

From Swarm Robotics to Smart Materials

Nikolaus Correll

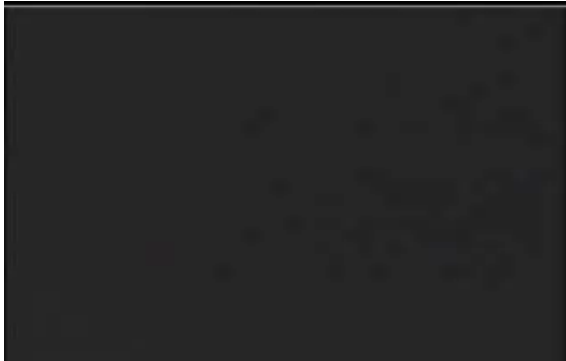
University of Colorado at Boulder

The ultimate robotic swarm: a liquid that thinks

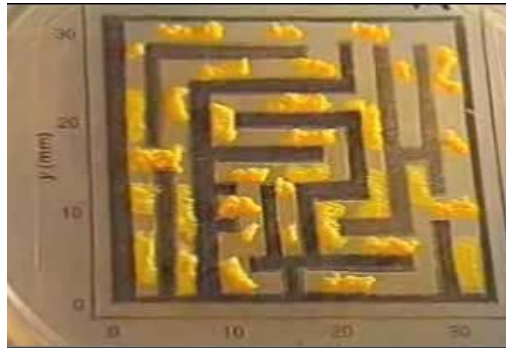


Subsets of Liquids that think

Construction



Distributed Computing



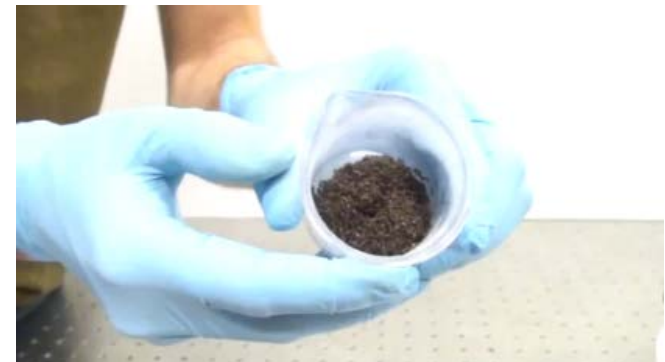
Collective Motion



Appearance Change

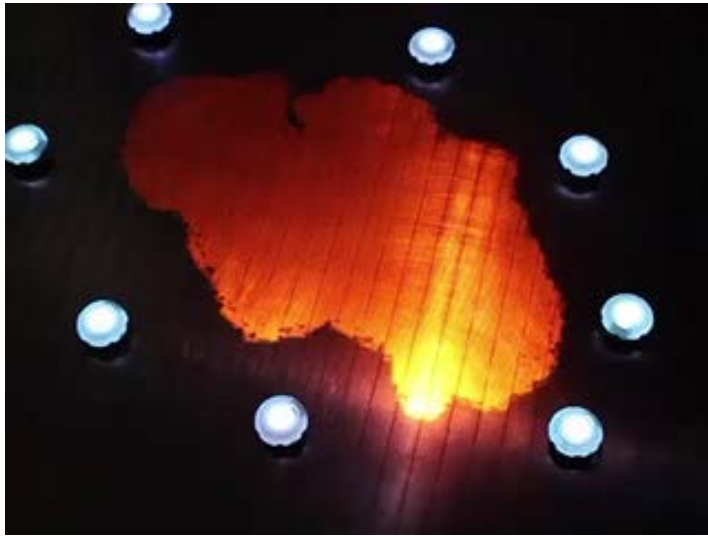


Intelligent function



Viscoelasticity

Making a liquid that thinks

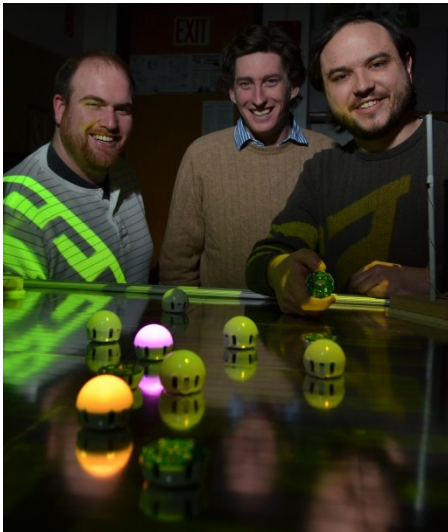


“Droplets”



“Liquid that thinks”

Liquid that thinks



“Droplets”



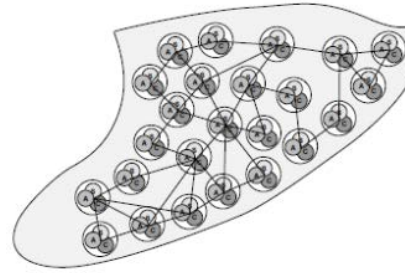
Useful novel
materials?



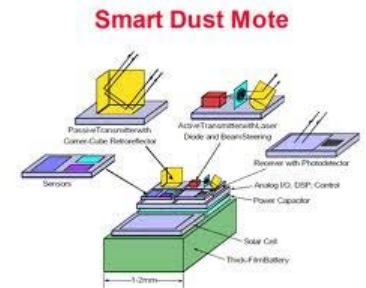
“Liquid that thinks”

Background: Materials that think

- Embedded...
 - Actuation
 - Sensing
 - Computation
 - Communication
- Periodic, amorphous



Distributed MEMS (Berlin, 1997)



Smart Dust (Pister, 1999)



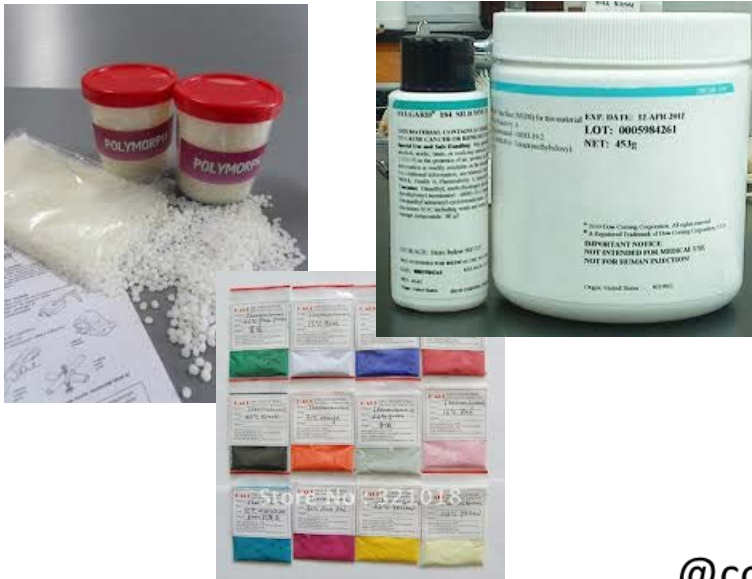
Amorphous Computing (Abelson, 2000)



