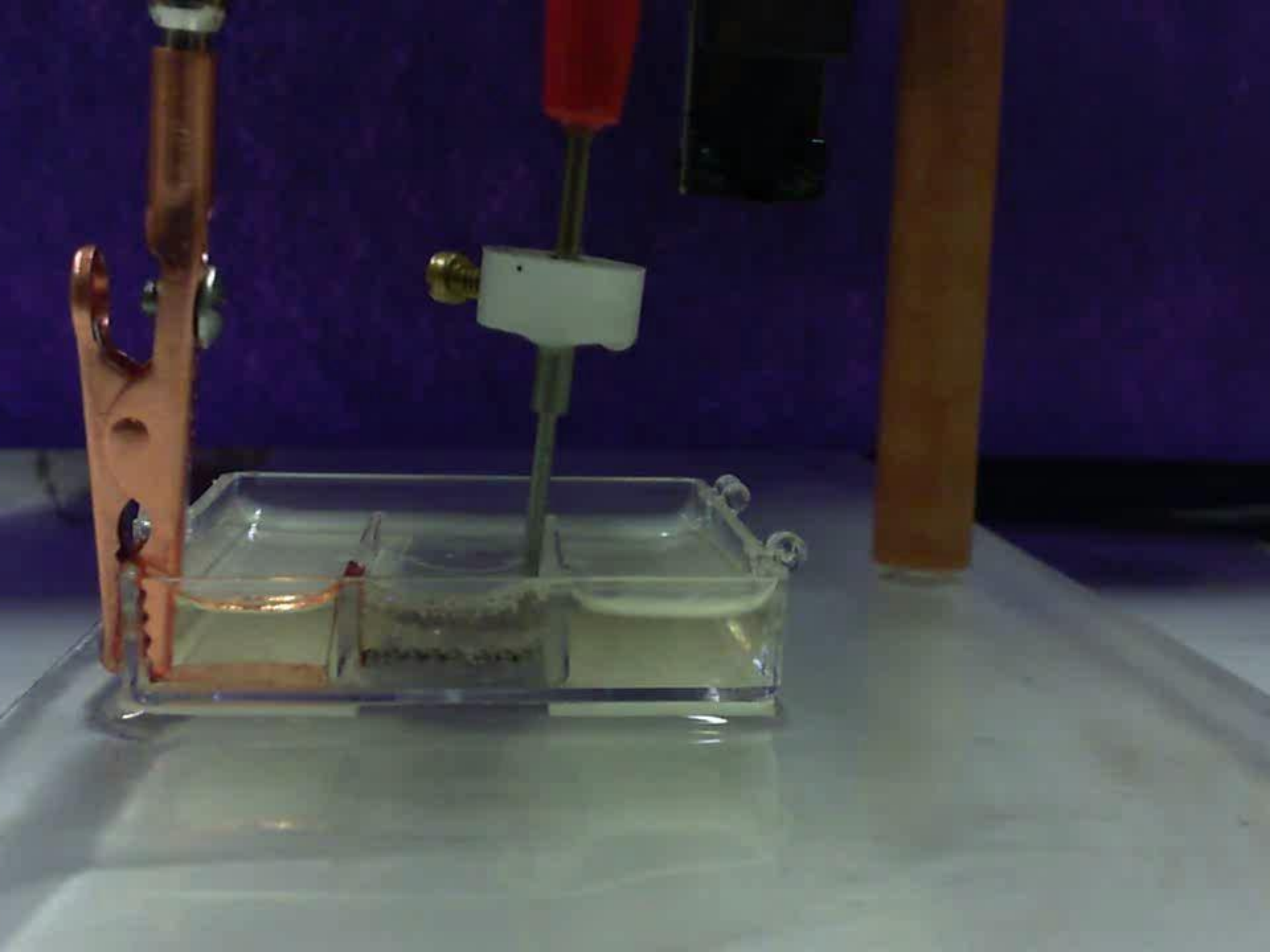


Fig 2 Decay time versus voltage





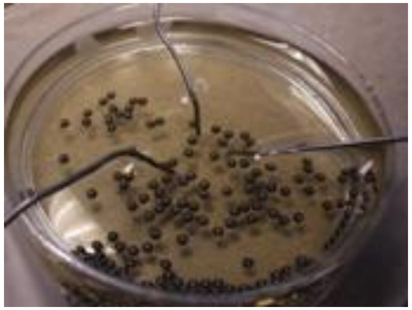
Experiment:
Arbortrons can learn the "and" rule, the "or" rule, and the "xor" rule

