Sensory Channel Grouping and Structure from Uninterpreted Sensor Data

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Presentation Outline

- Background
- Distance Metrics for Sensors
- Sensory Reconstruction Method
- Experiments and Results
- De-Scrambling of Vision Sensors
- Conclusions and Future Work

Background

Sensors are Important!

- Sensors decide what information an organism can have regarding its environment including other organisms and the environment.
- Nature has produced a wide variety of sensory organs that are well adapted to the specific animals and their respective environment.
- For example: echo-location in bats, navigation using magnetic forces by some bees and birds.
- Still, in robotics sensors are quite often seen as something “given” and fixed.

Background cont.

What I would like to achieve:

- A robot that can adapt and evolve its sensors to solve a certain task in a certain environment as efficient as possible.
- Ultimately build machines that can “discover” new sensory modalities, for example a robot with colour vision that discovers IR.
  (by hardware or wetware evolution)
- To do this we need to do *sensor evolution* and also to find methods to build models of the sensory input.

Background cont.

Where to start?

- Assume that a robot receives a number of streams of sensory data with no knowledge of its structure.
- The problem is to build a model of this raw uninterpreted data.
- In order to compare different sensory channels we need a method to compute the informational distances between sensors.
- Given the possibility to compare sensory channels it should be possible to build a model of the sensory input.

Distance metrics

For a measurement to be a metric the following should hold:

- $d(X, Y) = d(Y, X)$. Symmetry.
- $d(X, Y) = 0 \quad \text{iff} \quad Y = X$. Equivalence.
- $d(X, Y) + d(Y, Z) \geq d(X, Z)$. Triangle Inequality.

Distance metrics - cont.

Metrics used in Pierce and Kuipers (1997):

- $$d_1(x_i, x_j) = \frac{1}{t+1} \sum_{\tau=0}^{t} |x_i(\tau) - x_j(\tau)|$$
- Difference in frequency distribution:

  $$d_2(x_i, x_j) = \frac{1}{2} \sum_{\ell=1}^{n} |distr(x_i)_\ell - distr(x_j)_\ell|,$$

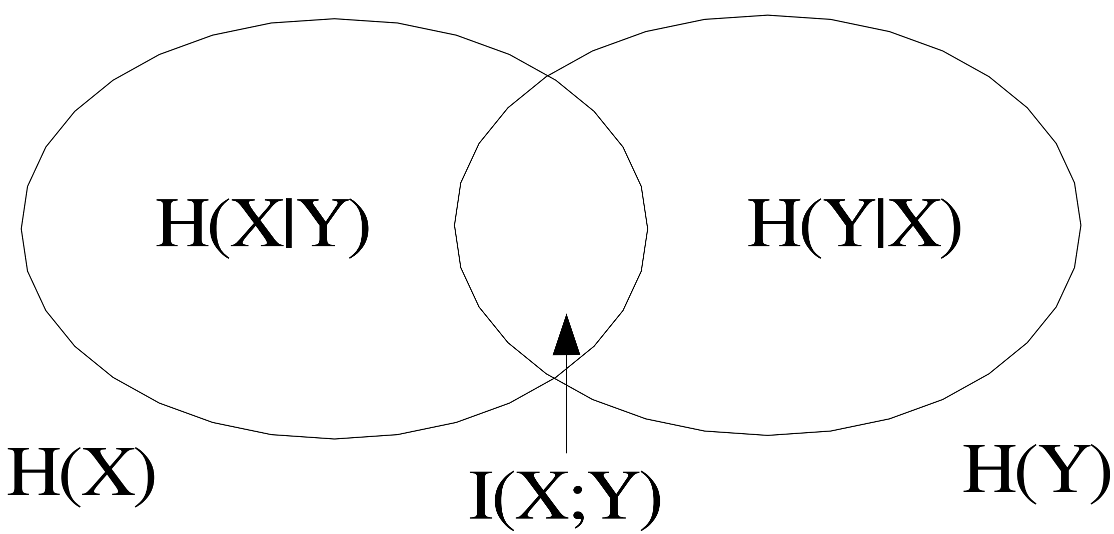
  where $distr(x_i)_\ell$ is the percent of observations within the ℓth subinterval.
- Observe that these two metrics do not messure correlation between the the sensors.