Programmable Matter (Goldstein, 2005)

Enablers

- Cheap sensing, computation, actuation
- Cheap manufacturing
- Available polymers



Materials that Sense

- Prosthetic / augmented limbs
- Improved situational awareness for robots
- More subtle Human / Robot Interaction
- Structural monitoring



Materials that change Appearance

- Smart facades
- Camouflage
- Smart clothes



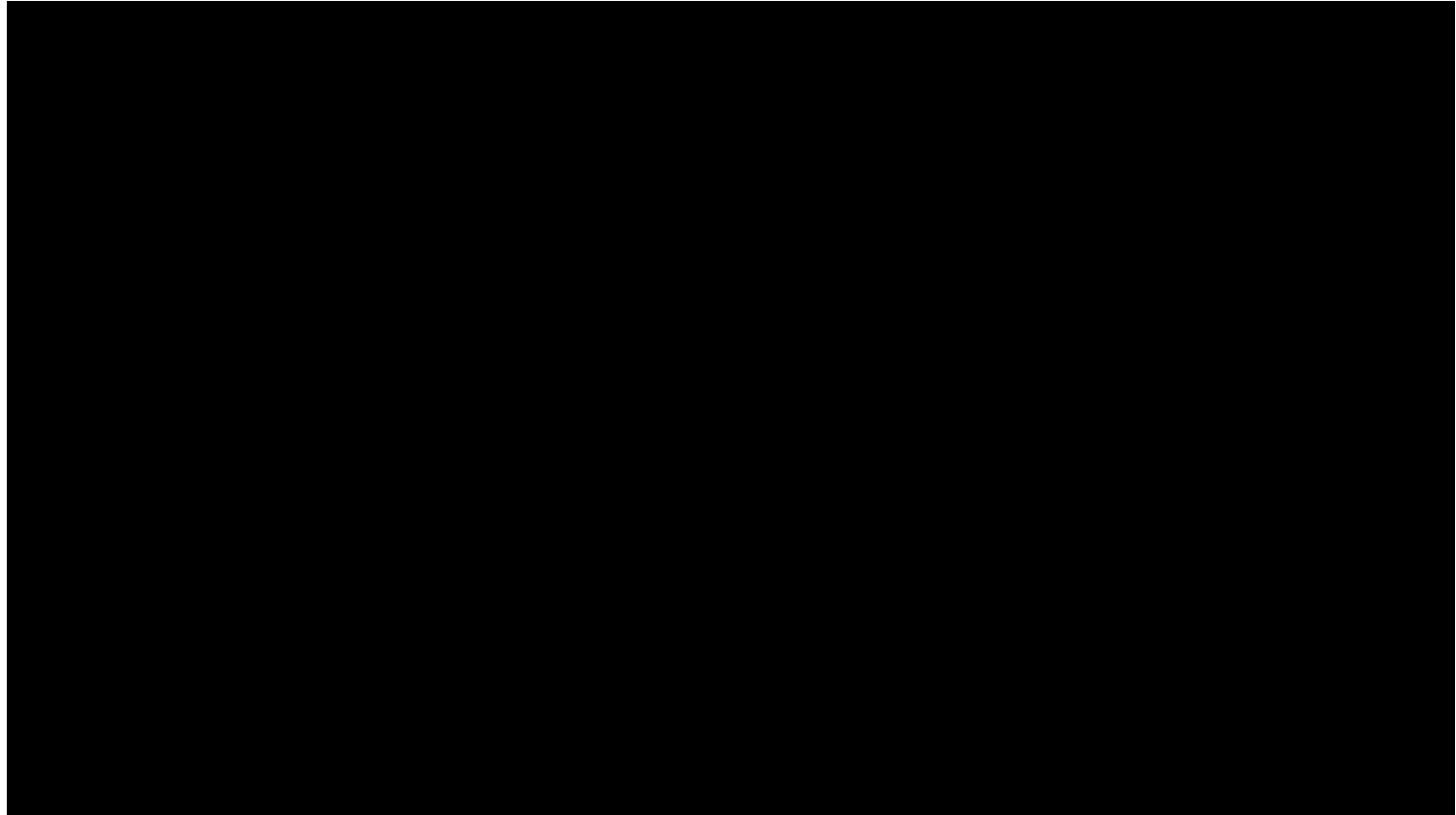
Materials that change Shape

- Reconfigurable airplane wings
- Reconfigurable aerodynamic structures
- Reconfigurable architecture
- Reconfigurable furniture



@correlllab

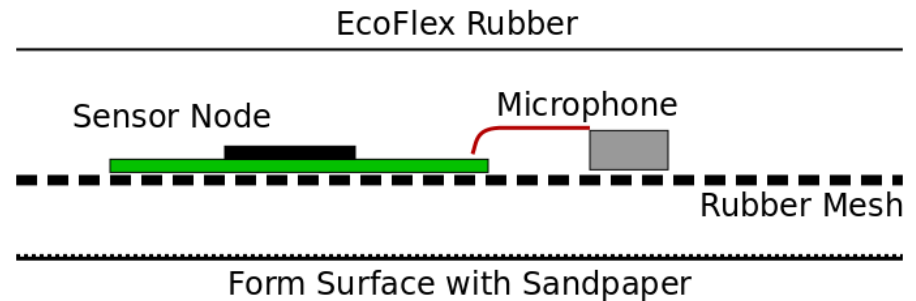
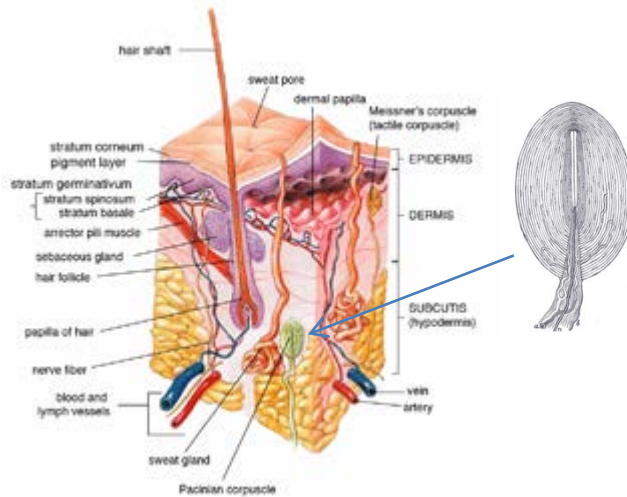
New forms of artistic expression



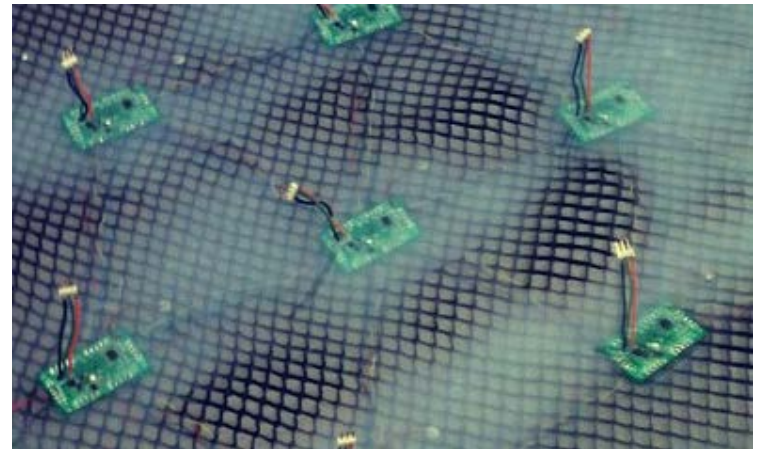
K. Sugawara, K. Hata, N. Correll, M. Theodore (2013): 群れ行動の数理モデルとその応用～ 群れお絵かきツールとSwarm Wall ～. 1st International Conference on Human Agent Interaction (HAI), Sapporo, Japan, 2013.