"and" rule (nonlinear)

<u>2 non-elevated input electrodes:</u>
A, B

<u>1 elevated output electrode:</u>
A *and* B
1 common ground

no input

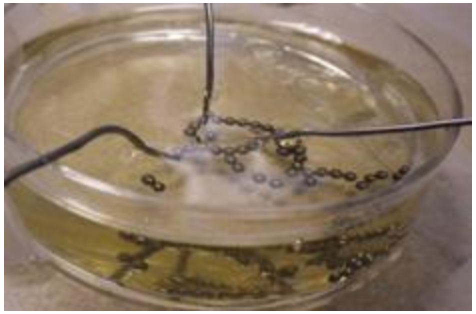


no output current

A = 1mA

no output current

A=1mA, B=1mA



large output current

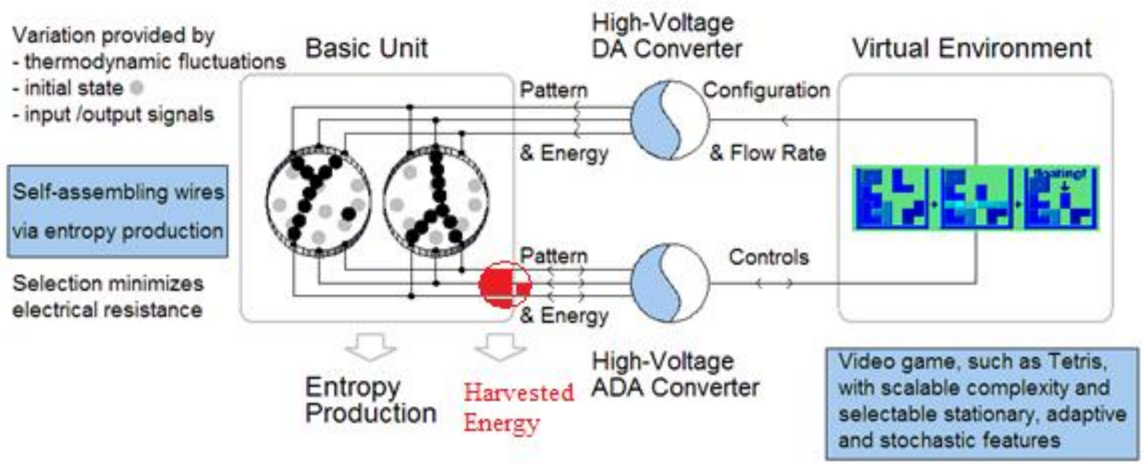
<u>Learning "*and*":</u> Formation of a y-shaped wire with threshold t, where 1mA < t < 2mA

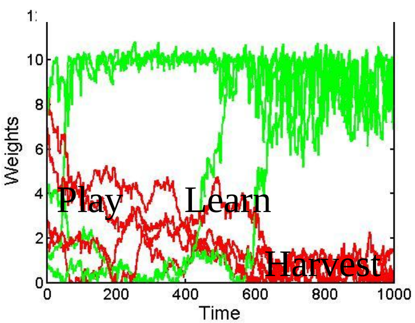
"or" *rule* (linear)

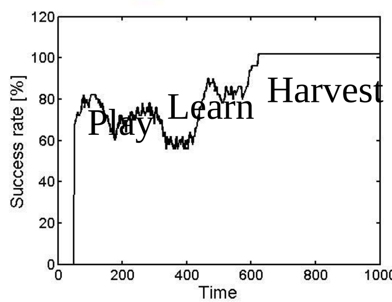
2 non-elevated input electrodes (A,B), 1 non-elevated output electrode (A *or* B)
<u>Learning "*or*":</u> Formation of a y-shaped wire