Crutchfield's Information Metric

The distance between two information sources, e.g. two sensors, is defined as

$$d(X, Y) = H(X|Y) + H(Y|X)$$

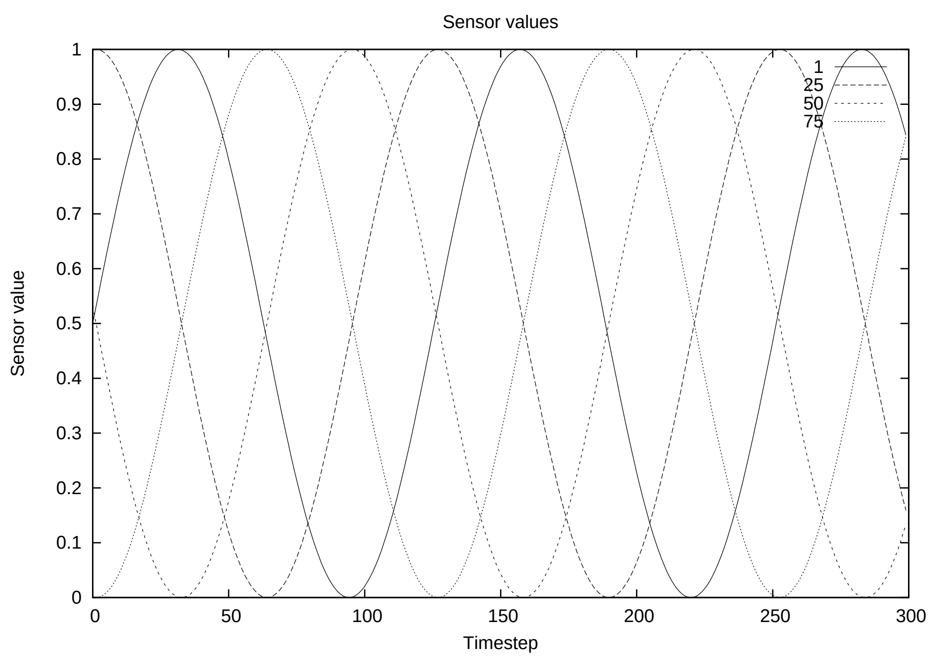
where $H(Y|X)$ is the conditional entropy for Y given X.



Crutchfield's Information Metric cont.

Advantages:

- Domain independent.
- Distance is related to correlation. For example:



Sensory Reconstruction Method

First described by Pierce and Kuipers

- Given a number of sensors, find their relative positions and dimensionality.
- The result is a metric projection (map) of the sensors.

Pierce and Kuipers. Map Learning with Uninterpreted Sensors and Effectors, in *Artificial Intelligence*, volume 92, 1997

Method

- Let the agent move more or less at random for t timesteps.
- For each timestep the value of each sensor is saved.
- After the t timesteps, perform the following steps:
  1. Compute the distance between each sensor using the distance metric d_k.
  2. Compute the dimensionality and positions of the sensors.

Dimensionality and Positions

Given a group of sensors, find the dimensionality and the layout.