Materials that Sense

Soft Sensing Skin



- Sensor network woven in rubber mesh
- Embedded in EcoFlex silicone rubber
- Surface textured using 60-grit sandpaper during curing



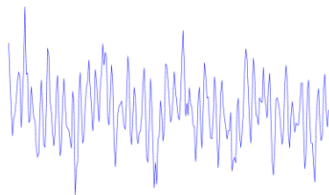
D. Hughes, N. Correll (2014): A Soft, Amorphous Skin that can Sense and Localize Texture . IEEE International Conference on Robotics and Automation (ICRA), Hong Kong, 2014.

@correlllab

Soft Sensing Skin



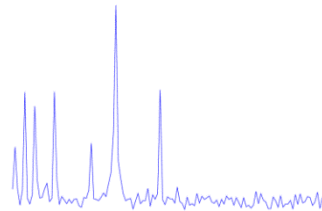
Measured Signal



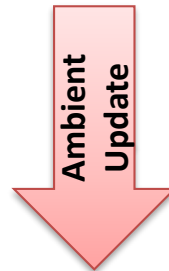
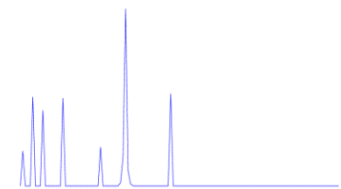
1000 Hz



Signal FFT

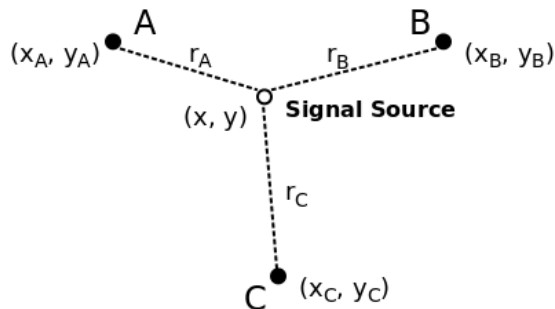
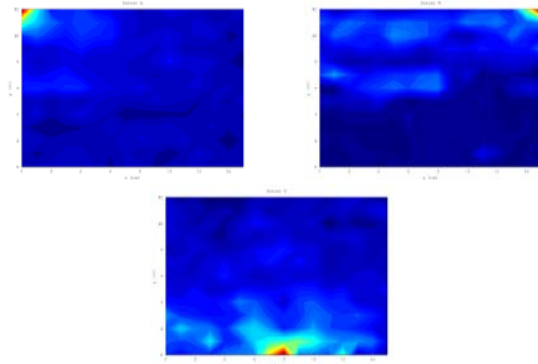


Transient Signal



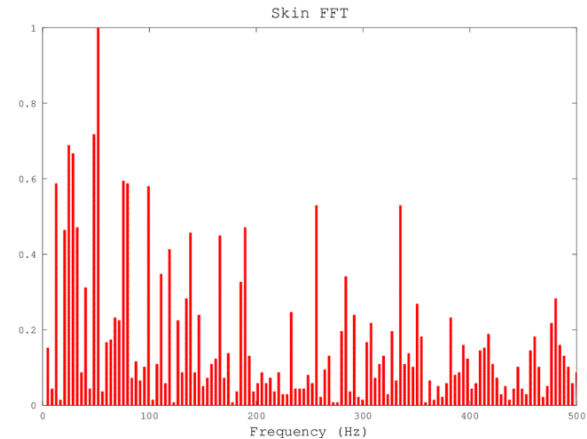
Ambient Signal

1. Texture localization



2. Texture Classification

- Logistic regression
- Classifier trained on 15 predefined textures
- 128 inputs
- 15 outputs
- 1935 weights stored on board



$$y = g(\theta_0 + \theta_1 f_1 + \theta_2 f_2 + \cdots + \theta_n f_n)$$

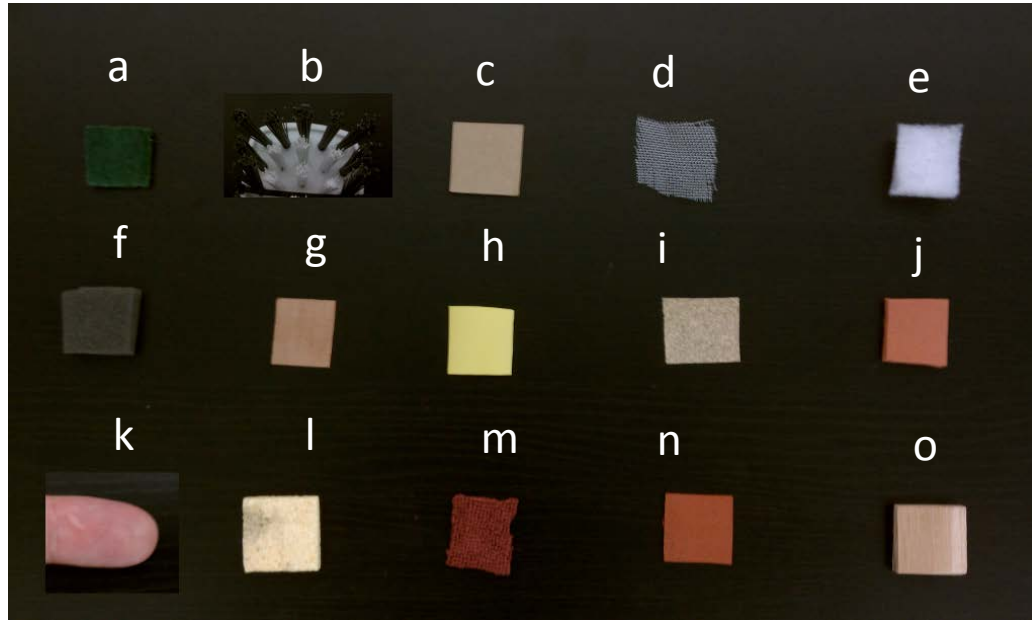


Brillo: 2.4%

Skin: 93.5%

...