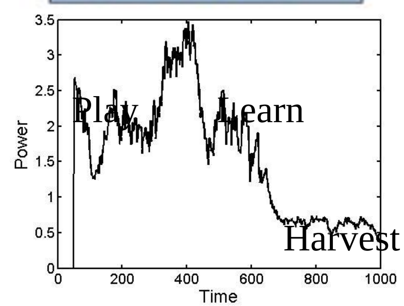
Simulation: Arbortron controlled Tetris

A simple form of Tetris controlled by a numerical simulation of a linear self-assembling wire network (single layer perceptrons)









Simulation results:
- Linear self-assembling wire network learns to control the game.
- The dynamics can be split in three phases: play, learn, harvest.
- The heating of the oil (entropy production) often reaches a peak during learning phases.
- There is no play phase without (thermal) noise. Without the play phase the learning phase can not reach a high success rate.
- Noise limits the power that can be harvested.

Tetris rules and pay-off:

State	New	Con-trol	Pay-off	Next state
00	01	no	1	01
00	01	yes	1	10
00	10	no	1	10
00	10	yes	1	01
01	01	no	0	01
01	01	yes	1	00
01	10	no	1	00
01	10	yes	0	01
10	01	no	1	00
10	01	yes	0	10
10	10	no	0	10
10	10	yes	1	00

Location of incoming particle is random.

Experiment: Arbortron controlled Tetris

-Six cells that are all inter connected in a way that the positive electrodes are connected to each other.
- The cells are numbered from the top left and counted across from in three rows.

Description:

(1) Make sure that all of the ball bearings are mixed in a way that they are concentrated at the middle of the cell (this makes the connection processes quicker). Start Tetris.

(2) Connect to instructed electrode.

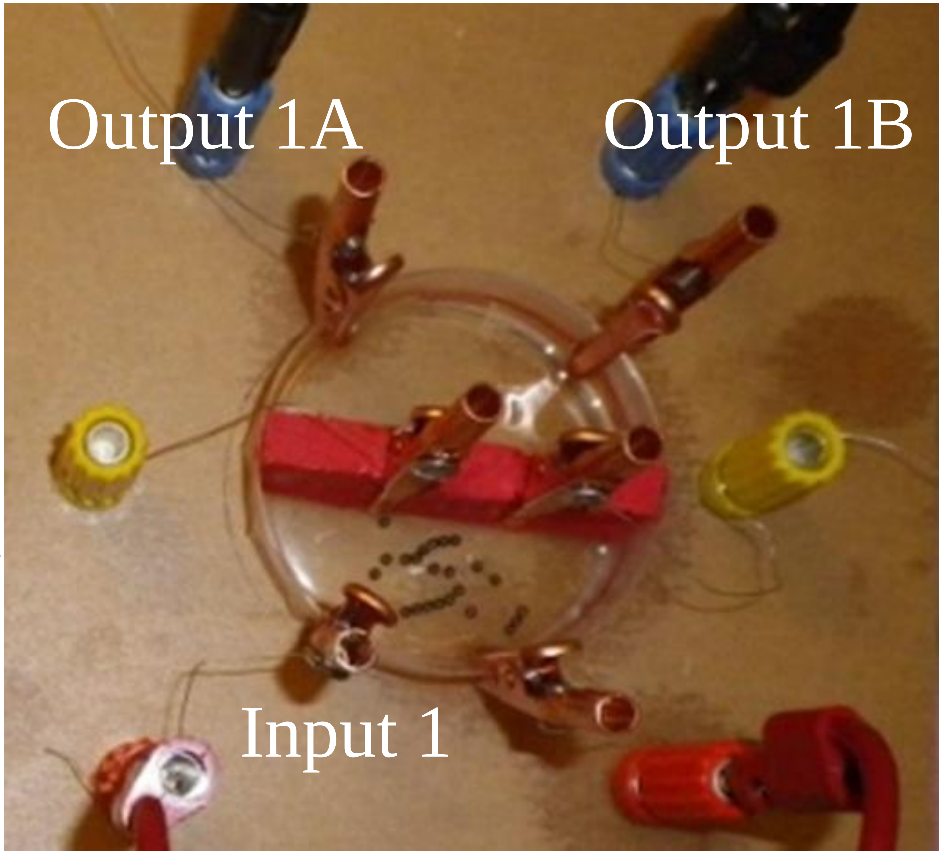
(3) Check which output electrode arcs and carry out the control.

