

Symmetry and Structural Bootstrapping



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Structural Bootstrapping (from Xperience URL)

a method of building generative models

- leverage existing experience
 - to **predict unexplored action effects**, and
 - to **focus the hypothesis space** for learning novel concepts
- A **developmental approach** enables
 - rapid generalization, and
 - acquisition of new knowledge and skills from little additional training data
- shared concepts enable enactive agents to communicate effectively with each other and with humans.
- can be employed at all levels of cognitive development (e.g. sensorimotor, planning, communication).

rewrite rule

S := T, Rf, Ro(90)

P := T, Rf, Ro(2pi/n)

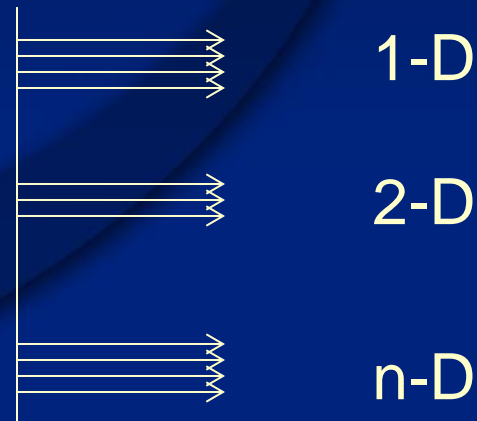
Symbol Strings

Modes

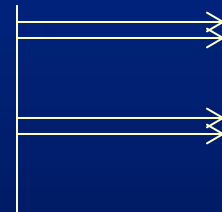
Xperience: Oct. 5, 2013

Overall Idea

Sensor signals



Actuator command
signals



How to represent, correlate, store and re-use sensorimotor combinations (affordances)?



G-Reps

- Parse 1-D, 2-D, ... n-D signals into basic symmetries (represented as **symbols**)
- Build sequences
- Store and index

- Filter by affordance
- Affordances keyed to 3D space group operations (translation, rotation)

- Each sequence grounded in particulars (shape basis, color, etc.)

Example: Square Shape

Leyton's characterization:

1. Translation symmetry of line (T): gets one side



2. Acted on by cyclic (rotation) group (C₄): gets rest

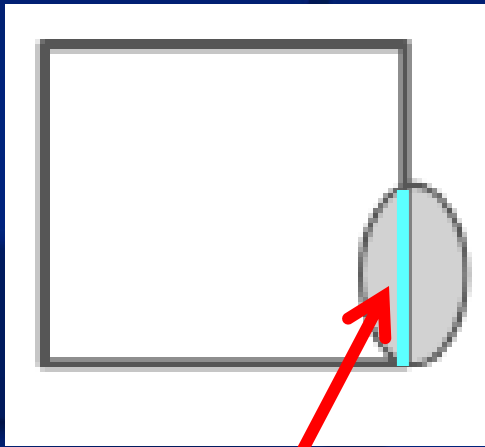


etc.



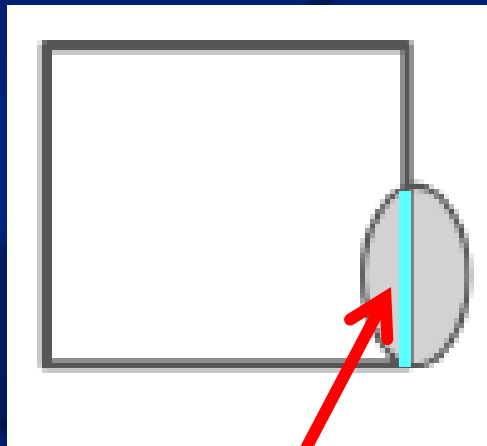
This is a generative
model to create shape

G-Reps: Putting Symmetries Together

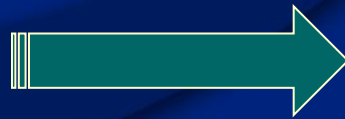


Shape Basis

G-Reps: Putting Symmetries Together

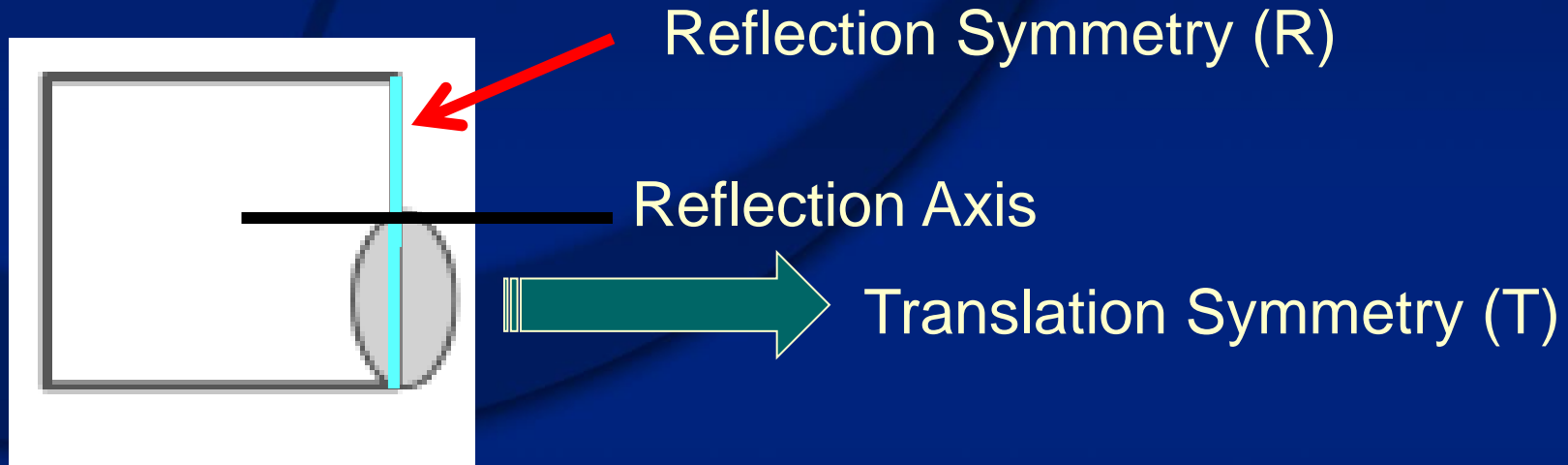


Shape Basis



Translation Symmetry (T)

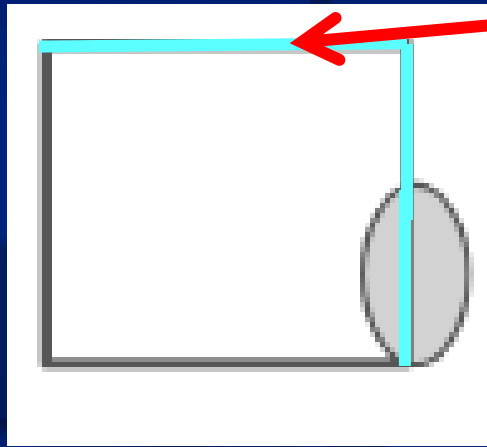
G-Reps: Putting Symmetries Together



G-Rep: $T < R$

G-Reps

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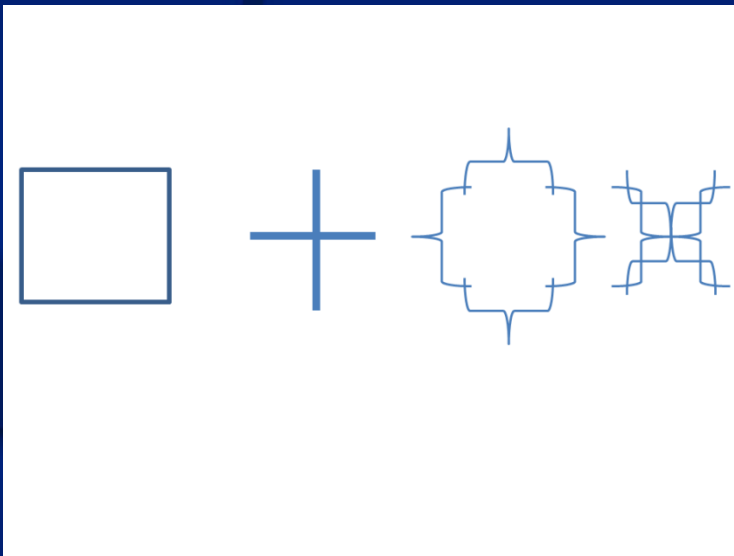


Rotation Symmetry (C)

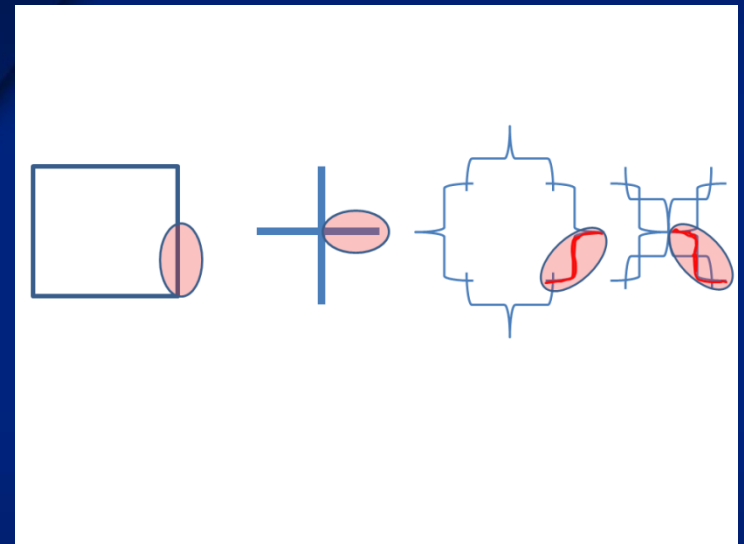
Rotation Axis

G-Rep: $T < R < C_4$

G-Reps Abstract Shape



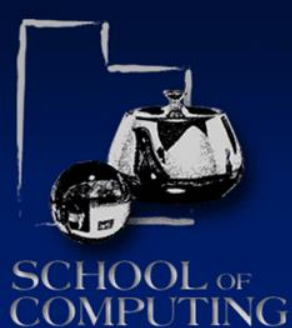
All these shapes have
Same G-Rep



But these shapes have
different shape basis

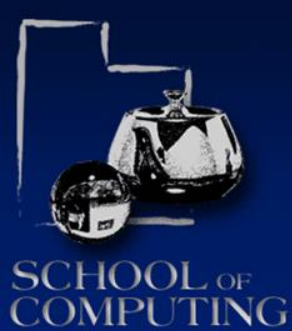
Group Product Scene Description





G-Rep: Wreath Product

- Symmetry group of regularly branching, rooted trees
- Relabelings that only permute nodes at fixed distance from root.
- Group-based convolutions (e.g., DFT)
- Think of cognitive wreath product as capturing combinatorics of object structure



Wreath Product (cont'd)

The connection between the DFT and group theory is immediate from its definition. Given an input $f = (f(0), \dots, f(N-1)) \in \mathbb{C}^N$, its DFT is defined as the collection of sums (Fourier coefficients)

$$\hat{f}(k) = \sum_{n=0}^{N-1} f(n)W^{nk} \quad (2.1)$$

where $W = e^{2\pi j/N}$ for $j = \sqrt{-1}$. The N^{th} roots of unity W^{jk} are the values of the irreducible characters (or in this case, equivalently, the irreducible matrix elements) of the cyclic group $\mathbb{Z}/N\mathbb{Z}$. If computed for all $k \in \{0, \dots, N-1\}$, the expression (2.1) computes the change of basis for the function $f : \mathbb{Z}/N\mathbb{Z} \rightarrow \mathbb{C}$ from the basis of delta functions

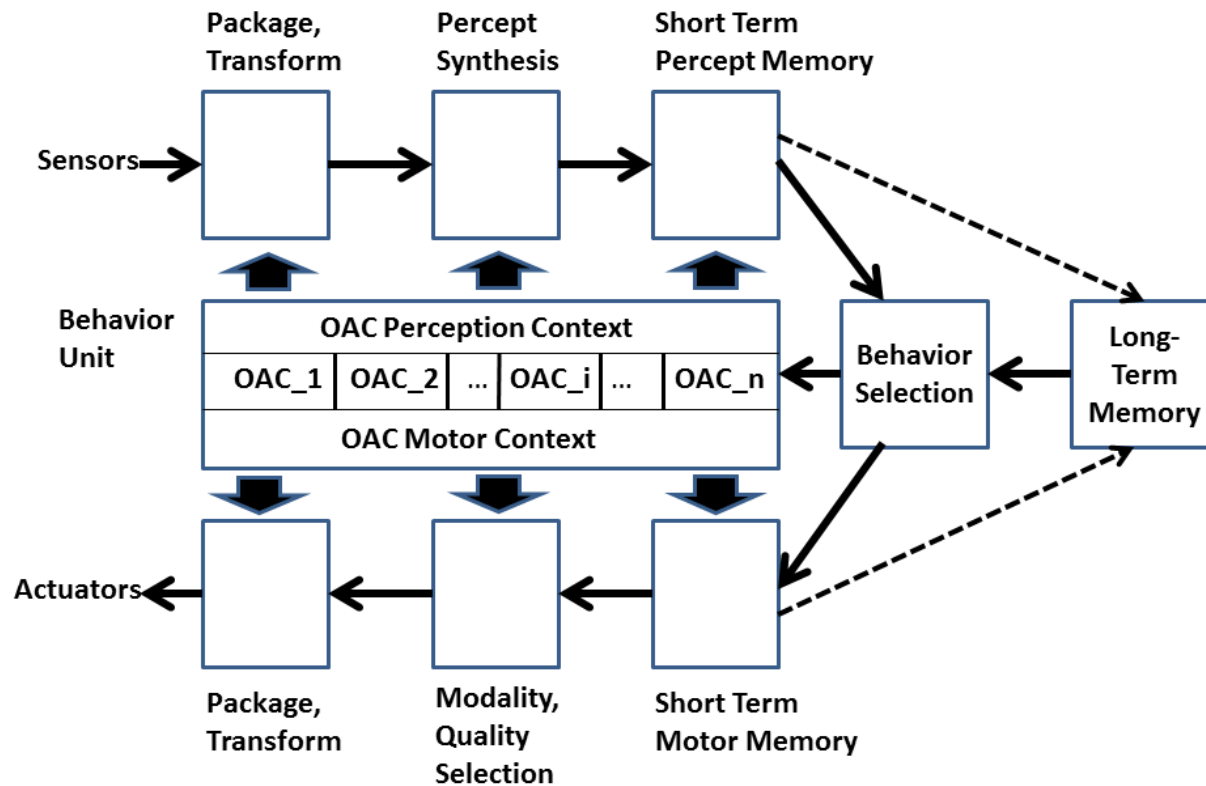
$$\delta_n(k) = \begin{cases} 1 & \text{if } n = k \\ 0 & \text{otherwise} \end{cases}$$