Classifier Training



- a) brillo
- b) brush
- c) cardboard
- d) coarse wire mesh
- e) cotton
- f) dense foam
- g) fine wire mesh
- h) plastic
- i) sandpaper
- j) silicone foam
- k) skin
- l) sponge
- m) terry cloth
- n) textured silicone
- o) wood

- Classifiers trained using 15 textures
- 100 samples per texture
- 10-fold cross-validation used to determine accuracy

Classification Results Summary

- Logistic Regression
 - Overall Classification Accuracy: 71.2%
 - Total Number of Weights: 1,935
- Possible improvements
 - Multi-modal sensing
 - Joint classifiers
 - Better classifiers

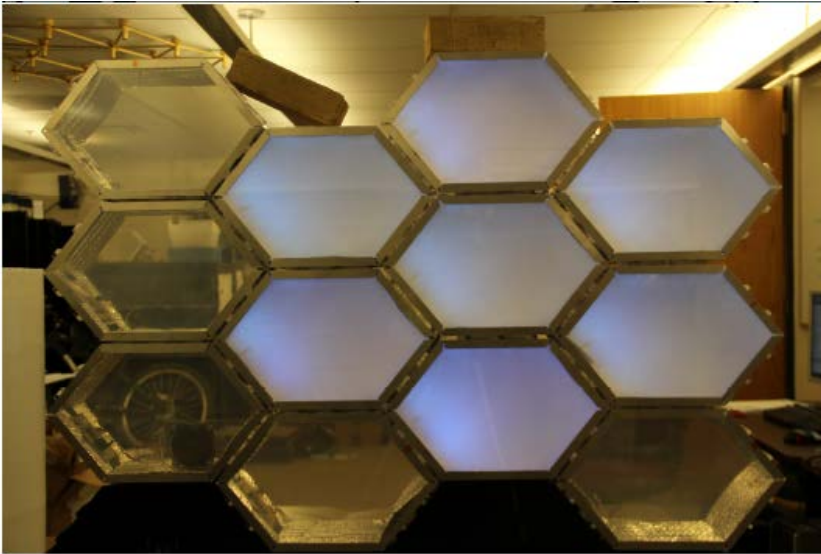
Actual Textures	Predicted Textures														
	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o
Brillo Pad (a)	89	0	0	1	0	0	0	1	2	0	0	0	1	1	1
Brush (b)	2	59	4	6	0	3	0	1	9	2	1	3	6	4	0
Cardboard (c)	1	1	77	0	2	2	5	2	1	1	4	3	0	0	1
Coarse Wire Mesh (d)	3	7	3	64	2	2	1	4	2	1	5	2	3	1	0
Cotton (e)	0	1	1	1	69	15	0	1	1	0	1	3	2	1	3
Dense Foam (f)	2	3	3	2	14	54	3	0	4	3	1	3	3	1	4
Fine Wire Mesh (g)	2	1	4	2	0	0	80	3	2	0	2	1	2	1	0
Plastic (h)	1	3	1	0	3	0	2	78	6	1	4	0	1	0	0
Sandpaper (i)	1	8	0	6	2	4	0	3	58	1	4	6	3	0	4
Silicone Foam (j)	1	1	1	1	2	3	2	0	3	77	1	3	1	4	0
Skin (k)	0	1	0	3	2	1	2	1	1	1	81	3	2	0	2
Sponge (l)	0	3	5	5	4	3	1	1	0	2	3	65	3	2	3
Terry Cloth (m)	2	2	1	6	2	4	1	1	2	0	0	1	70	2	5
Textured Silicone (n)	2	2	1	4	0	5	1	1	0	5	0	3	3	72	1
Wood (o)	1	3	1	0	1	0	0	2	4	1	0	5	2	5	75

Confusion Matrix

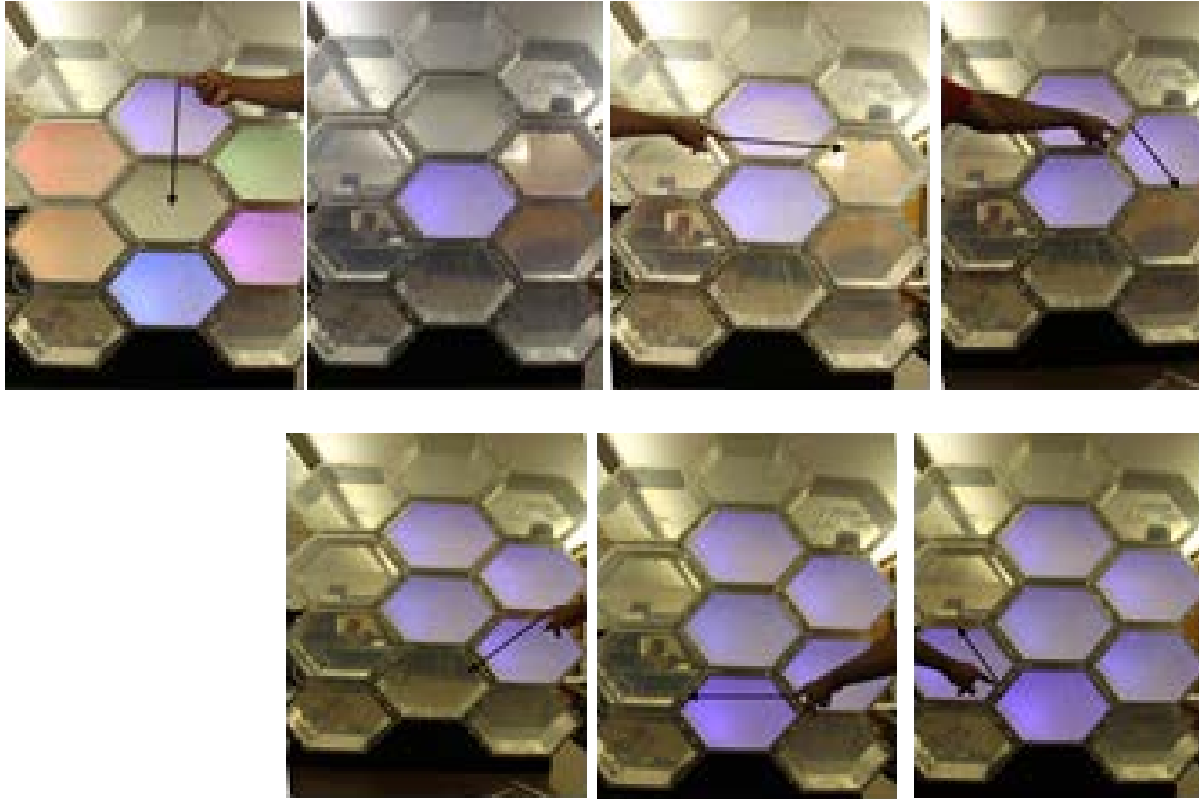
Non-trivial, material-centric computation

Materials that Change Appearance

Appearance changing materials

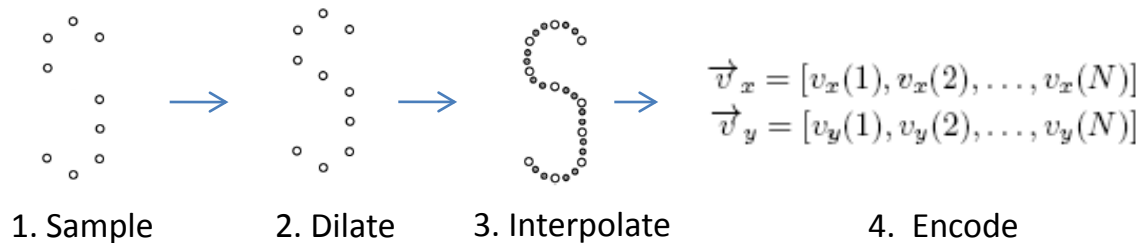


Interacting with a Distributed System



N. Farrow, N. Sivagnanadasan, N. Correll (2014): [Gesture Based Distributed User Interaction System for a Reconfigurable Self-Organizing Smart Wall](#). In: Proceedings of the 8th International Conference on Tangible, Embedded and Embodied Interaction (TEI), pp. 245-246 , ACM 2014.