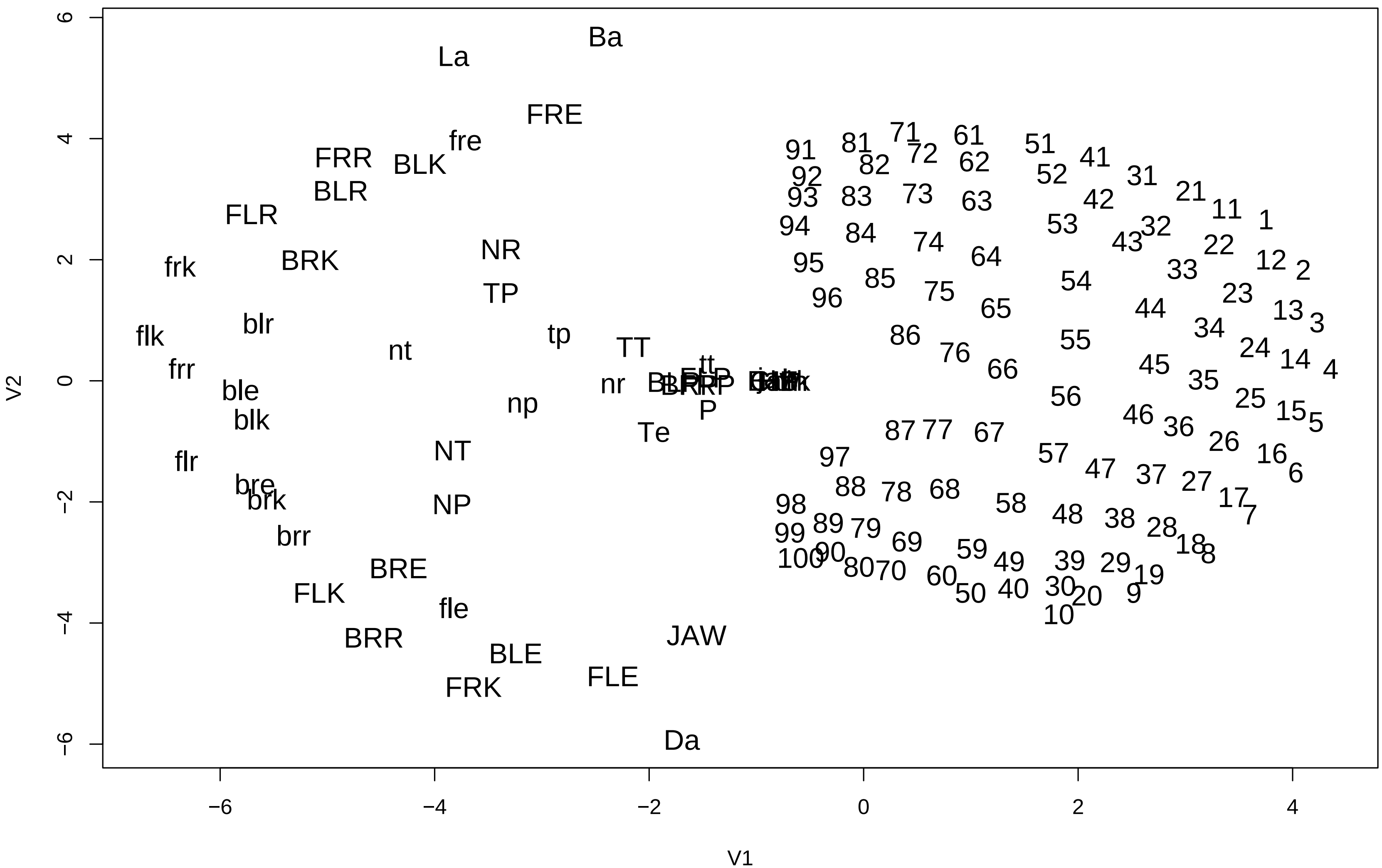
- The dimensionality of the data is computed by finding the dimension that accounts for the most variance in the data.
- Find an assignment of positions of the sensors that reflects the distance metric d_k.
- This is a constraint-solving problem that can be solved with a number of different methods.
- We have used metric-scaling and relaxation.