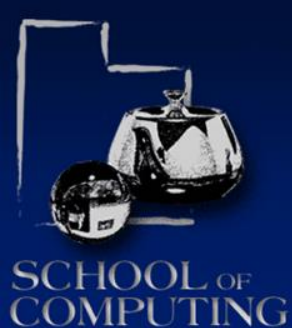
to the basis of irreducible matrix elements

$$\chi_n(k) = W^{nk}.$$

Taken from: "A Wreath Product Group Approach to Signal and Image Processing: Part I – Multi-resolution Analysis," Foote et al. 1999

Current Work: OAC Architecture

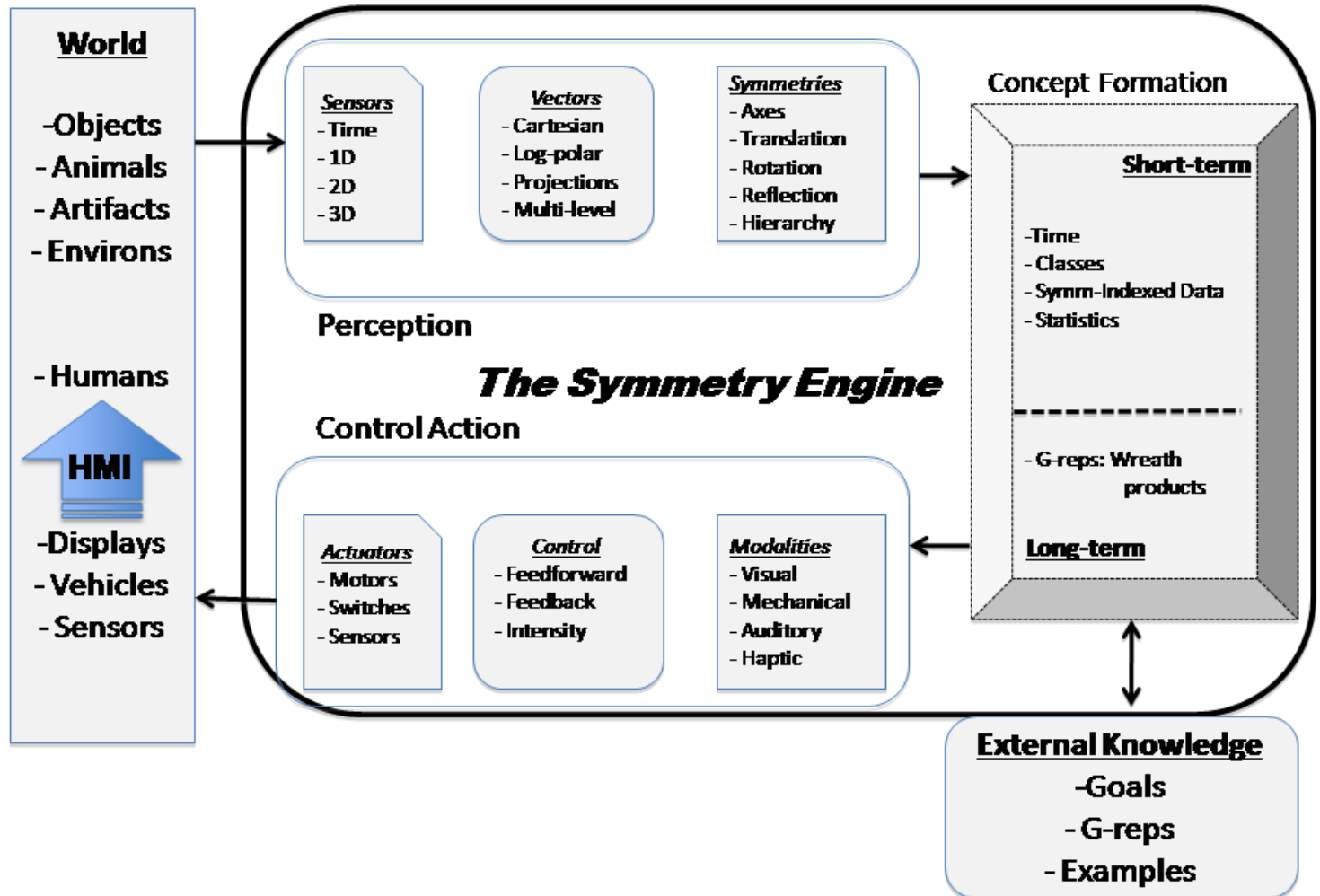




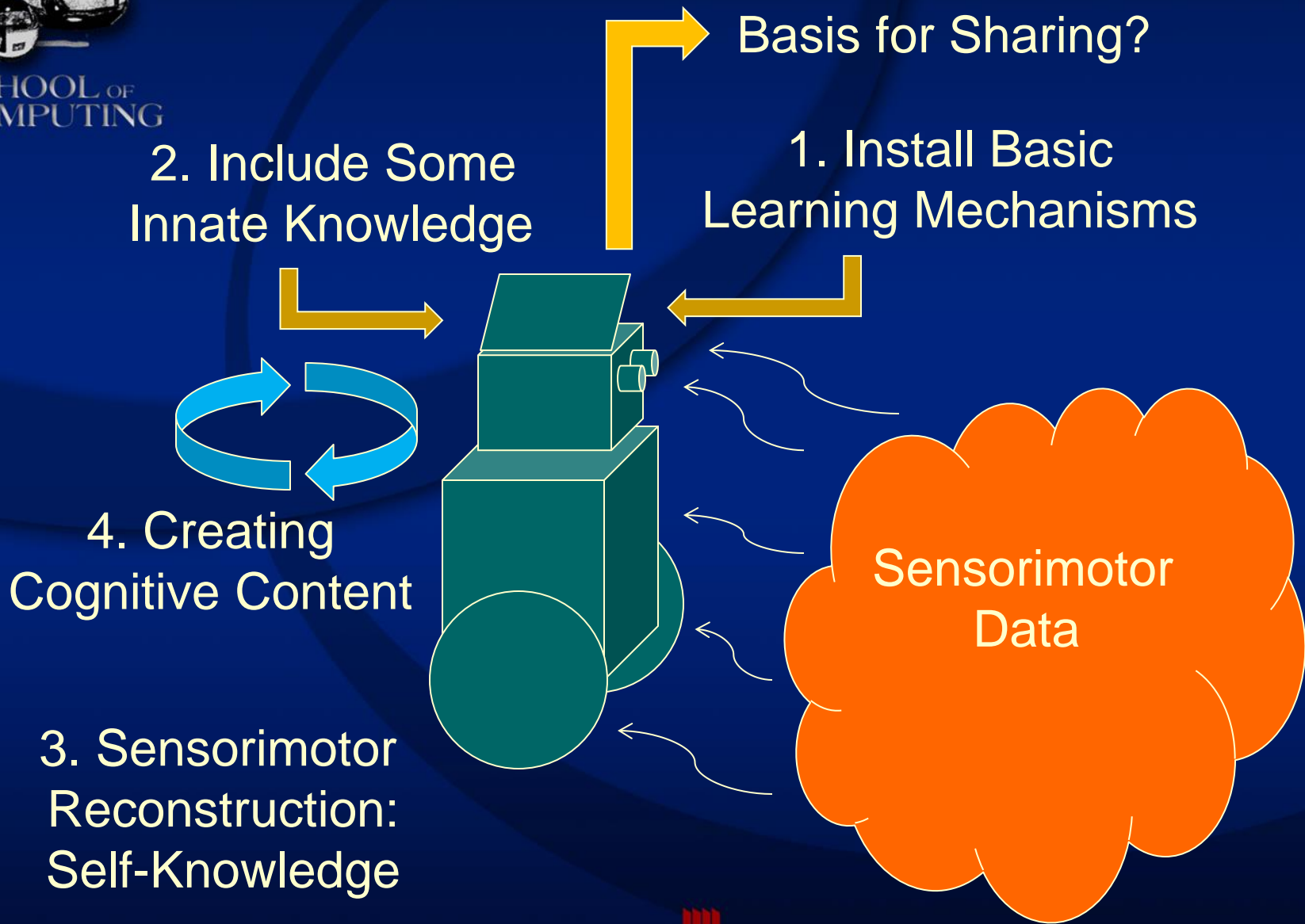
Using Symmetry in OACs

- Symbolic representations of perceptual symmetries
- Symbolic representations of actuation symmetries
- Parameters for symbols
- Context (from position of symbols in string)

Goal: The Symmetry Engine



Issue: Percepts → Knowledge



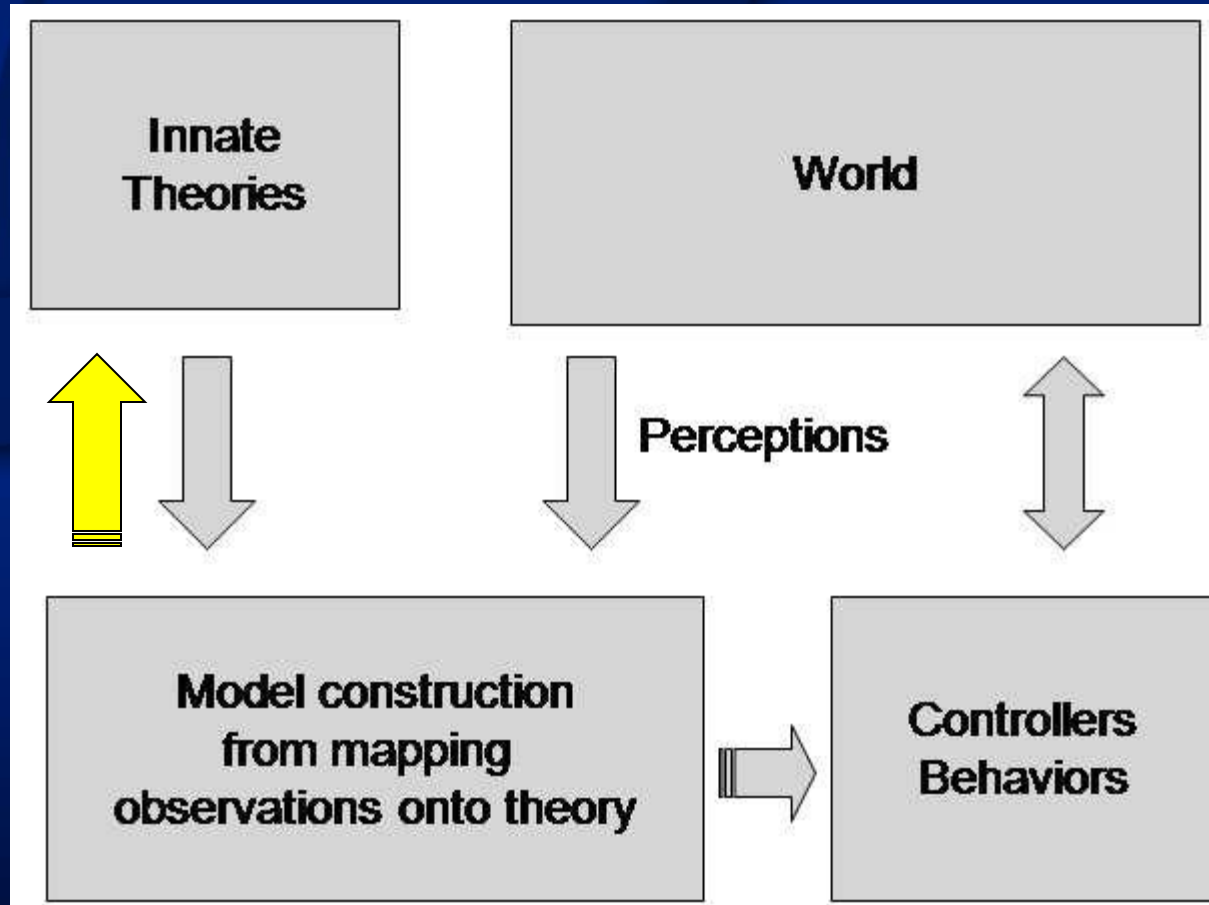
Innate Knowledge Options (see Sloman's work)

Much knowledge, including how to acquire knowledge in domain, is innate

versus

All knowledge derived from experience using general learning methods (e.g., reinforcement learning)

Innate Theories



Evolution

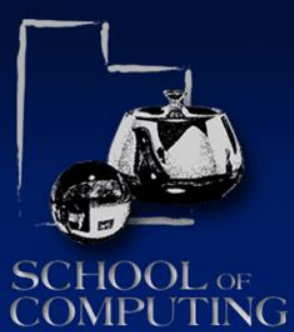


Does Anybody In Robotics Use Innate Theories?

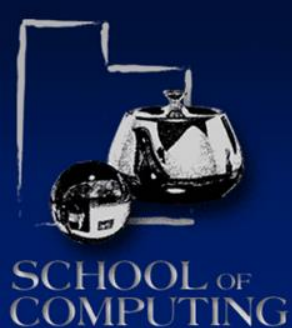
In fact, almost everybody:

- **Subsumption**: innate knowledge in HW
- **RoboEarth, ARMAR III, SOAR**: innate knowledge about sensors, actuators, world objects and actions, language, etc.
- **Arny**: spline way points for throwing motion

→ **Exceptions**: some bootstrapping systems (but even they have some innate things!)



SO, WHAT SHOULD BE INNATE?

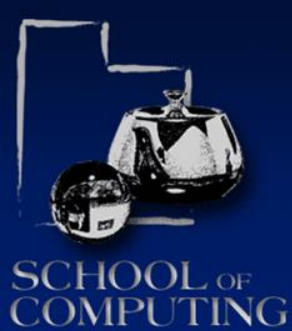


Basic Questions

1. What are the sensorimotor grounds of higher cognition?
 2. What kinds of mental representations, if any, are necessary as explanatory constructs and which are innate?
- I.e., **What can we use to structure (inform) sensorimotor data to obtain useful knowledge?**

Current Approaches

- Ontologies
- Coordinate Frames
- Models (2D and 3D representations of faces, animals, things, ...)
- Goals
- Language (both speech processing and synthesis)
- ...