Distributed Gesture Recognition



4. Encode



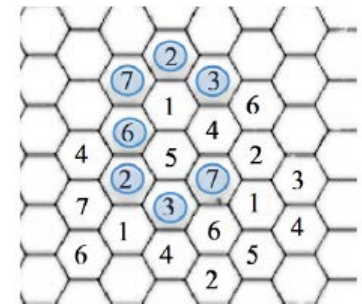
k-NN



5. Consensus



"S"



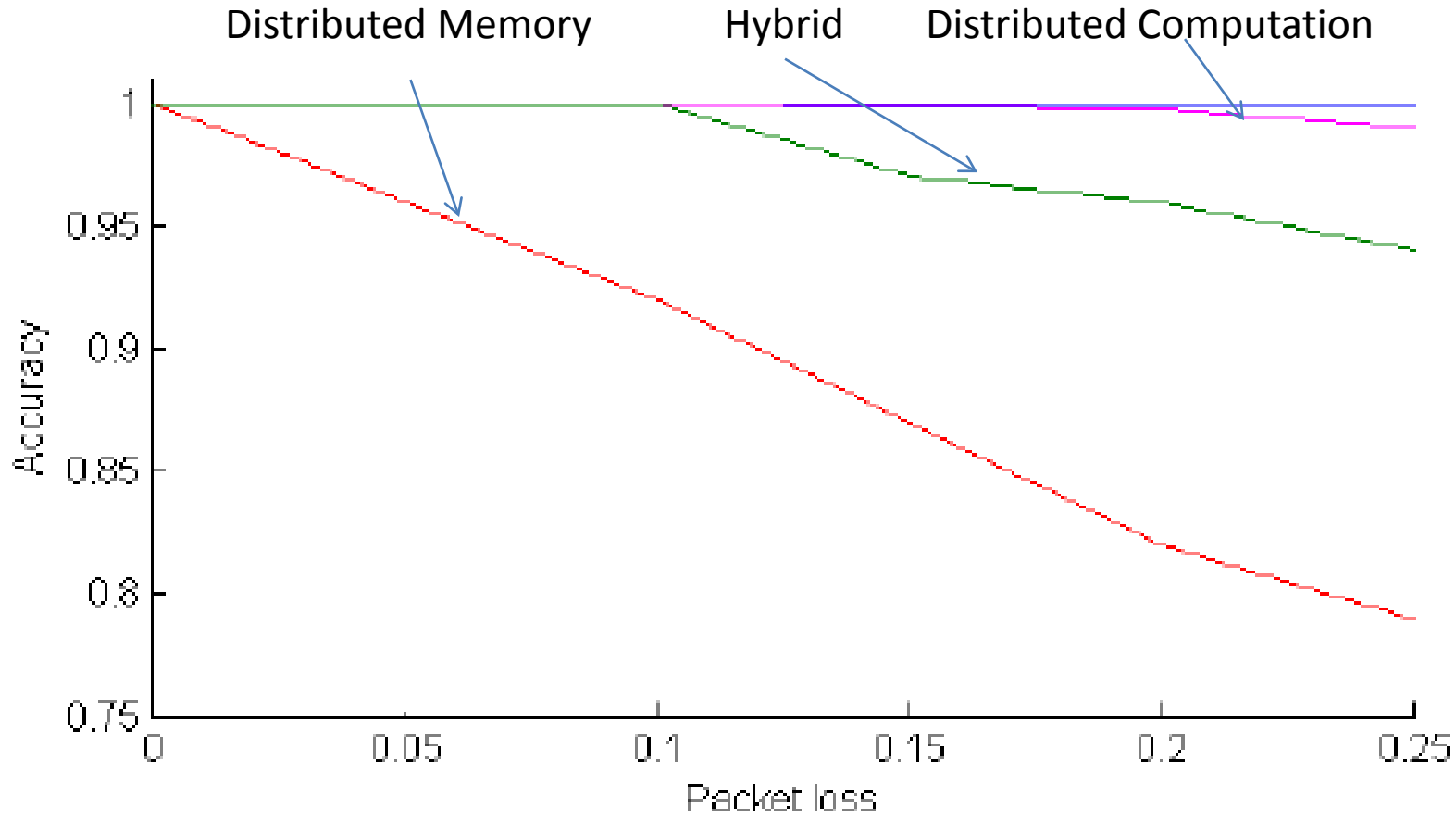
Distribute Memory



Distribute Computation

with Rick Han

Accuracy vs. Packet loss



Tight relationship between material and algorithm design trade-offs

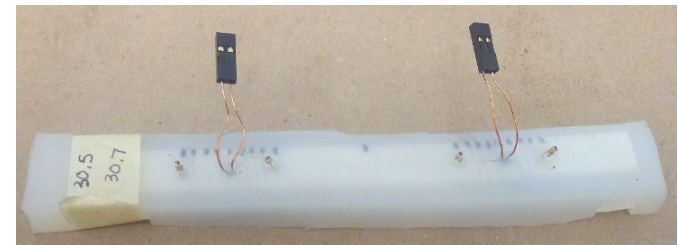
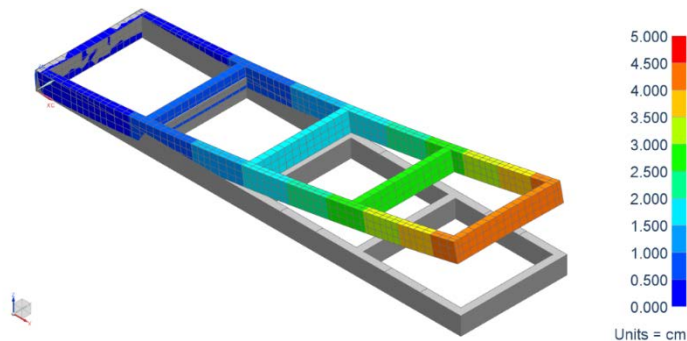
Materials that Shape Change

Variable Stiffness Control

- Stiffness control = shape control
- Melting of PCL
- 2-200MPa change in Young's M .
- Local feedback temperature control
- Global distributed shape control