Metric Projections of AIBO Data

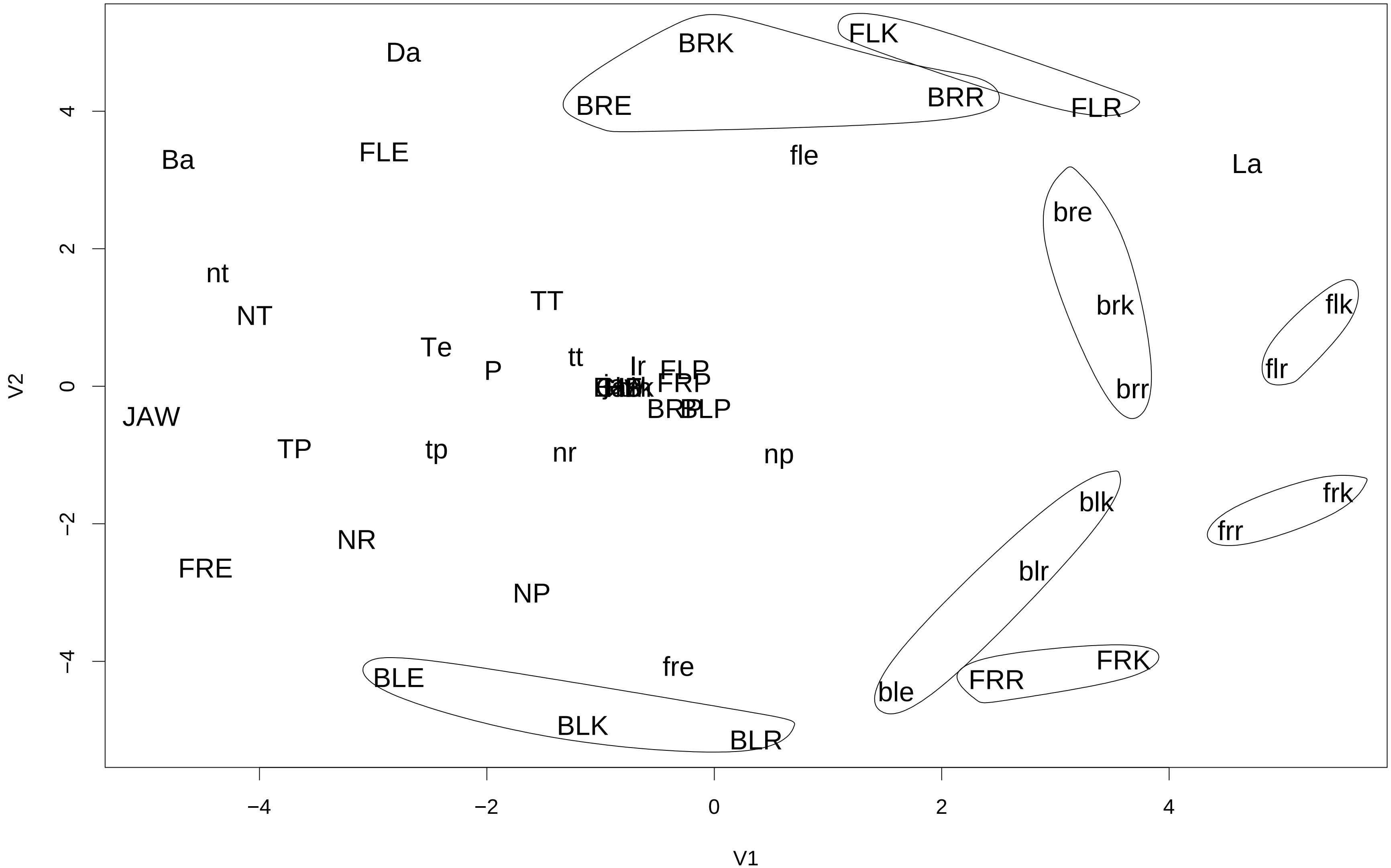
SONY AIBO sensors: IR, colour camera, microphones, gravitational sensors, position of joints, and touch sensors. We used 10x10 pixels from the upper left corner of the camera.

Collect all sensor data (except audio) from a SONY AIBO robot dog chasing a ball with a framerate of roughly 10 fps.

Metric Projections of AIBO Data cont.

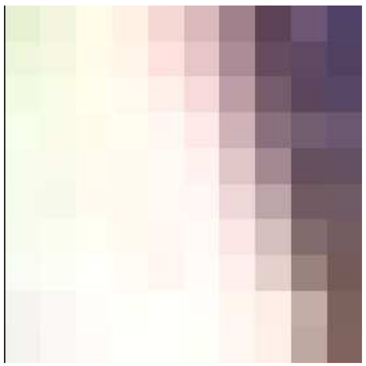


Metric Projections of AIBO Data cont.

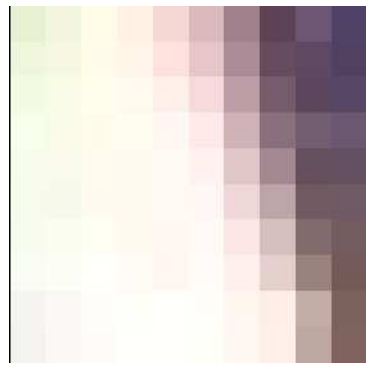


De-Scrambling of Vision Sensors

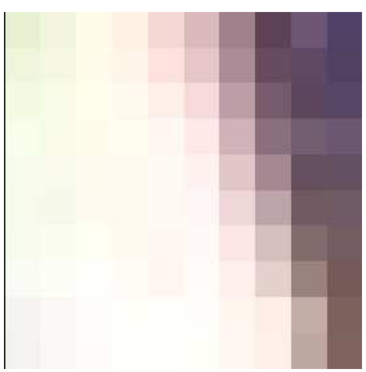
Problem: How to find to find the applied map?