(4) If there is extra energy correct then leave the Voltage on for approximately 5 seconds.

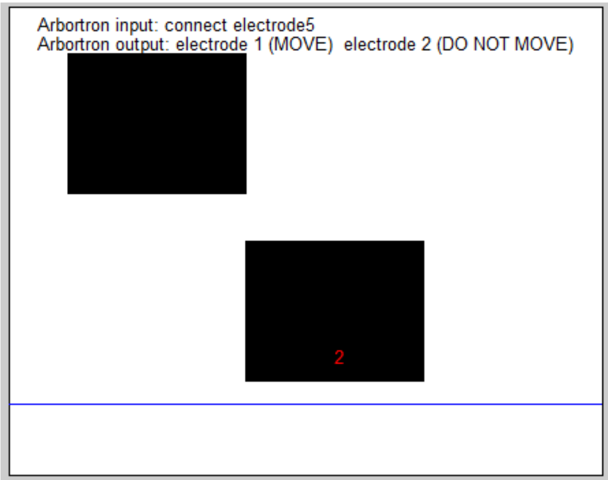
(5)If there is no extra energy then turn off voltage.

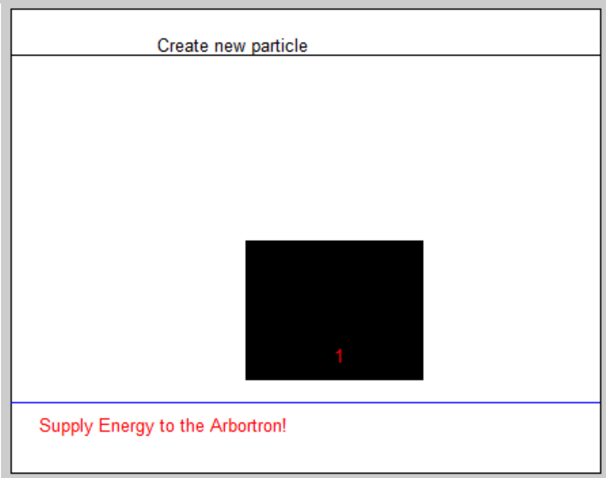
(6) Disturb the connection (add noise).

(7) Goto (2) .