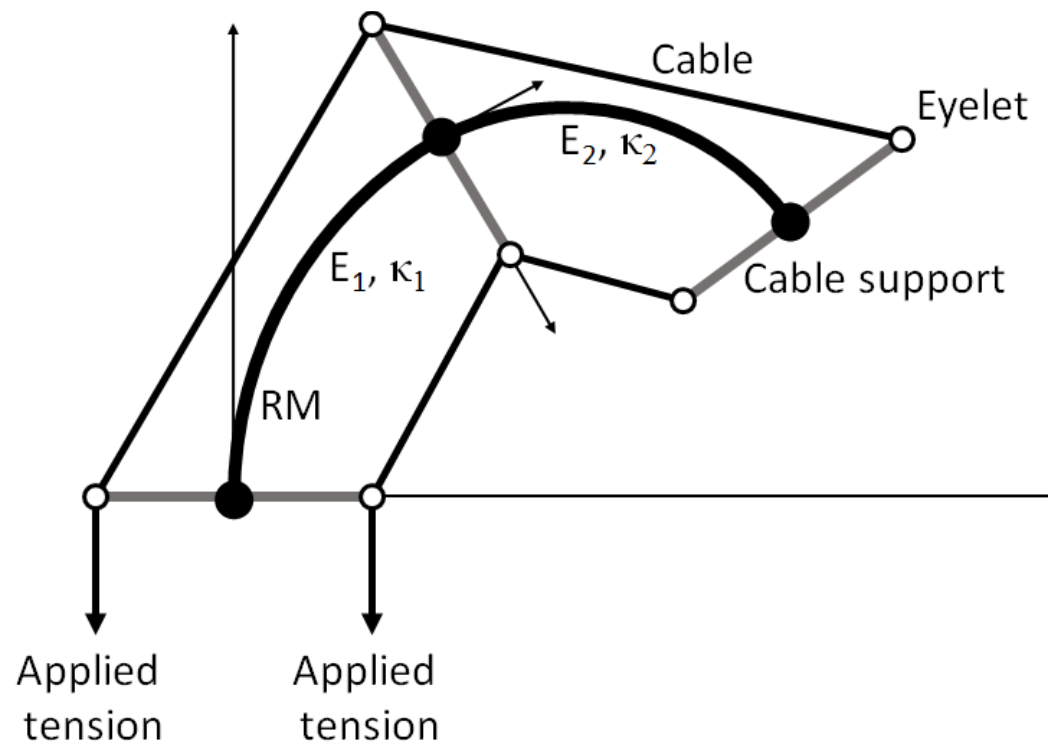


Displacement - Nodal, Magnitude

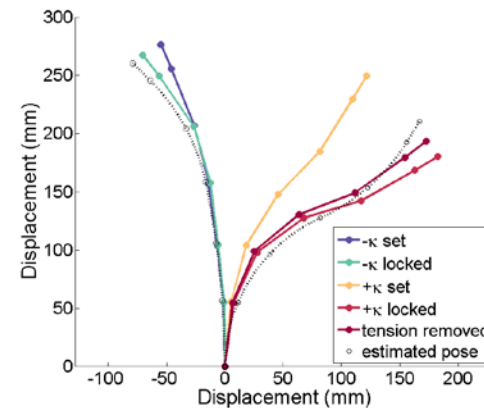
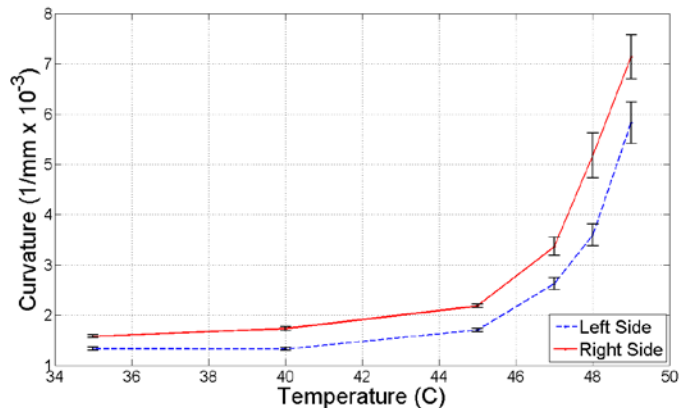
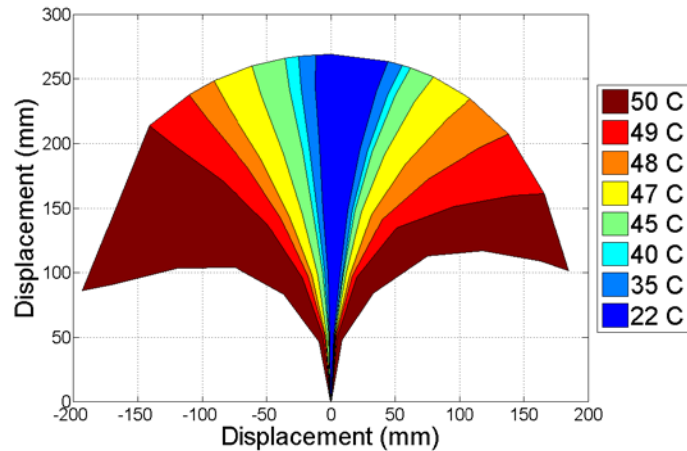


M. A. McEvoy, N. Correll (2014): "Thermoplastic variable stiffness composites with embedded, networked sensing, actuation, and control. In: Journal of Composite Materials, 2014.

Principle of Operation

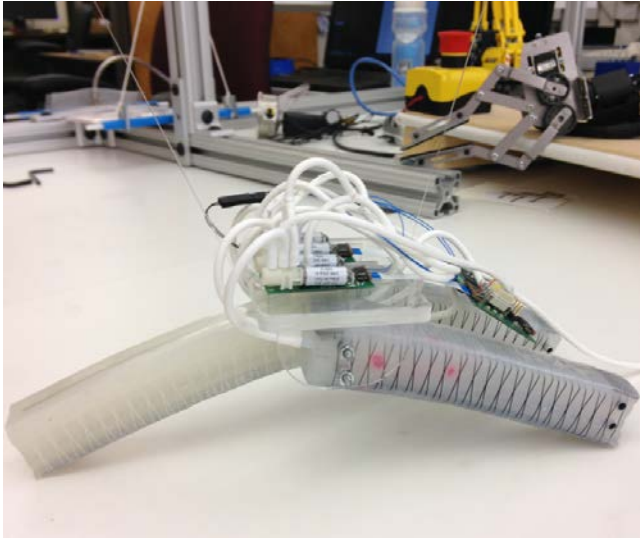


Resulting Shape Change

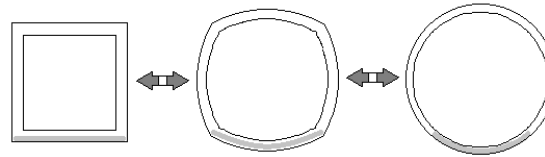


M. A. McEvoy, N. Correll (2014): Shape Change Through Programmable Stiffness. International Symposium on Experimental Robotics (ISER), Springer Verlag, Marrakech, Morocco, 2014.