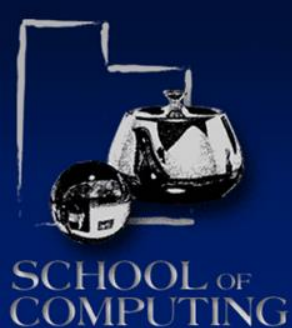


A Proposal: Symmetry Theories

A symmetry defines an invariant.

Let's consider a simple example:

Group Theory (important for symmetry!)



E.g., Group Theory

Suppose we have a set of elements, S , an operator (+) and the following four axioms:

1. **Closure**: $a, b \in S \rightarrow a+b \in S$
2. **Associativity**: $a+(b+c) = (a+b)+c$
3. **Identity element**: $\exists e \in S \ni \forall a \in S (a+e) = a$
4. **Inverse element**: $\forall a \in S \exists a^{-1} \in S \ni (a+a^{-1}) = e$



Group Theory Example

Consider translations as elements and application of a translation as the operator [called $T(a)$]:

1. **Closure**: $T(a_1) + T(a_2) = T(a_1 + a_2)$
2. **Associativity**: $T(a_1) + T(a_2 + a_3) = T(a_1 + a_2) + T(a_3)$
3. **Identity element**: $T(a_1) + T(0) = T(a_1)$
4. **Inverse element**: $T(a_1) + T(-a_1) = T(0)$

This is then a **model** for group theory.



Group Theory (cont'd)

How is this useful?

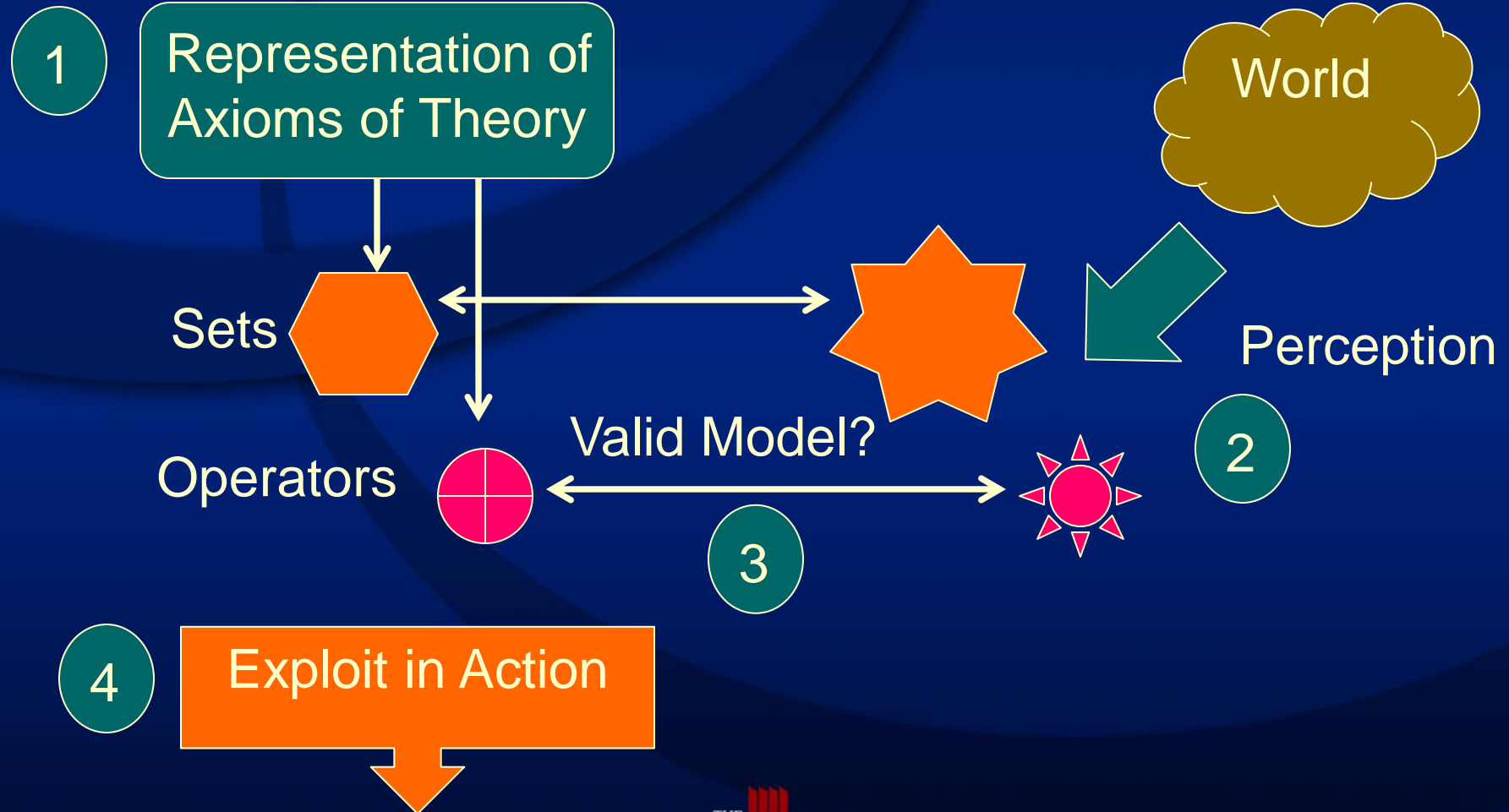
- If we determine that a specific actuator has this property, then we know it is a prismatic joint and we can exploit this knowledge using the theory
- Moreover, we will know that the actuator is similar to other actuators with this property (they are all models of a group)



Symmetry Theory Hypothesis

Semantic cognitive content may be effectively discovered by restricting sensor-actuator solutions to be models of specific symmetry theories intrinsic to the cognitive architecture.

Symmetry Theory Operational Issues



Theory Benefits

1. Similarities between different models can be known because they model the same theory
2. True statements can be known about the model as derived from the theory without any experiential basis by the individual
3. Conflicting models can co-exist because the theories differ (thus, there is not one logical system which is inconsistent)

Symmetry Based Cognition

Can be stored,
compared, and
applied



Can be shared →

Group Products

(see Leyton,
Rhodes, ...)

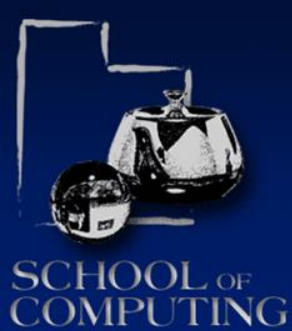
Prime Factorization

1D, 2D, 3D Symmetries

Symmetry Detectors

Sensorimotor Data

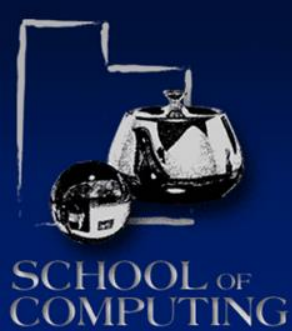
**Innate
representations**



Symmetry Based Cognition

Major points:

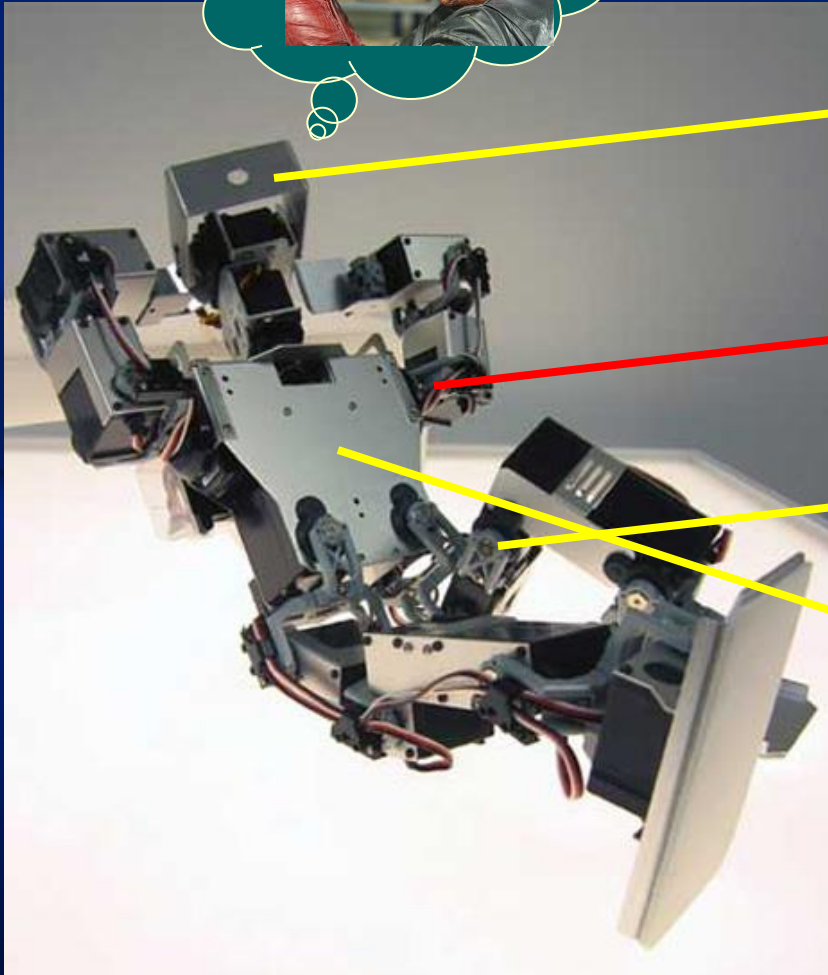
- Built-in symmetry analysis
- Symbolic vocabulary
- Hierarchical structure



Phases of Cognition

- Phase I: Self-Discovery
 - Aka: Sensorimotor Reconstruction
- Phase II: Learning from Others
- Phase III: Interaction and Long-Term Cognition

Robot Wakes up & Learns Own Structure



Camera is just a collection
of 1D pixel streams

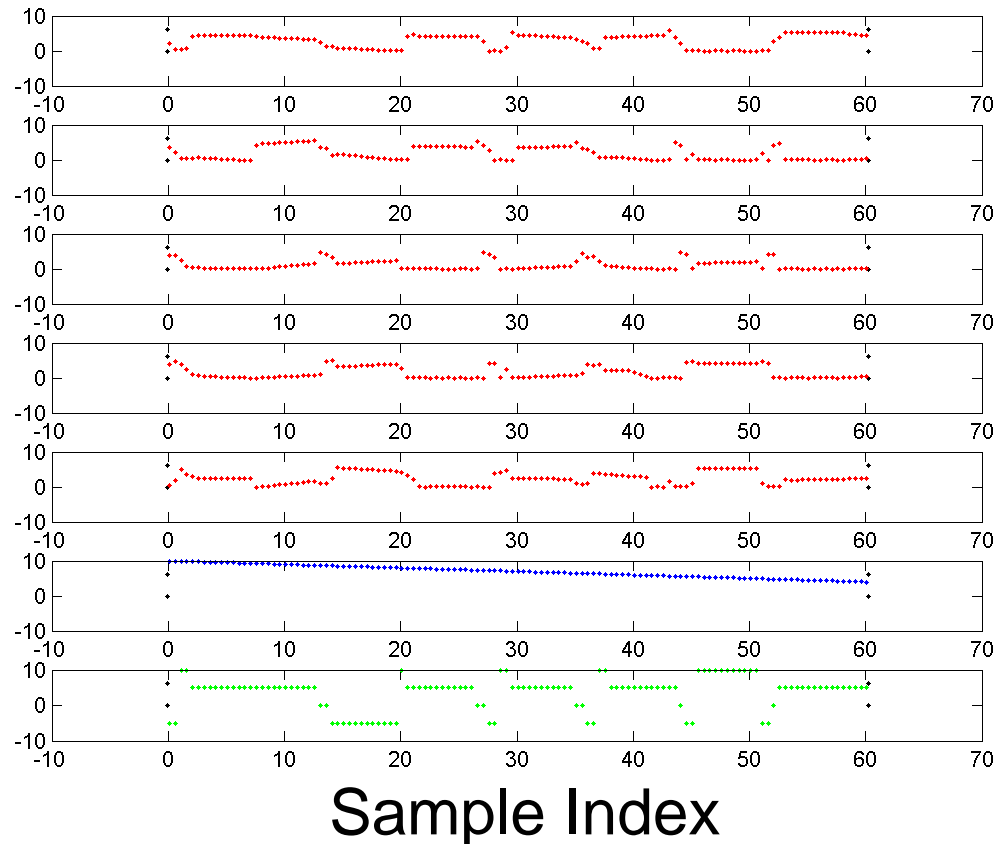
Actuators receive
Command streams

Joint sensors deliver
1D streams

Power level is data stream

Goal: Identify similar sensors/
actuators and their relations

Robot Data Streams

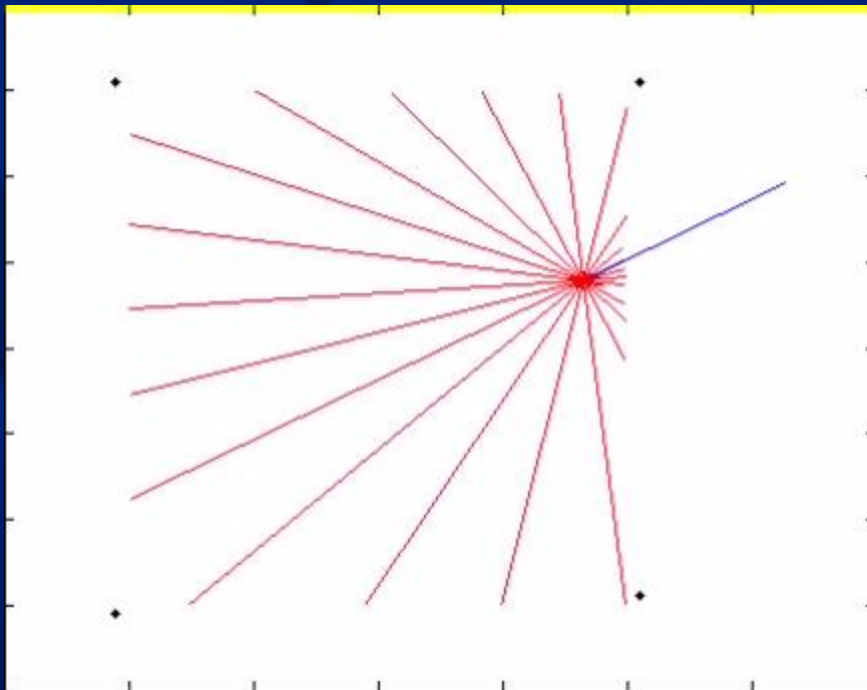


Range Sensors
1,5,10,15,20

Energy Sensor

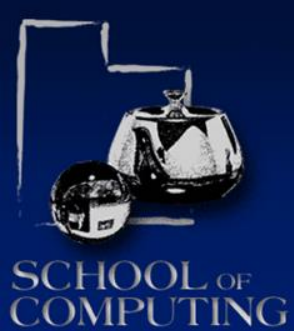
Direction Sensor

Pierce, Kuipers Scenario

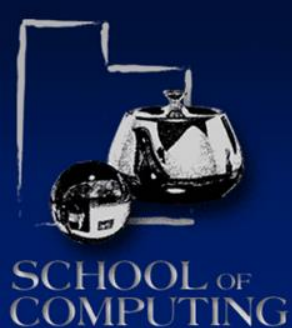


Robot wanders randomly
for 5 minutes:

- 4x6 rectangular area
- 20 range sensors
- NSEW direction sensors
- Energy sensor



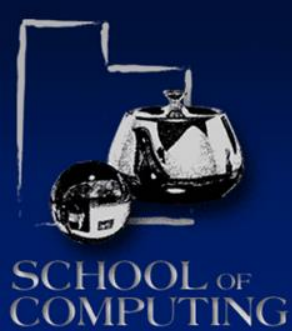
SYMMETRY ANALYSIS IN SENSORIMOTOR RECONSTRUCTION



Our Approach: Exploit Symmetry

Similarity is basis of symmetry; here, we determine if 1D signals (samples y) are:

- **Constant** : exactly the same $y(t) = c$
 - Any point maps to any other
- **Periodic** : $y(t') = y(t)$ where $t' = [1 \ T] \begin{bmatrix} t \\ 1 \end{bmatrix}$
 - No point maps to itself



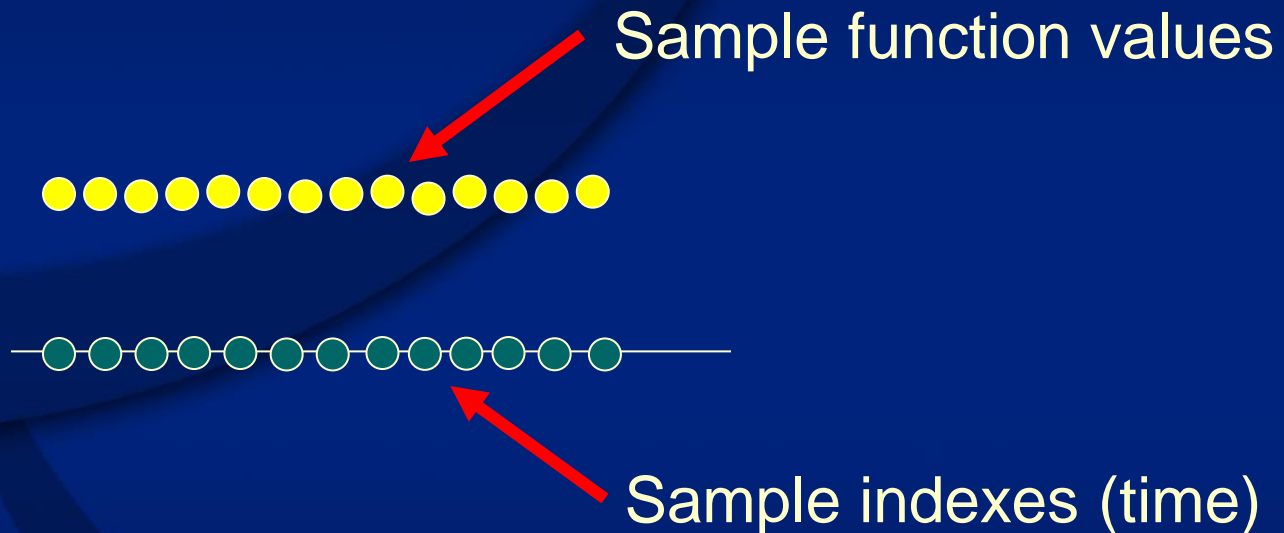
Exploit Symmetry (cont'd)

- **Reflection** : reflection point origin: $y(t) = y(-t)$
 - Only one point maps to itself
- **Linear** : $y = at + b = [a \ b] \begin{bmatrix} t \\ 1 \end{bmatrix}$
 - Take the derivative and find constant signa;
- **Gaussian** : $\sim N(\mu, \sigma^2)$ symmetry of variance or histogram or autocorrelation

Symmetries (1D)

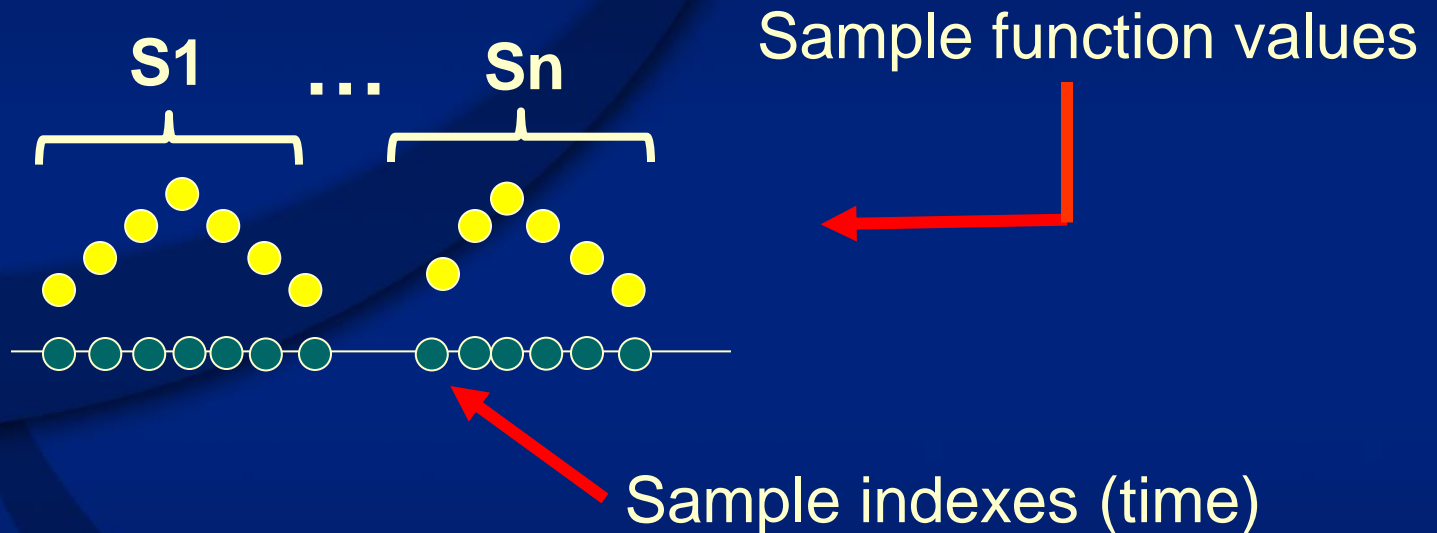
- Constant: **equality** symmetry
- Periodic: (discrete) **translation** symmetry
- Reflection: **reflection** symmetry
- Linear: (continuous) **translation** symmetry
- Gaussian: **reflexive** symmetry on histogram
(and on autocorrelation of samples)

Permutations as Symmetries



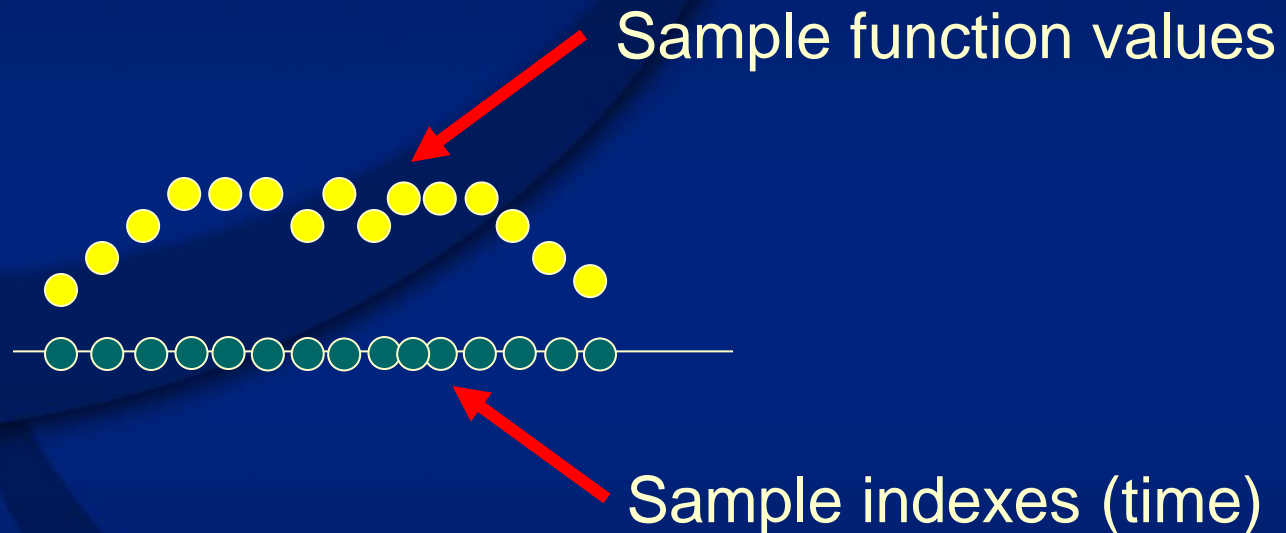
If any permutation results in the same function, then this is a constant signal

Permutations as Symmetries

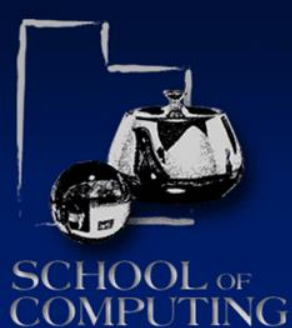


If all permutations of S_i are the same function, then this is a **periodic** signal

Permutations as Symmetries



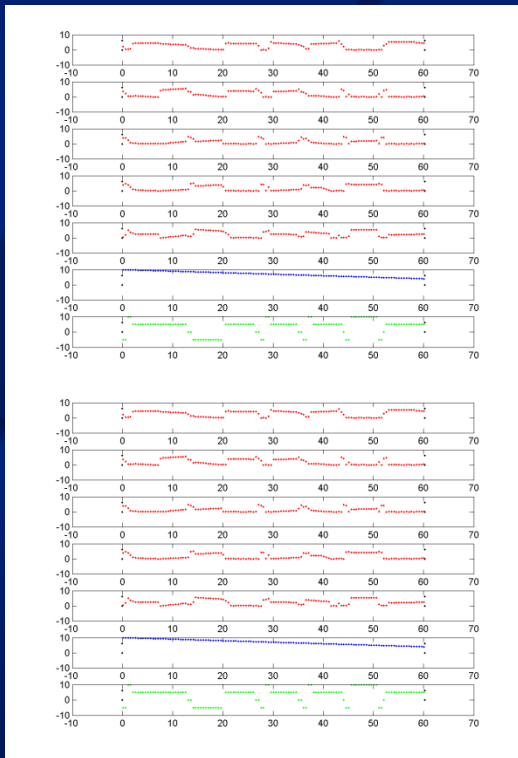
If $(1\ n)(2\ n-1)\dots((n-1)/2\ (n+3)/2)$ permutation, is the same function, then this is a **reflective** signal



Permutations as Symmetries

- Each of these permutation sets forms a subgroup of the full permutation group on n objects (called S_n)