Experiment: Arbortron controlled Tetris



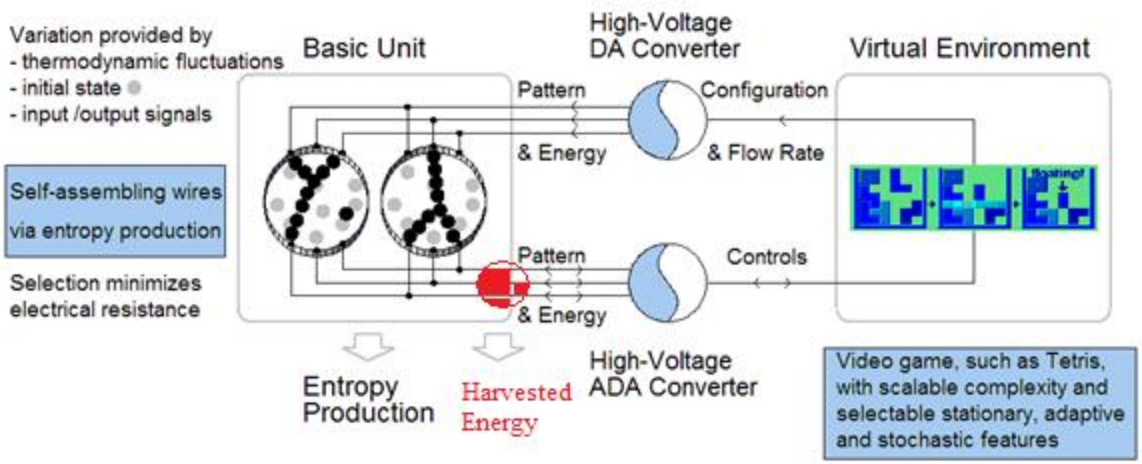


Experimental data:

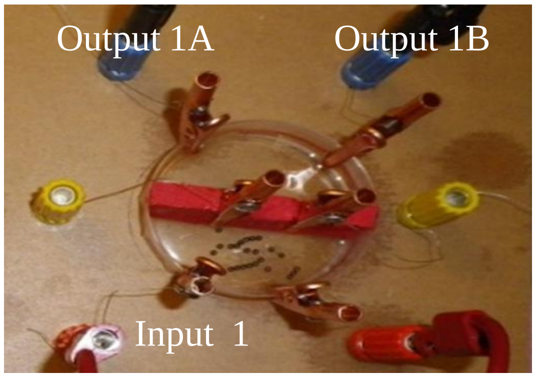
Electrode 4 –connection 1→move (to left side)
Electrode2 –conection1→move (to right side) (good move)
Electrode4-connection1→move (to left side)
Electrode2-connection1→move (to right side) (good move)
Electrode1-connection2→do not move (left side)
Electrode5-connection1→move (to left side) (BAD move)
Electrode6-connection1→move (to left side) (BAD move)
Electrode4-connection1→move (to right side) (good move)
Electrode6-connection1→move(to left side) (BAD move)
Electrode2-connection1→move(to right side)(good move)
Electrode1-connection2→do not move(right side) (good move)
Electrode4-connection2→do not move(right side)
Electrode6-connection1→move (to left side) (good move)
Electrode1-connection1→move(to right side)
Electrode6-connection1→move(to left side) (good move)
Electrode4-connection2→do not move (right side)
Electrode3-connection2→do not move (left side) (good move)
Electrode1-connection1→move(to right side)
Electrode6-connection1→move (to left side) (good move)
Electrode 4-connection2→do not move (right side)

Experiment: Arbortron controlled Tetris

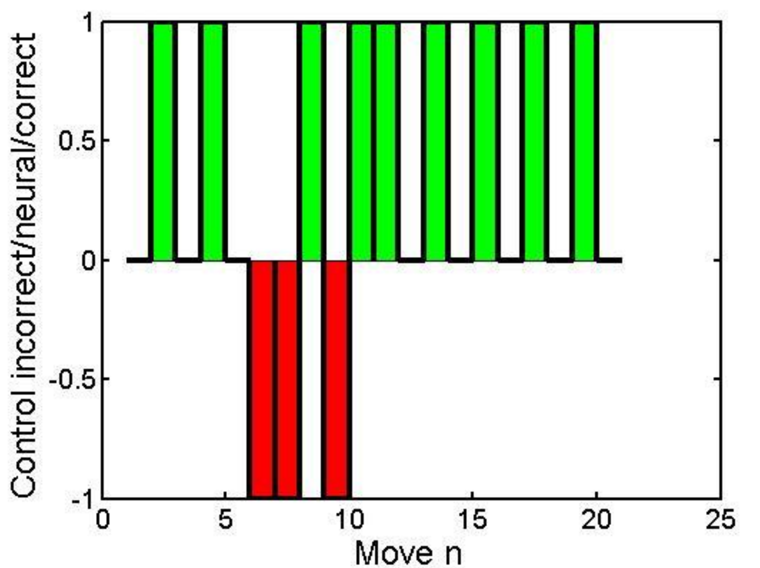
A simple form of Tetris controlled by a network of **six base units** with arbortrons. The arbortrons receive an energy reward for "correct" controls.