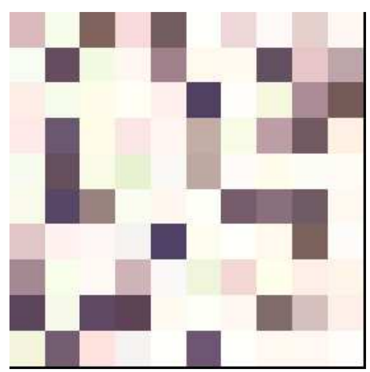
1	2	3	4	5	6	7	8	9	10
11	12	13	14	15	16	17	18	19	20
21	22	23	24	25	26	27	28	29	30
31	32	33	34	35	36	37	38	39	40
41	42	43	44	45	46	47	48	49	50
51	52	53	54	55	56	57	58	59	60
61	62	63	64	65	66	67	68	69	70
71	72	73	74	75	76	77	78	79	80
81	82	83	84	85	86	87	88	89	90
91	92	93	94	95	96	97	98	99	100



Real image | Map | Result

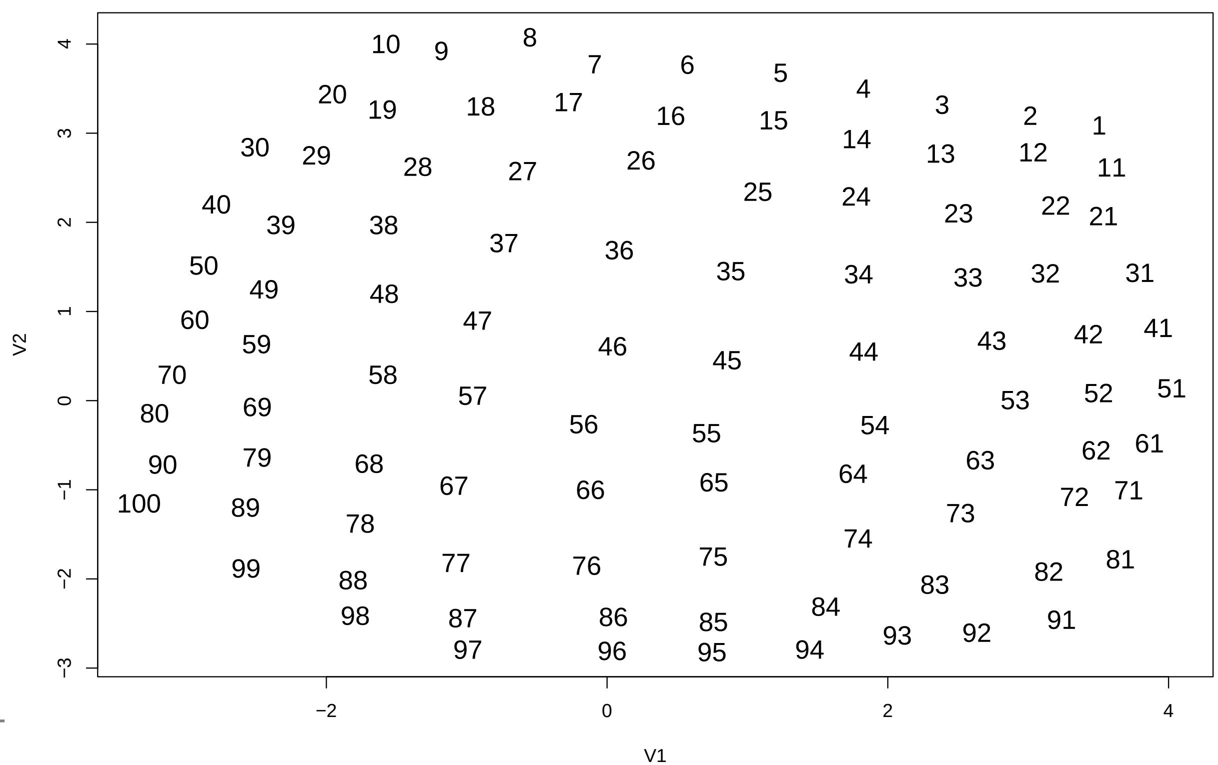


44	91	33	40	77	1	15	84	96	65
76	28	23	80	93	19	29	12	83	26
13	37	78	16	90	4	38	57	81	52
72	43	48	66	10	31	74	58	92	32
2	51	68	85	73	62	61	71	42	18
22	82	17	60	99	63	7	20	39	59
41	54	24	98	14	8	34	89	88	5
11	49	6	50	35	47	25	9	53	30
64	45	100	86	97	27	55	21	36	69
94	75	70	67	95	56	87	79	46	3