Symmetries



Gaussian

Linear
Null

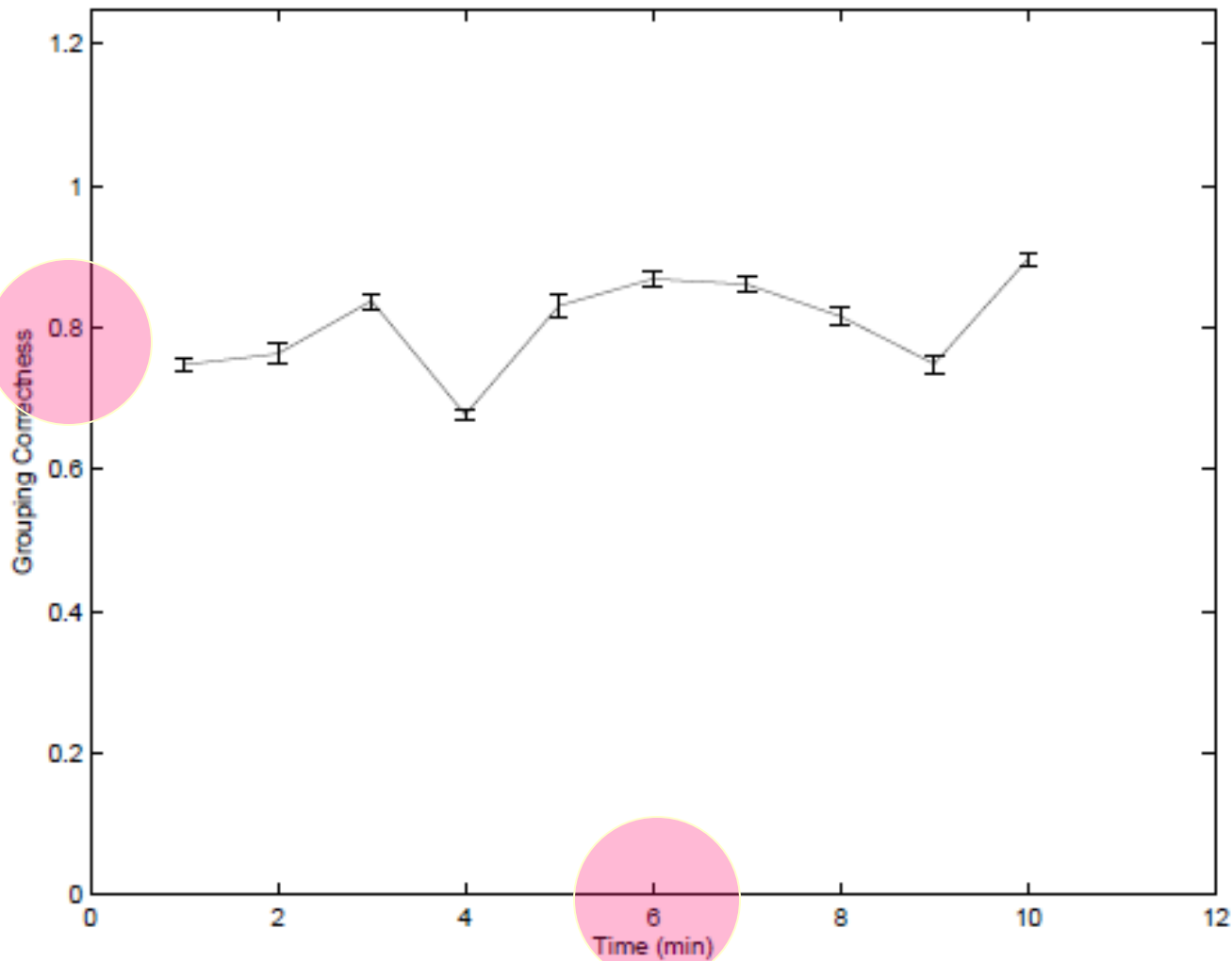
Gaussian

Linear
Null

Grouped by
Variance

Grouped by
Parameters

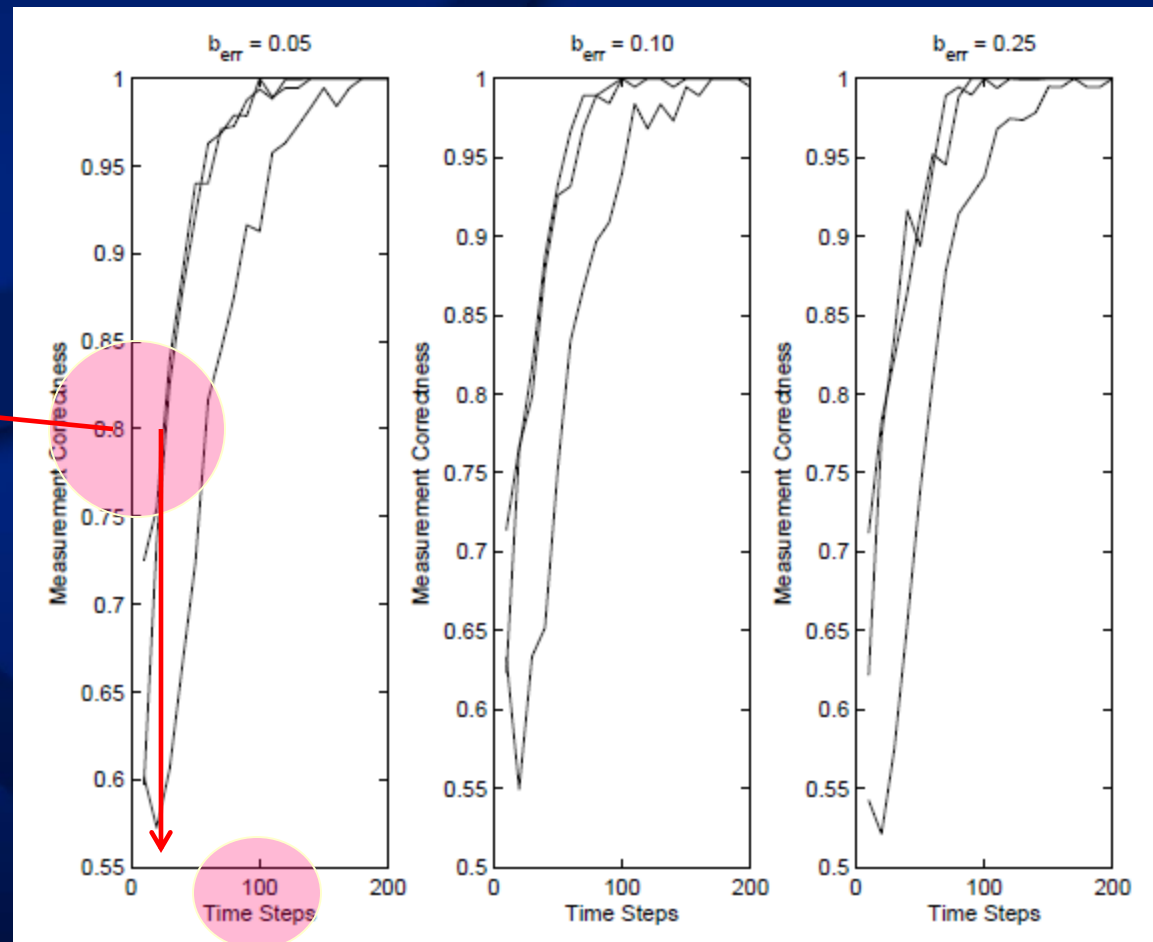
Pierce Results



Symmetry Based Results

Pierce's grouping
success value

Classifies signals
as similar, then
clusters based on
variance (range),
etc.



Do Real Pixels Work This Way?

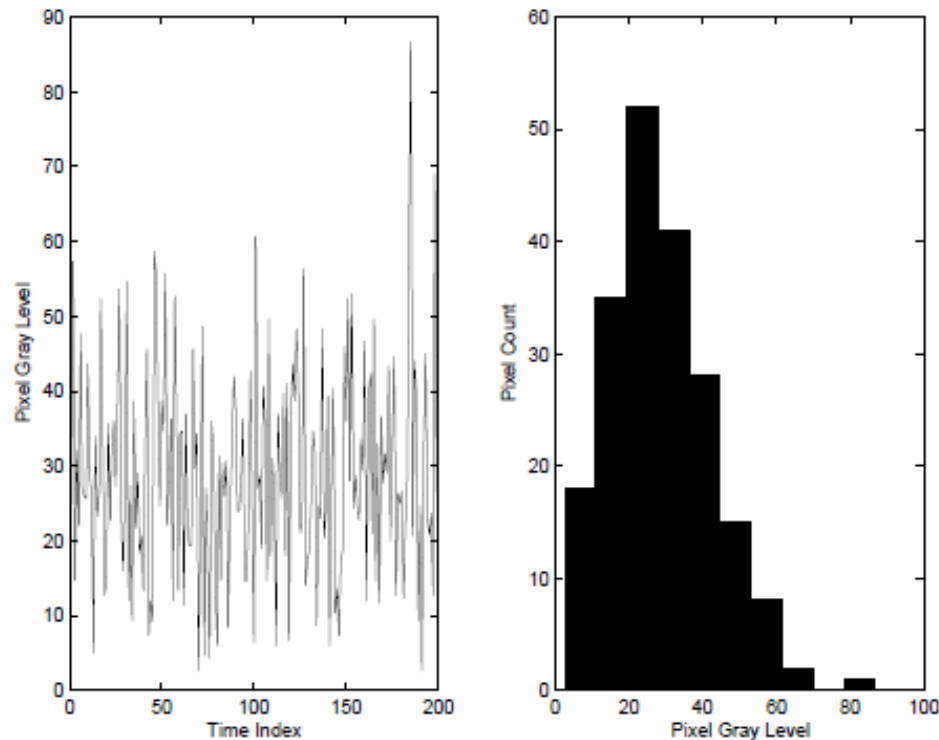


Figure 5: Trace and Histogram of the 200 Pixel Values of the Center Pixel of the Images.

Does Microphone Data Work This Way?

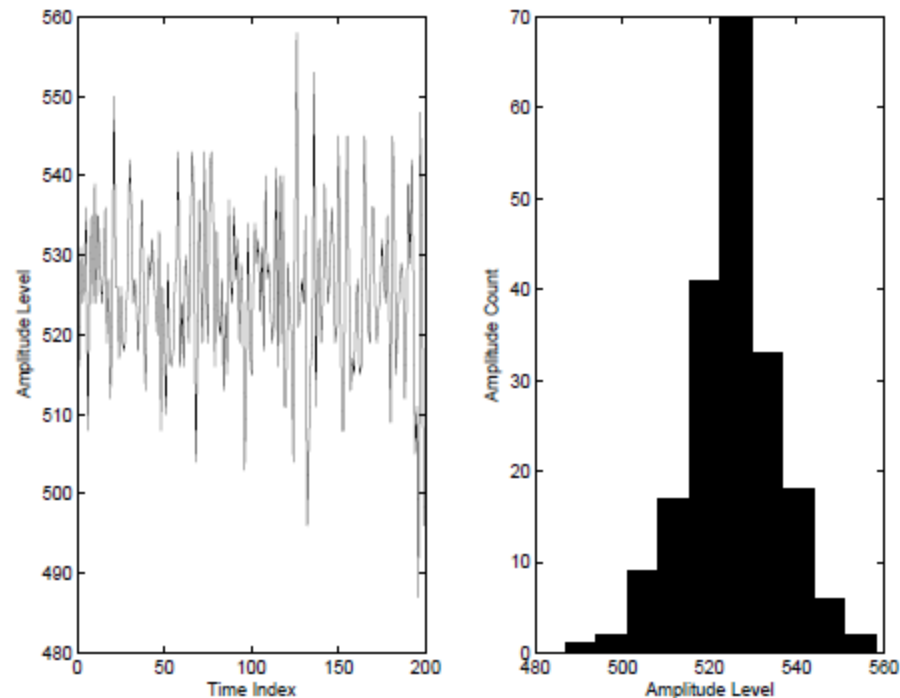
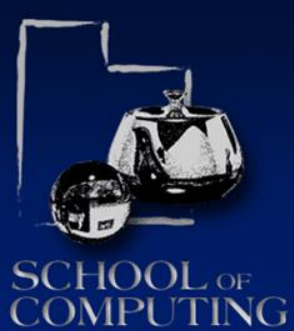


Figure 6: Trace and Histogram of the 200 Amplitude Values of the Microphone Data.



SYMMETRY DETECTION IN COMPUTER VISION (2D)

Berner et al. 2009



Figure 1.1: A 3D scan of a deformed plasticine sculpture with three snail figures. Our algorithm detects symmetries by looking at constellations of surface feature lines. This can be used for detecting deformable symmetries. Left: input data, middle: feature lines overlay, right: detected symmetries.

Loy and Eklundh, 2006



(a)

(b)

(c)

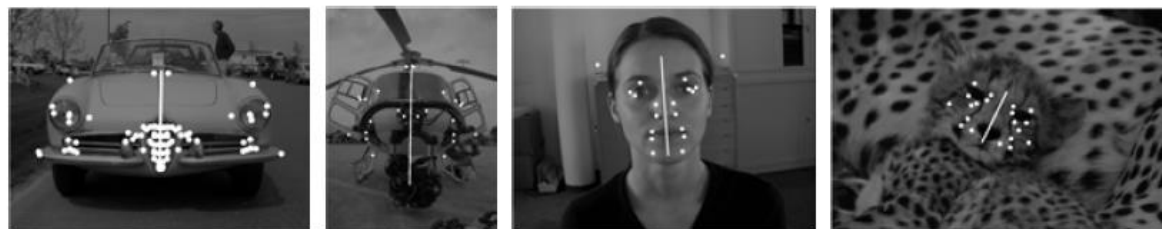
(d)



(e)

(f)

(g)



Original photographs (a) Sandro Menzel, (b) David Martin, (c) BioID face database, (d) Stuart Maxwell, (e) elfintech, (f) Leo Reynolds, (g) ze1, distributed under the Creative Commons Attribution-Non-Commercial-Share-Alike Licence, <http://creativecommons.org>.

Solomon, 2010

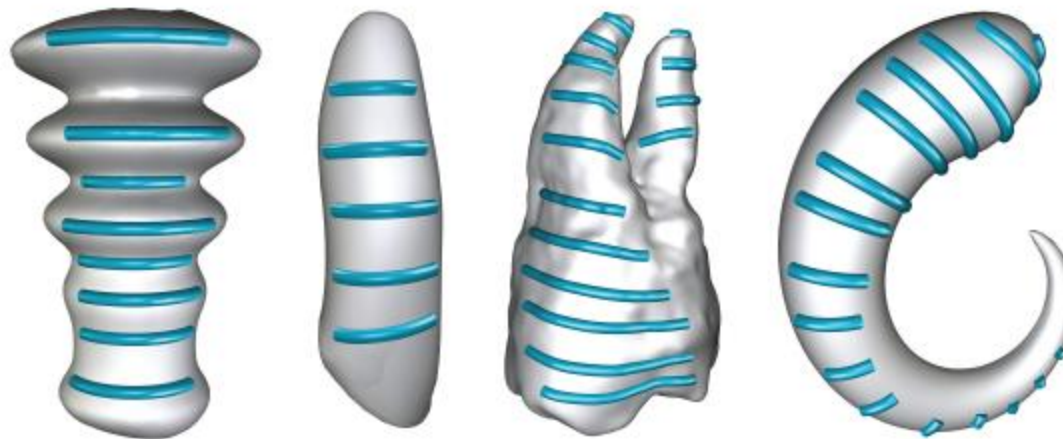


Figure 16: Flows of approximate Killing vector fields on some example surfaces.