Basic unit:

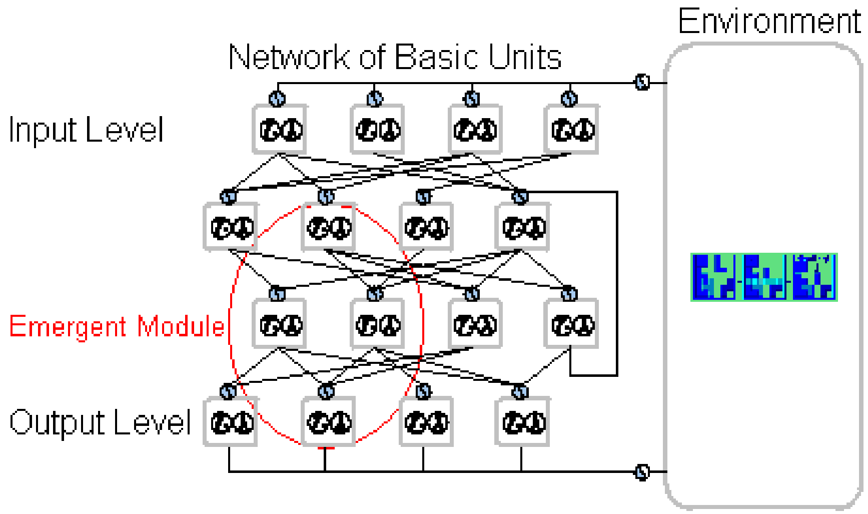


Experimental results for a system with 6 basic units:



Conclusion: The arbortron network spontaneously improves its ability to extract energy / minimizes entropy production / minimizes resistance.
If the pay-off is energy & the pay-off is not too much delayed & noise is sufficiently large
=> Aborton networks learn to play Tetris.

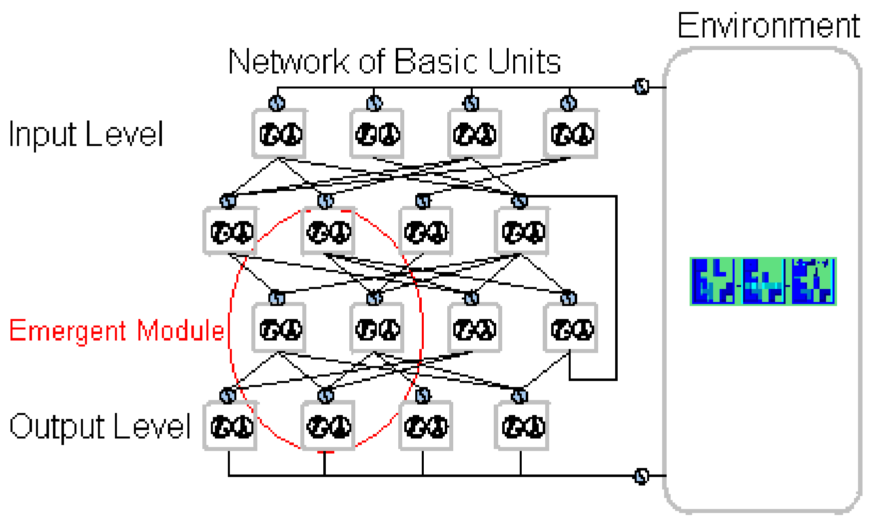
Summary: Self-assembling Wire Networks-Based Physical Intelligence



- Individual arbortrons maximize tensile strength and power consumption.
- Competing wires show neural plasticity.

Problem: How does such a thermodynamic nano particle system learn, become intelligent?

Summary: Self-assembling Wire Networks-Based Physical Intelligence



- Individual arbortrons maximize tensile strength and power consumption.
- Competing wires show neural plasticity.

Problem: How does such a thermodynamic nano particle system learn, become intelligent?