Pneumatic Shape Change



Modular soft robotic actuator with embedded sensing and control



Modeling

- Geometry
- Material properties
- Pressure
- Curvature
- Resulting force

Outside

Inside

$$\int_0^h \int_0^w \frac{E}{L} \left(\frac{yL}{r} \right) dx dy - \int_{h_t}^{h-h_t} \int_{w_t}^{w-w_t} \frac{E}{L} \left(\frac{yL}{r} \right) dx dy = \int_{h_t}^{h-h_t} \int_{w_t}^{w-w_t} P dx dy$$

Contraction force

Expansion force

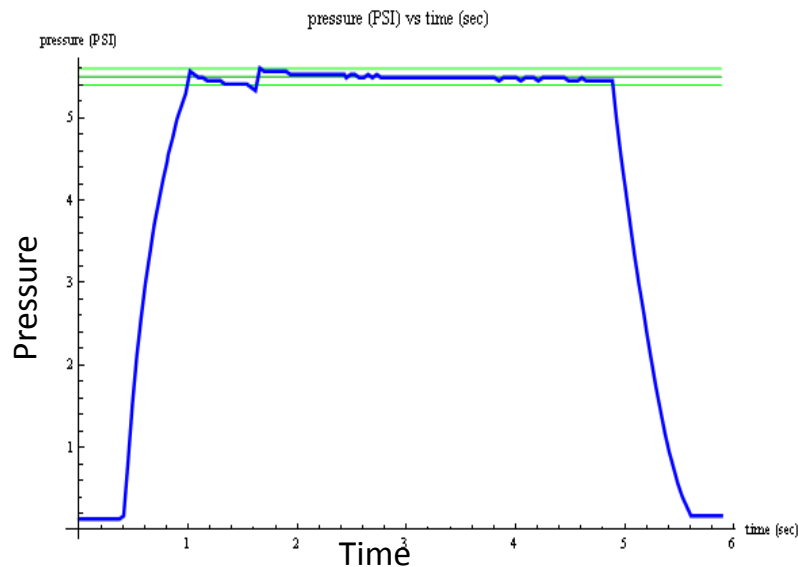
$$\kappa = \frac{1}{r} = \frac{(h - 2h_t)(w - 2w_t)P}{(h(w - 2w_t)h_t + h^2w_t)E}$$

Curvature

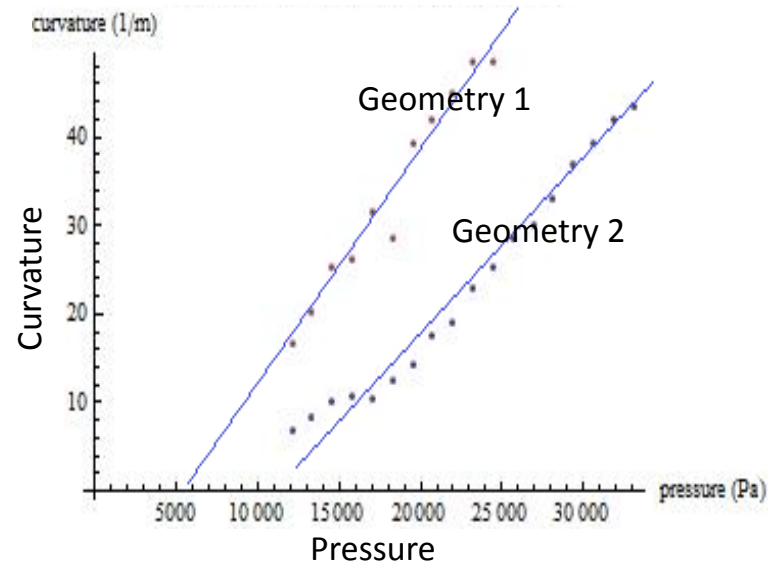
Geometry

Pneumatic Shape Change

Feedback control



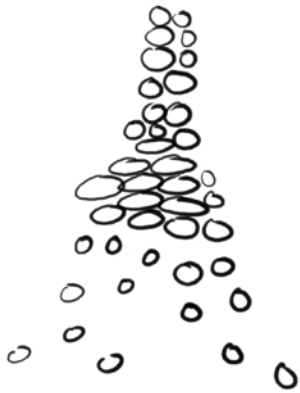
Model prediction



Tight interaction between distributed control and material physics

Materials that Self-Assemble

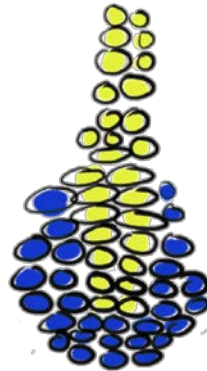
Vision



1. Self-assembly



2. Cell differentiation



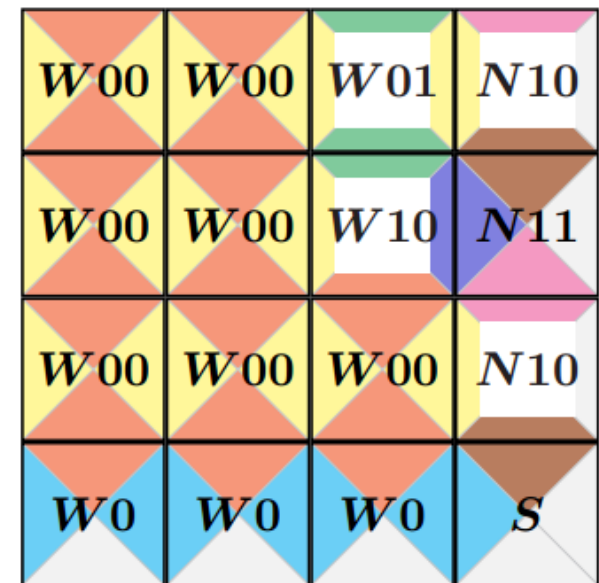
3. Collective behavior

DNA Tile Assembly Model

- Rules to encode neighborhood relationships
- Maximal N rules for structures with N tiles
- Many interesting structures can be made with fewer rules!