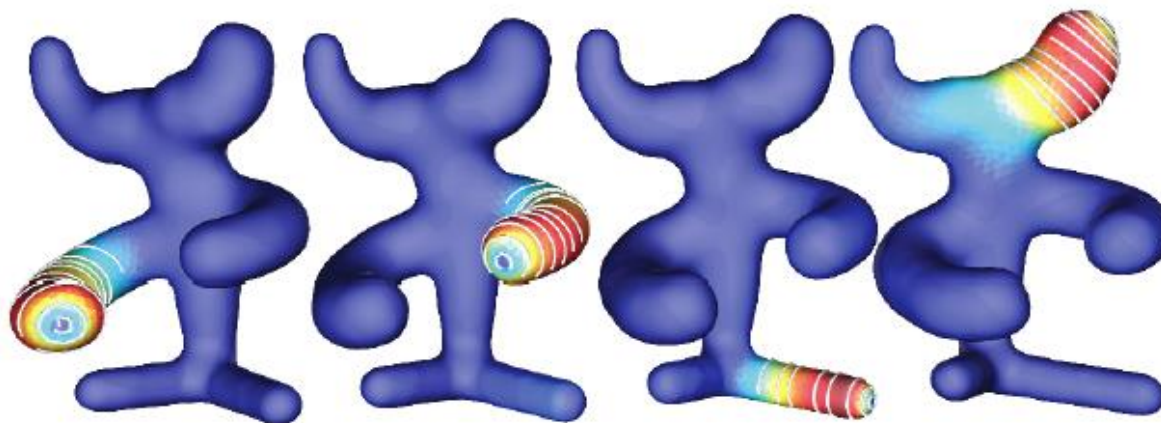
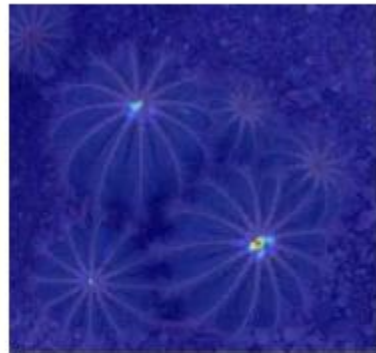


Figure 17: Vector fields corresponding to the four lowest eigenvalues of R ; colors indicate the norm of the approximate Killing field displayed.

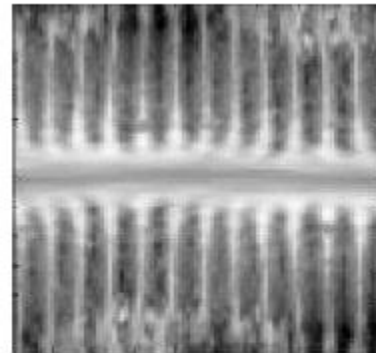
Liu et al., 2007



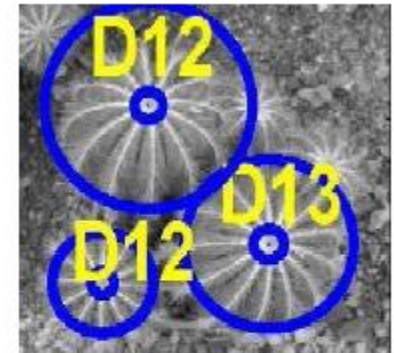
(a) Input



(b) RSS map

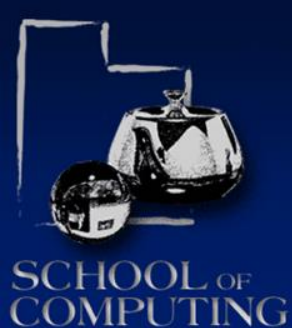


(c) Frieze-expansion



(d) Found symmetry groups

Figure 2: (a) Test image with multiple rotational centers and symmetry types. (b) Rotation Symmetry Strength (RSS) map overlaid on the original image (c) One sample of Frieze-expansion (d) Rotation symmetry group detection result



Desired 2D Symmetries

C1: identity map

C_n: rotation symmetry

D1: Single axis bilateral symmetry

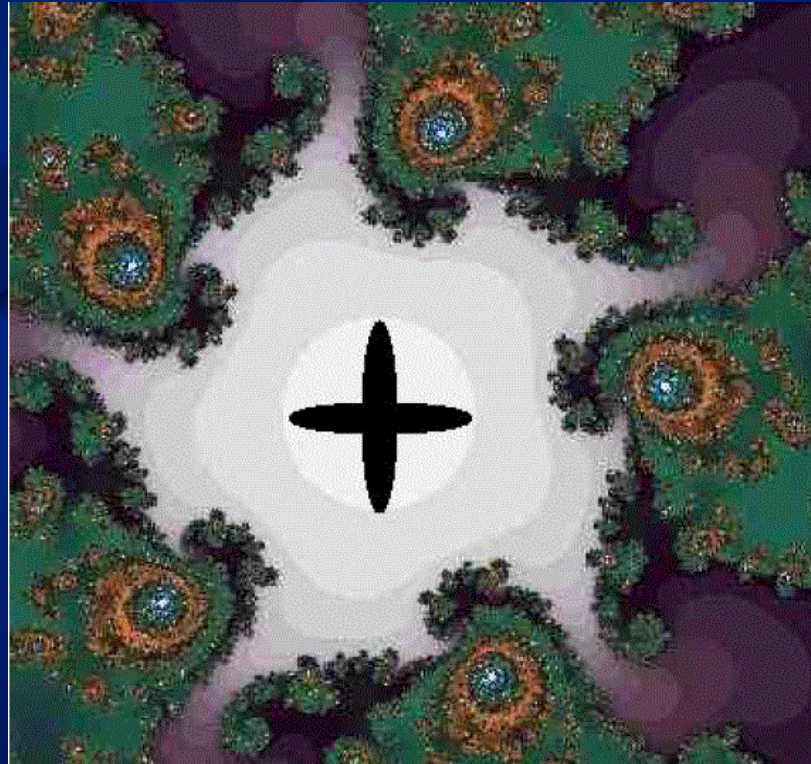
D_n: rotation and reflective symmetry

O(2): continuous 2D rotational symmetry

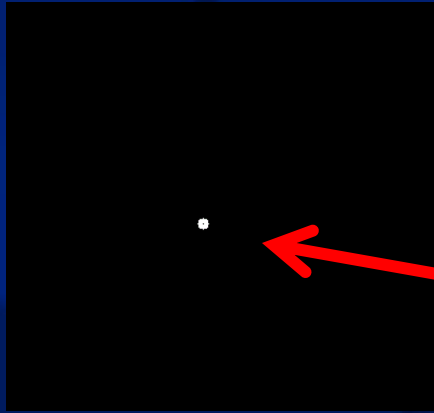
Lee-Liu Symmetry Detection

Example Image:

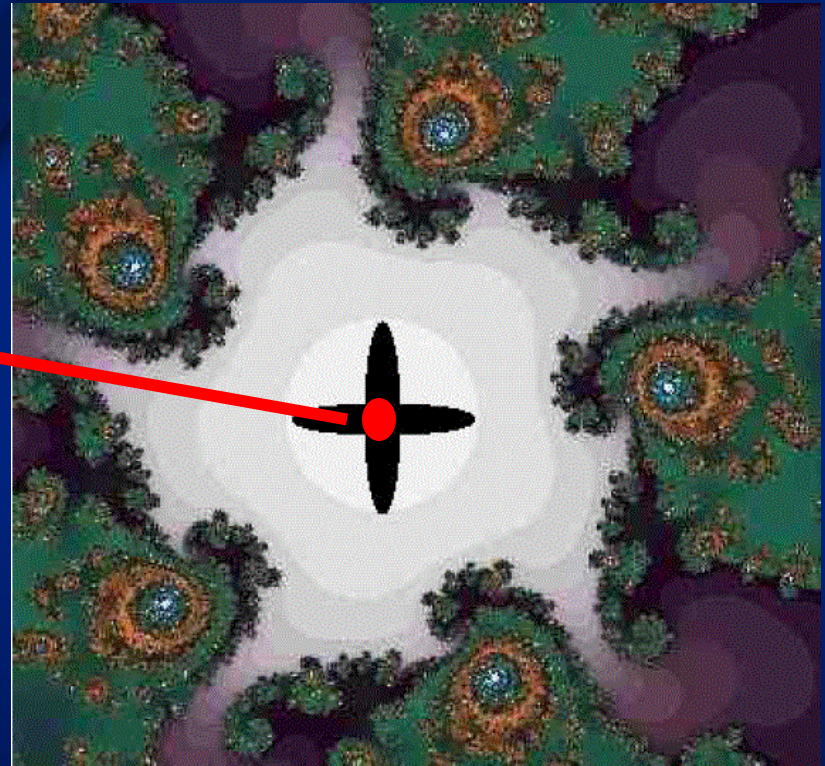
Several embedded
symmetries



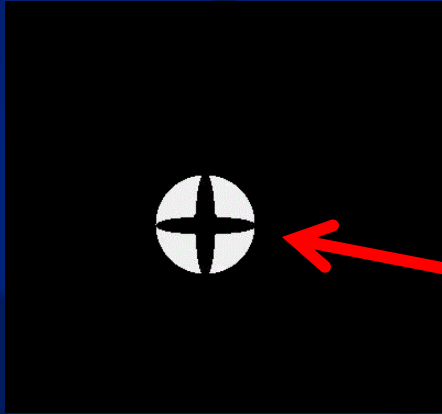
Symmetries



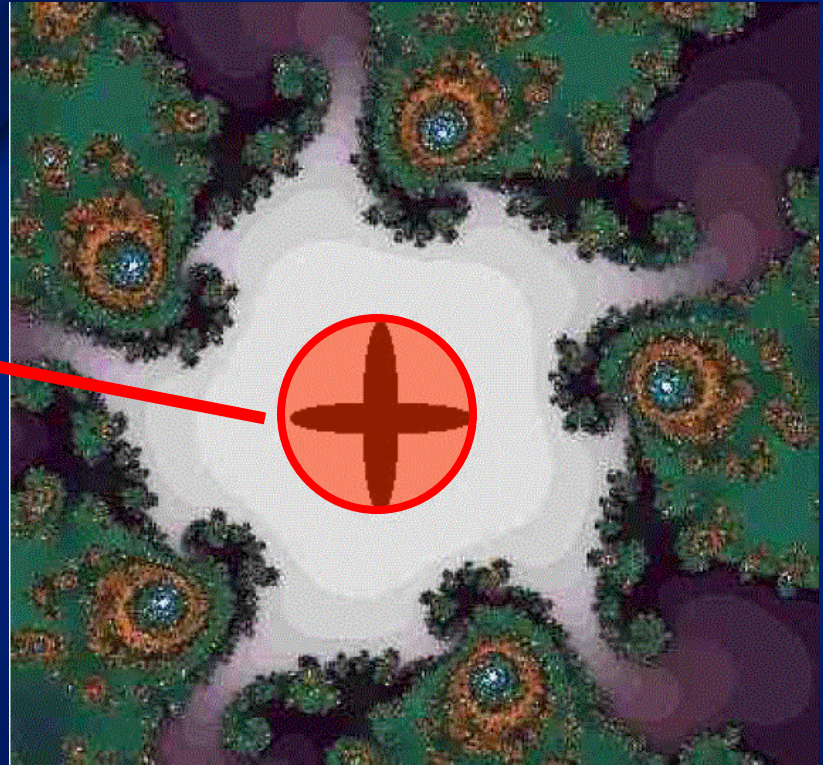
$O(2)$



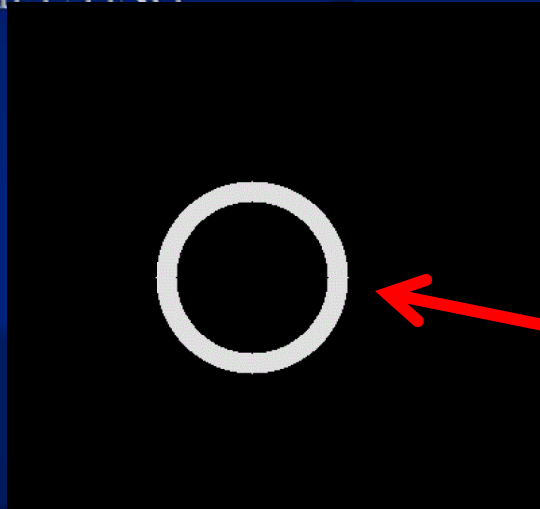
Symmetries



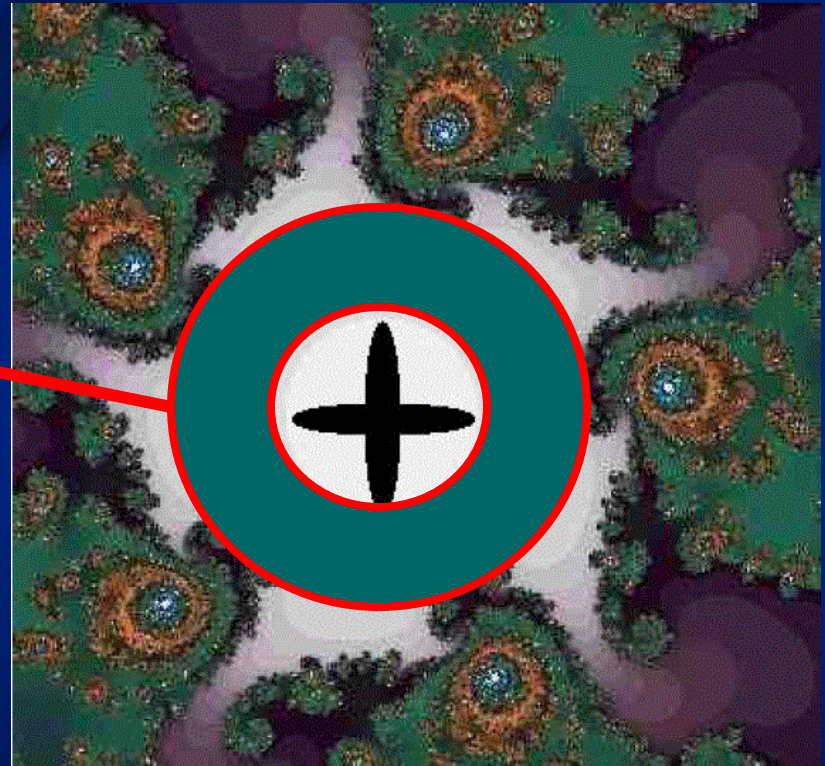
D₄



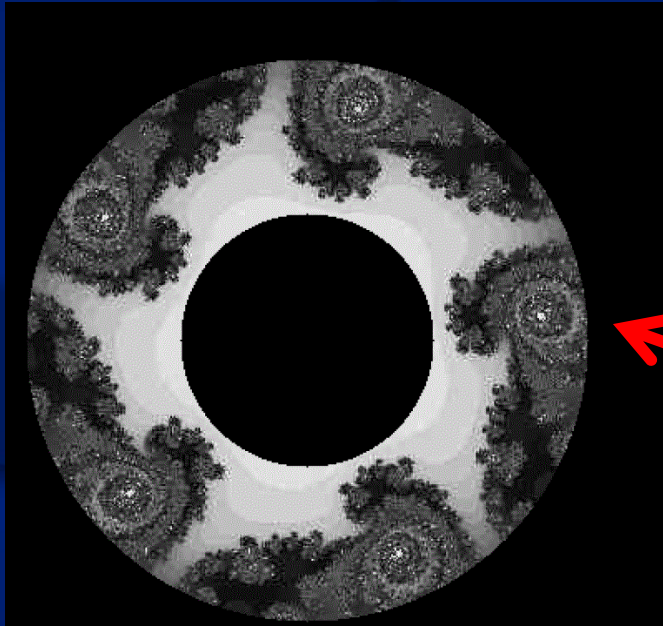
Symmetries



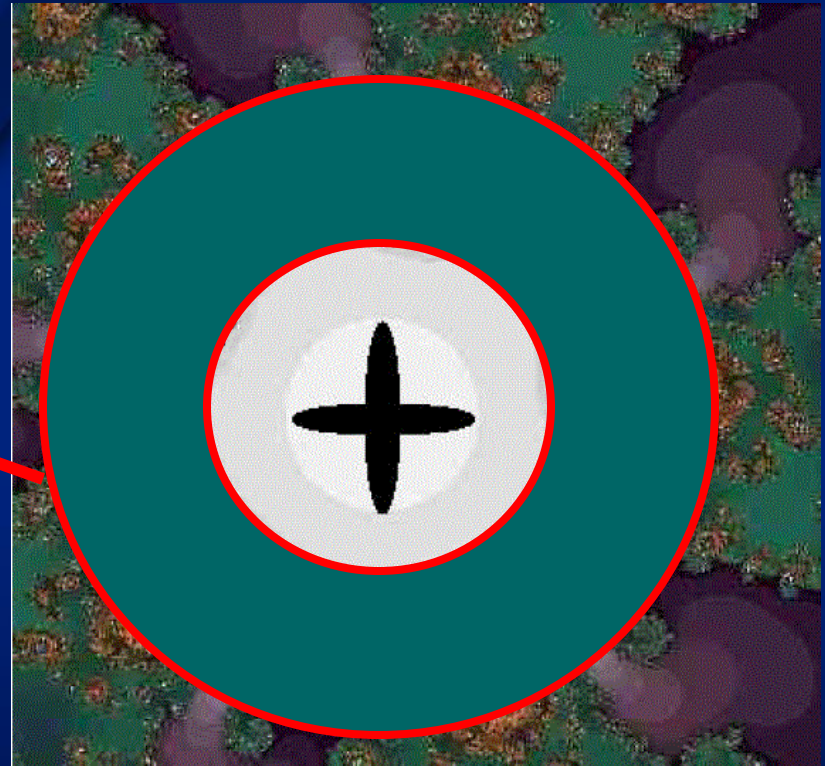
$O(2)$



Symmetries

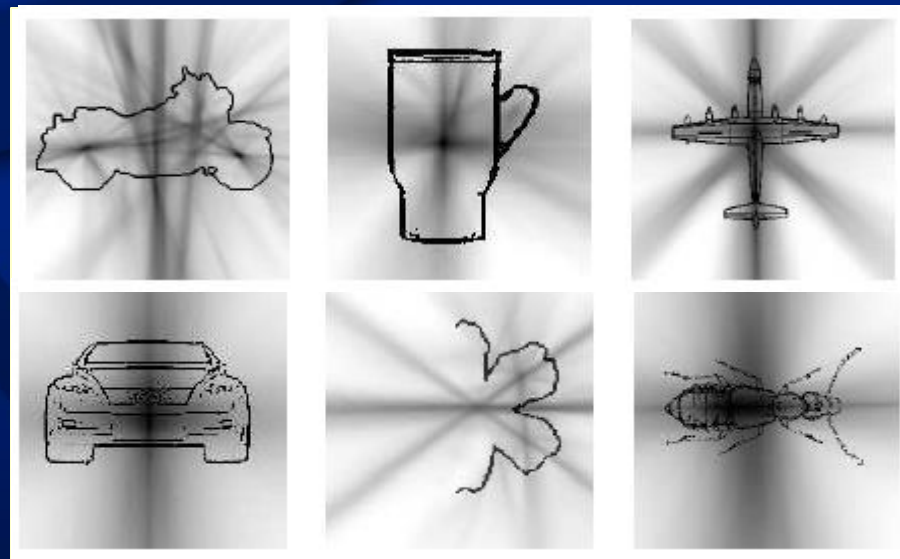


C₅

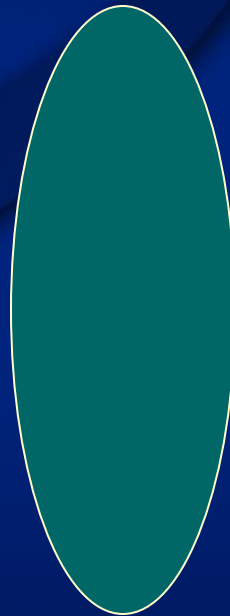


Podolak et al.

Planar-Reflective Symmetry Transform

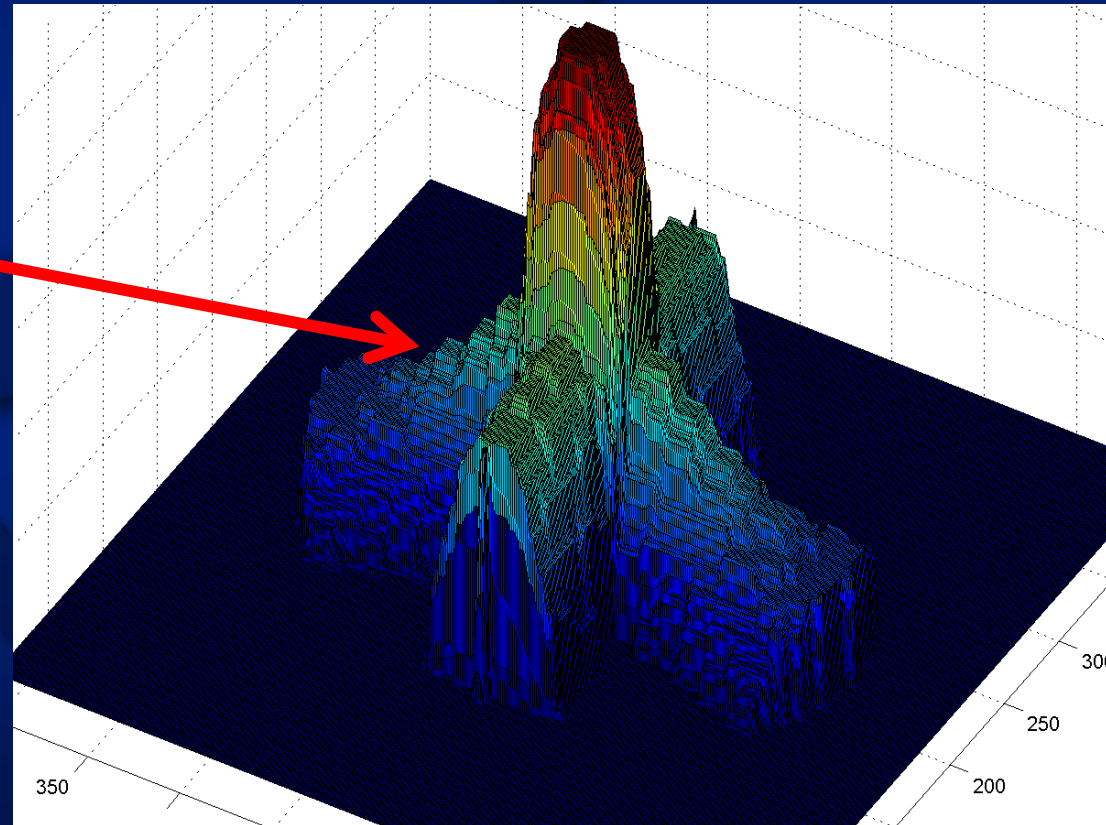


Ellipse Image



PRST for Ellipse Image

Note: Symmetry axes are found

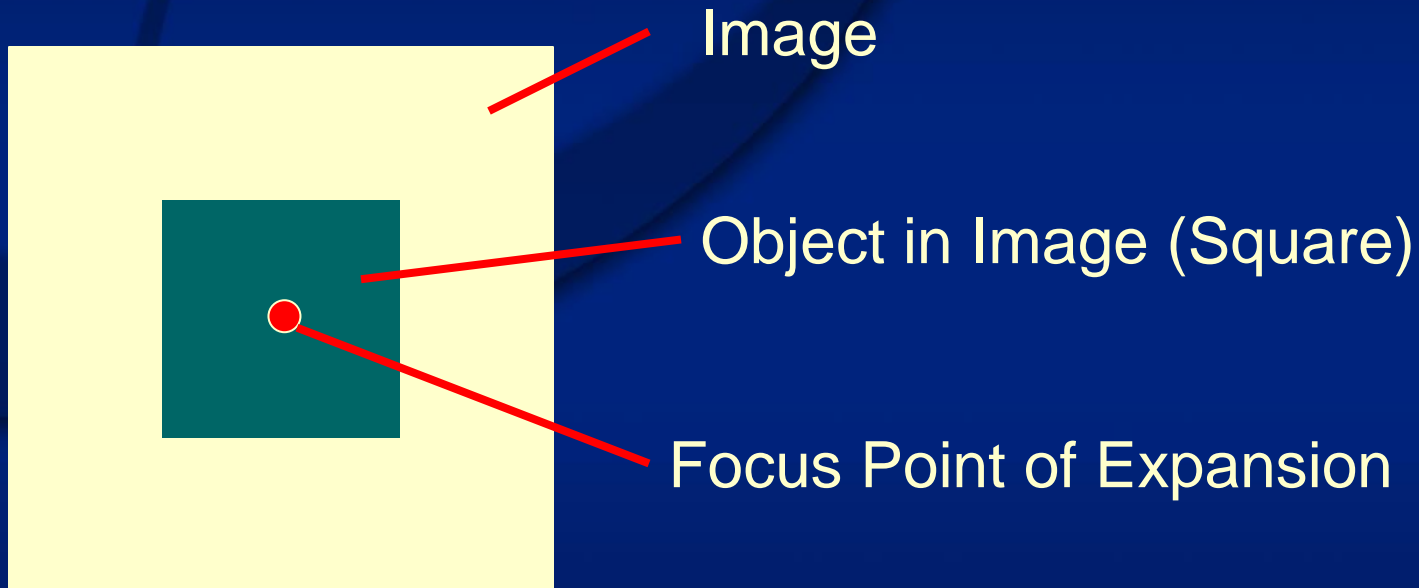


Major Issue

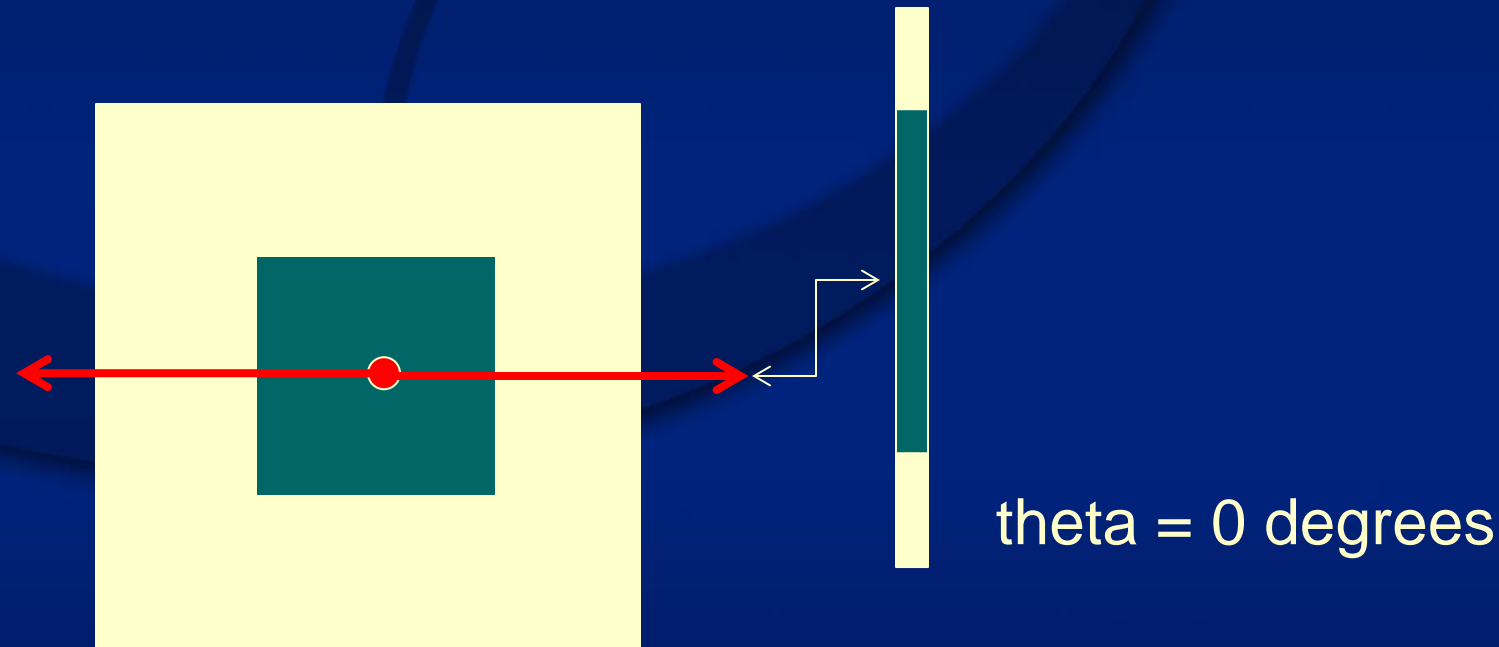
Too slow when applied to every pixel!