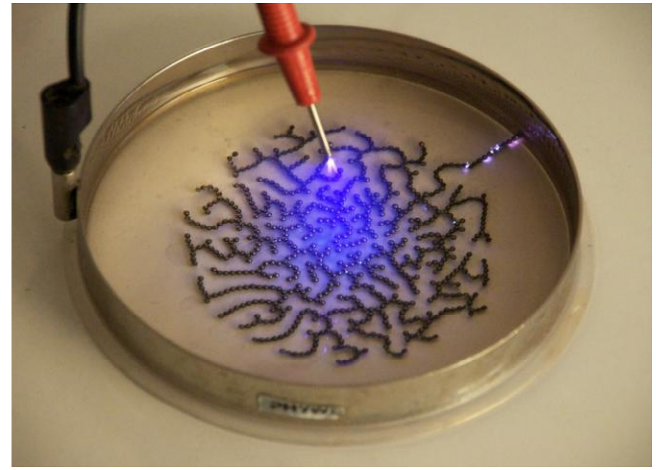
The wire network forms a structure which maximizes its access to energy.
Therefore, the network has to be trained like a pet – with rewards in terms of extra energy.

Thank You.

THERA

Physical Intelligence

Sponsors:
DARPA, Air Force



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- Singleton, M.; Heiss, G.; Hubler, A. Optimization of ramified absorber networks doing desalination, Phys. Rev. E 83, 016308 (2011)
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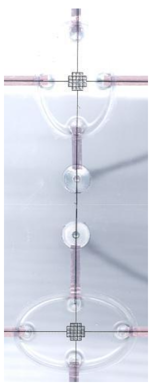
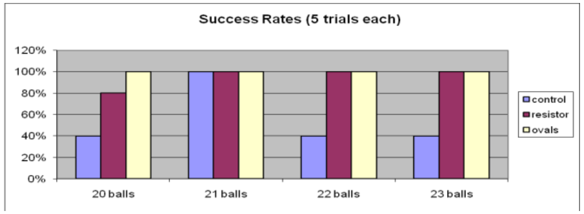
Emergence of Complex Functionality in Physically Evolving Networks

A.Hubler, A. Bezryadin, A. Belkin, D. Lyon, C. Stephenson, UIUC

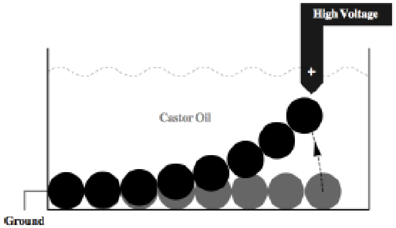
What patterns and functions can arbortron base units understand?
How do the design parameters influence performance?
Are there overarching principles?
How is the performance affected by thermal noise?



Networks with non-identical base units process input faster and more reliable.



3D arbortrons can process complicated functions.



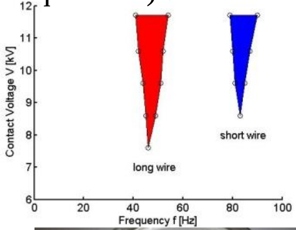
Thresholds enable arbortrons to learn nonlinear Boolean functions.

A=1mA, B=1mA

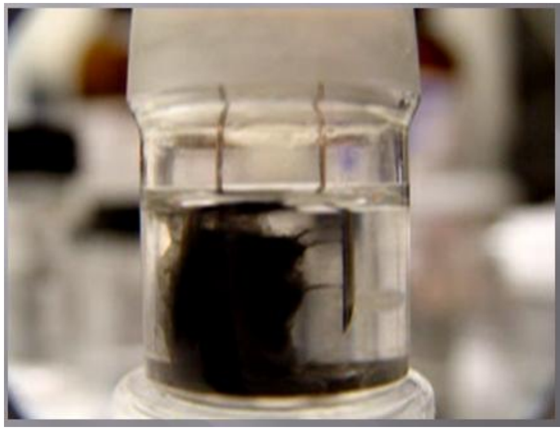
large output current

Thermal noise helps to unlearn and to break symmetries .

Arbortrons learn to recognize patterns (and frequencies) .



Nano implemenations require less voltage.



Entropy production is maximized if the voltage and temperature are kept constant