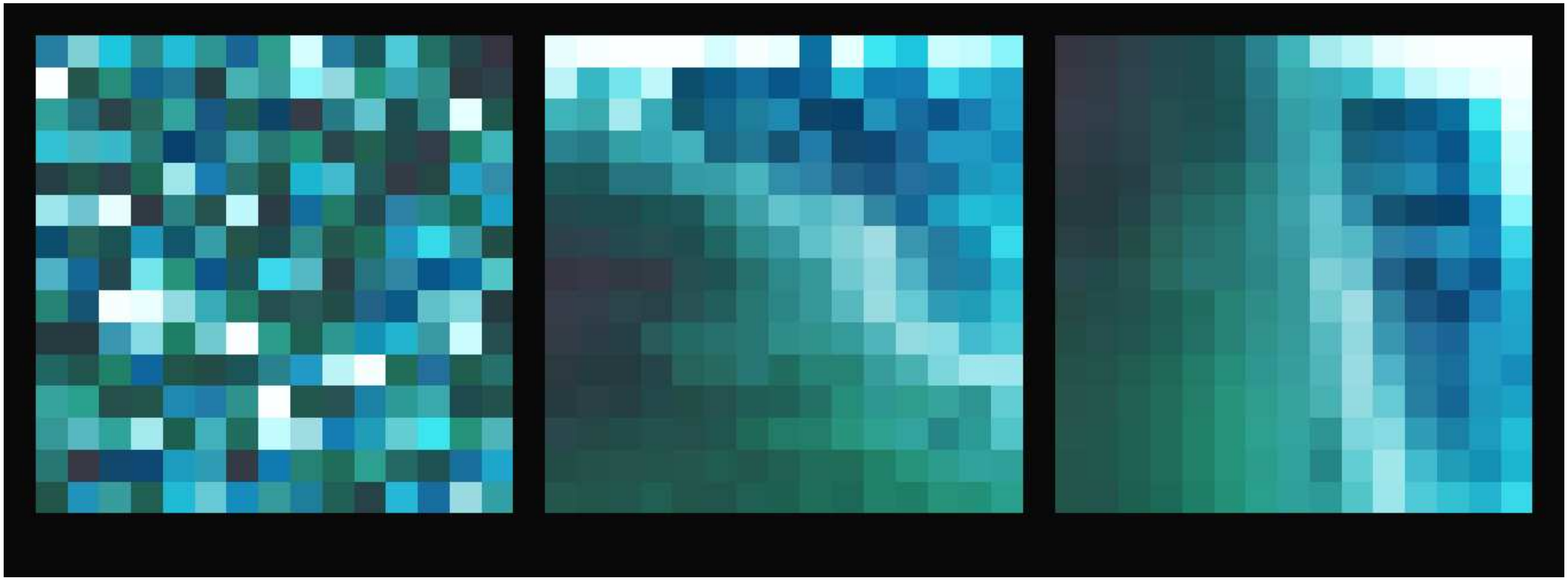
De-Scrambling of Vision Sensors cont.

Answer: Compute a 2-dimensional metric projection of the vision sensors. This metric projection can be used to approximate a discrete map that recover the original image (more or less).



De-Scrambling of Vision Sensors cont.

Demo:



Conclusions and Future Work

- The Sensory Reconstruction Method can be used to find structure in uninterpreted sensor data.
- Possible Applications: Optimization of sensor layouts, de-scrambling, sensor networks, etc
- Future work: Relevant Information Metric, Sensor integration, A control system that adapts its sensory systems according to the cost vs utility of using different sensors.