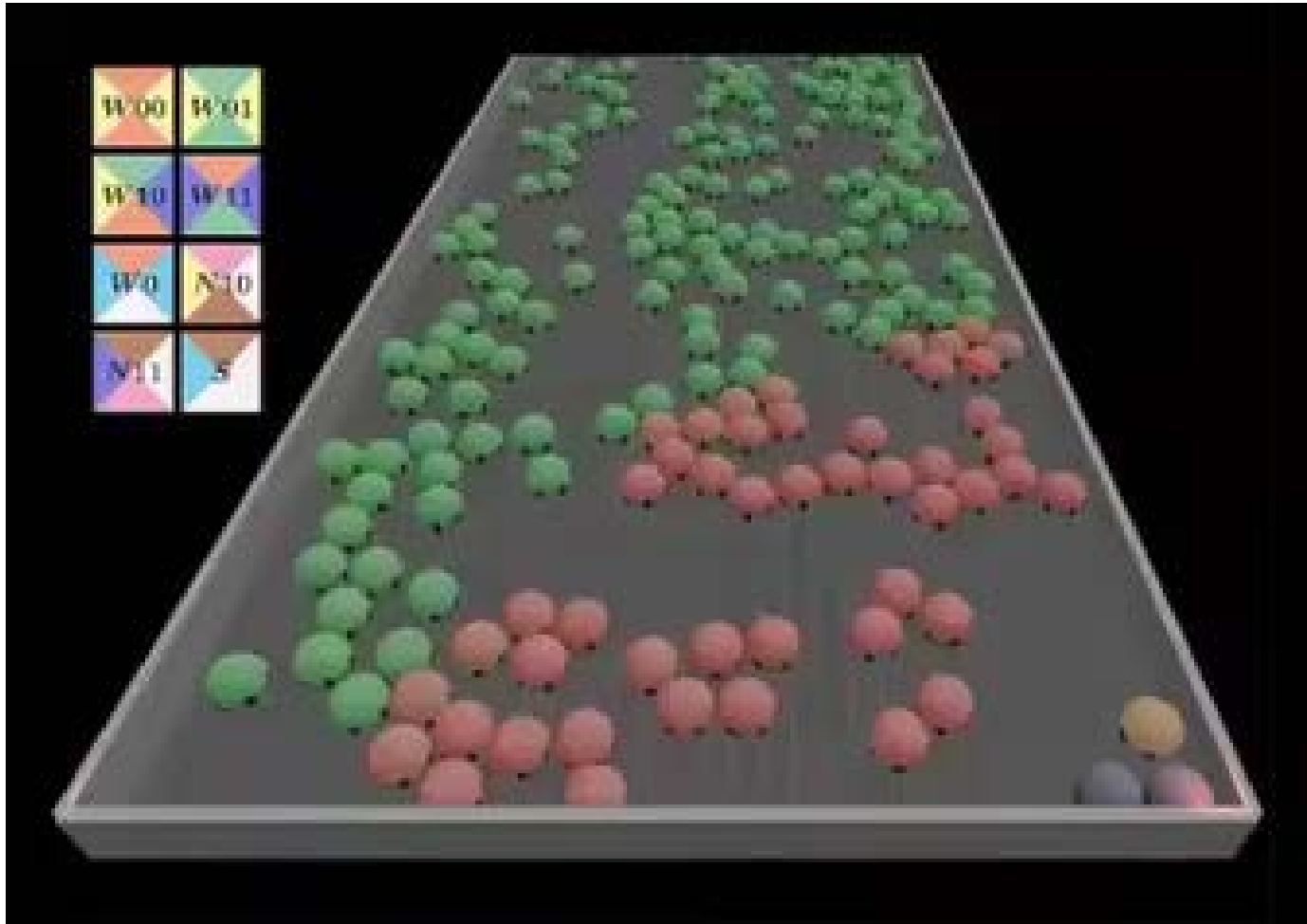


Rules

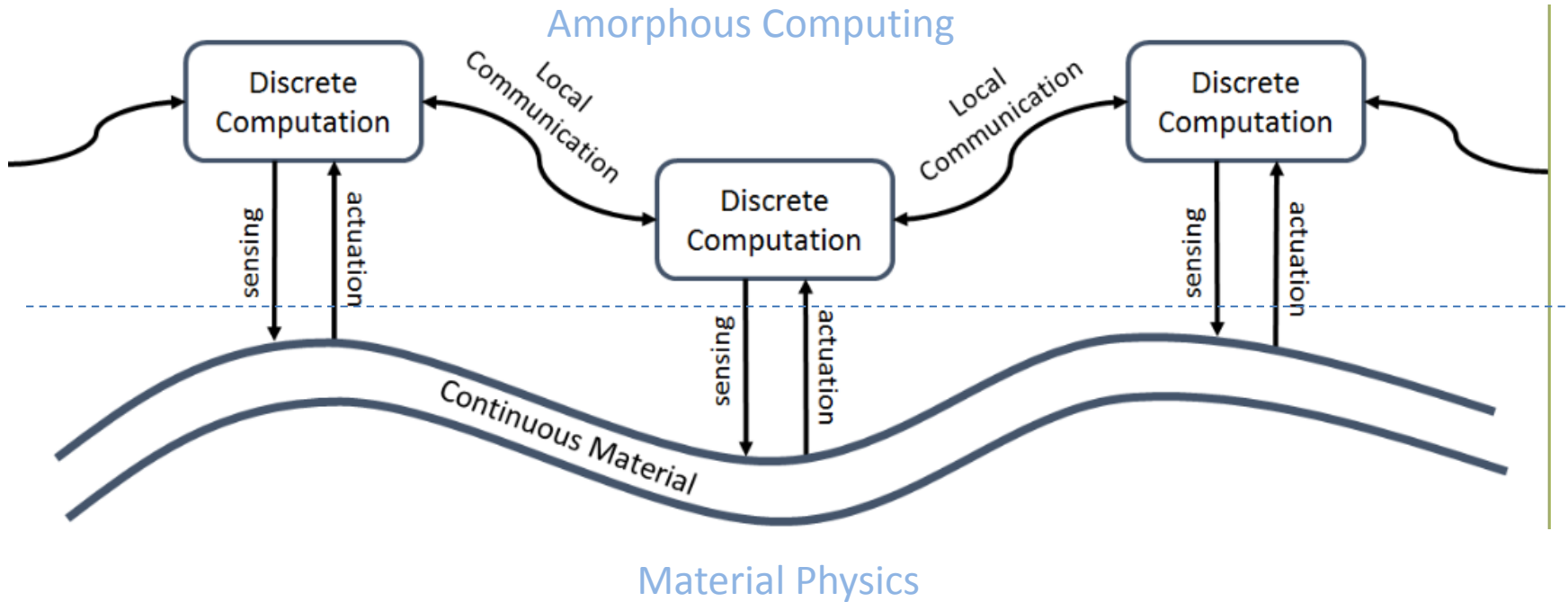


Yuriy Brun. Solving np-complete problems in the tile assembly model.
Theoretical Computer Science, 395(1):31–46, 2008.

Example



Robotic Materials



Robotic Materials: New challenges for Education



A soft skin that can sense distance and force

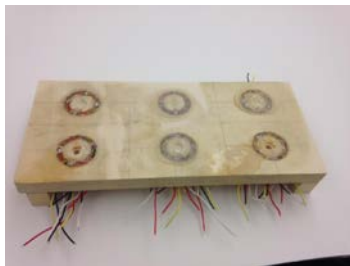


Variable Stiffness by Sheet Jamming

Computation X Materials



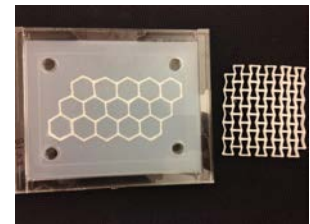
Shortest path routing in a distributed system



An interactive Sushi tray



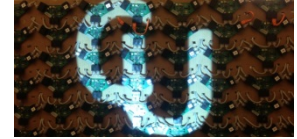
Wireless data transmission powered by Seebeck effect



Shape-changing materials that can self-restore

Conclusion

- Robotic Materials pose new opportunities and challenges in distributed algorithms
- Understanding the link between “crowd dynamics” and “material physics”
- Timely problems:
 - Novel capabilities for robots
 - Novel materials with revolutionary functionality for every-day applications



Acknowledgements