→ So we developed an interest operator

Frieze Expansion Pattern

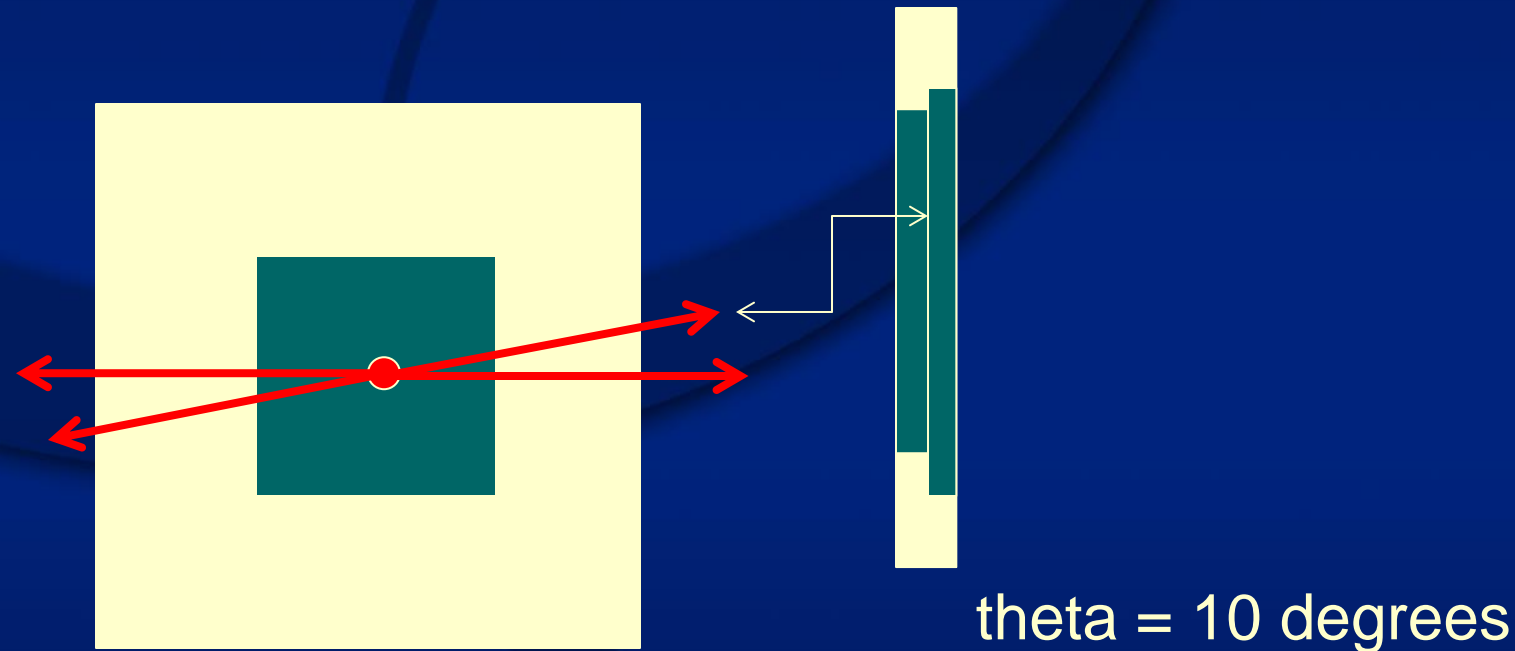


Frieze Expansion Pattern



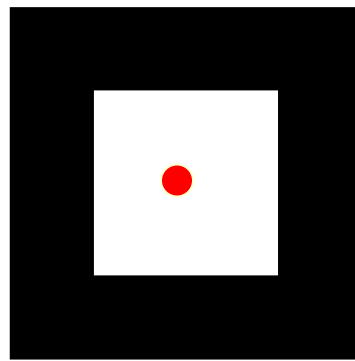
For each line through the focus point, map the focus point to the middle row, one direction from the middle row up, the other from the middle row down.

Frieze Expansion Pattern



For each line through the focus point, map the focus point to the middle row, one direction from the middle row up, the other from the middle row down.

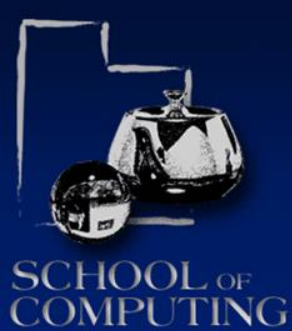
FEP for Square (in white)



Square



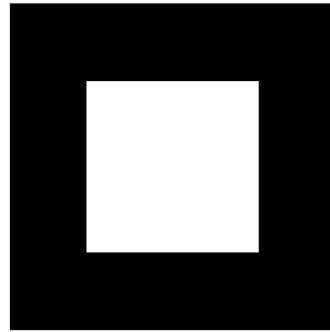
FEP of Square



FEP and Symmetries

- Center of mass of shape is on reflective axis for 2D shape
- Rotation symmetries exist if:
 - FEP has reflective axis through middle row
 - Upper half of FEP has translational symmetry
- If reflective symmetries exist:
 - Must occur at max or min of upper half of FEP for object boundary
 - Shape has reflective symmetry about axis

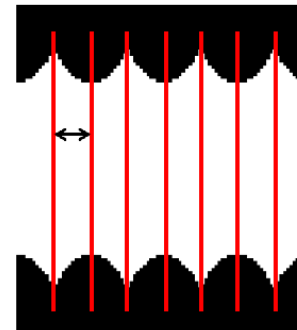
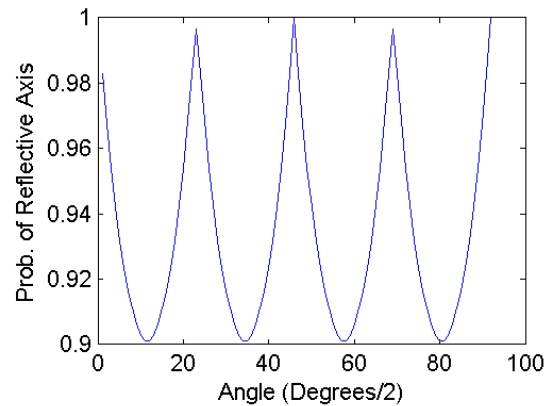
Possible Reflective Axes are Found at Max/Min's



Square



FEP of Square



Shape Basis Found Here

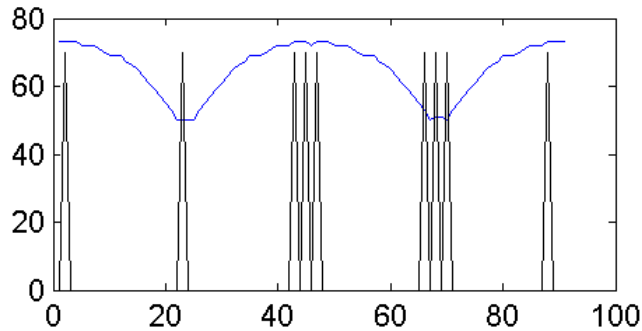
Ellipse Symmetries



(a) Ellipse Image



(b) Frieze Expansion Pattern



(c) FEP Curve with Min/Max Indicated



(d) Reflective Axis.



(e) Rotation Directions.



(f) Reflective Axes and Rotation Directions.

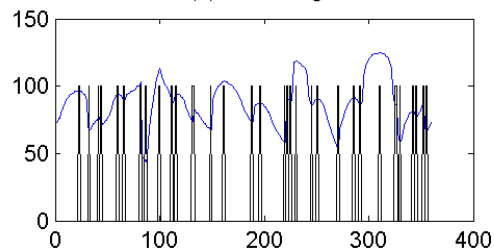
Another Example: Leaf



(a) Leaf Image



(b) Frieze Expansion Pattern



(c) FEP Curve with Min/Max Indicated



(d) Reflective Axis.

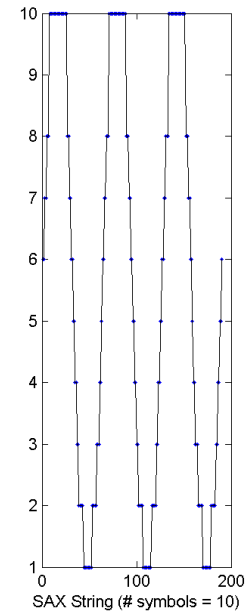
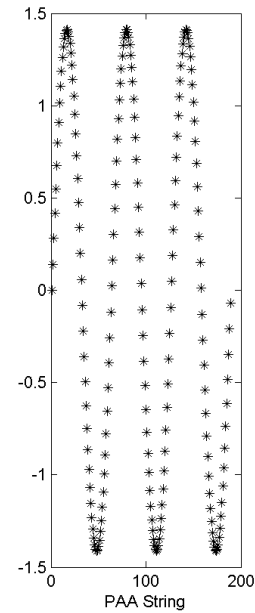
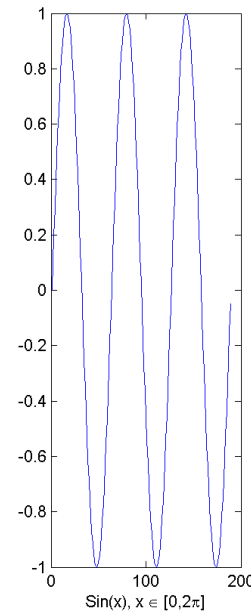
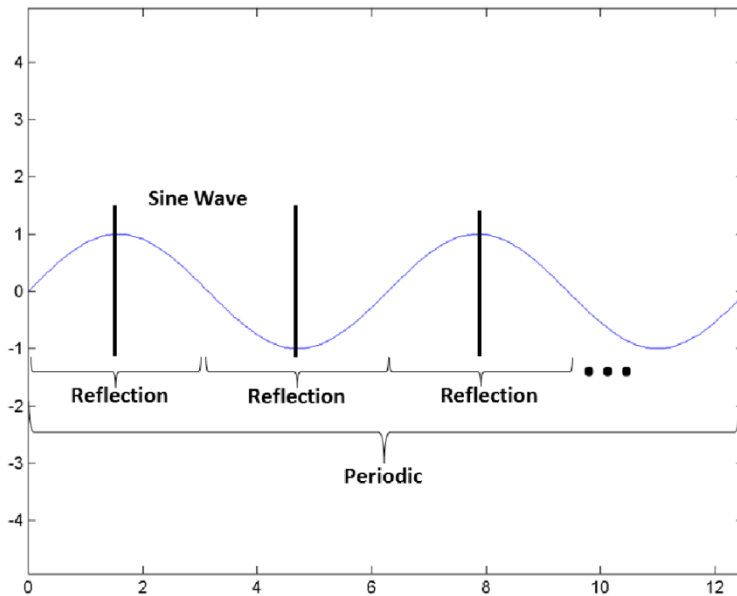


(e) Rotation Directions (None).

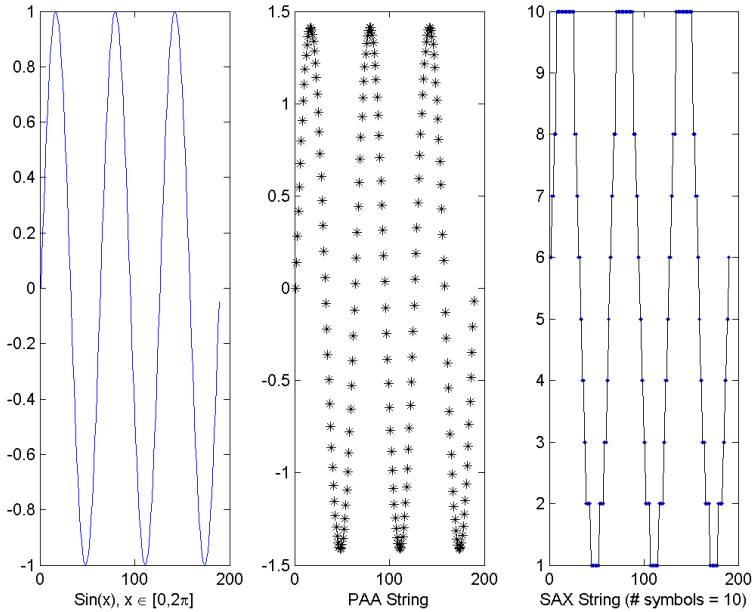


(f) Reflective Axes and Rotation Directions (None).

Symmetry Parsing



Symmetry Parsing



<i>Symmetry Type</i>	<i>Start Index</i>	<i>End Index</i>	<i>Basic Length</i>	<i>Symmetry Measure</i>	<i>Symmetry Index</i>
periodic	1	189	63	0.7663	
reflective	90	132	21	1.0000	111
reflective	27	69	21	0.9283	48
reflective	2	32	15	0.9239	17
reflective	159	189	15	0.9239	174
reflective	59	101	21	0.7334	80
reflective	121	163	21	0.7334	142

Symmetry Parsing

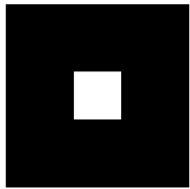


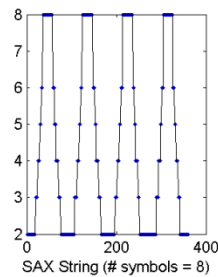
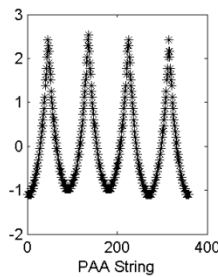
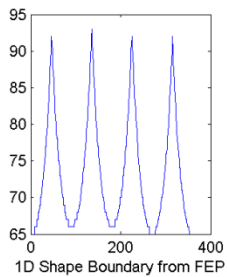
Image of Square



FEP



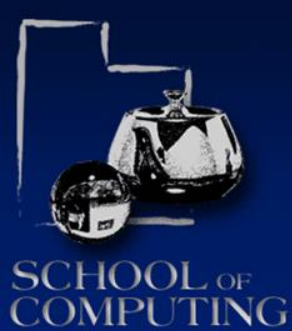
Inverse FEP



<i>Symmetry Type</i>	<i>Start Index</i>	<i>End Index</i>	<i>Basic Length</i>	<i>Symmetry Measure</i>	<i>Symmetry Index</i>
periodic	1	189	63	0.7663	
reflective	90	132	21	1.0000	111
reflective	27	69	21	0.9283	48
reflective	2	32	15	0.9239	17
reflective	159	189	15	0.9239	174
reflective	59	101	21	0.7334	80
reflective	121	163	21	0.7334	142

1D Symmetry Attribute Grammar

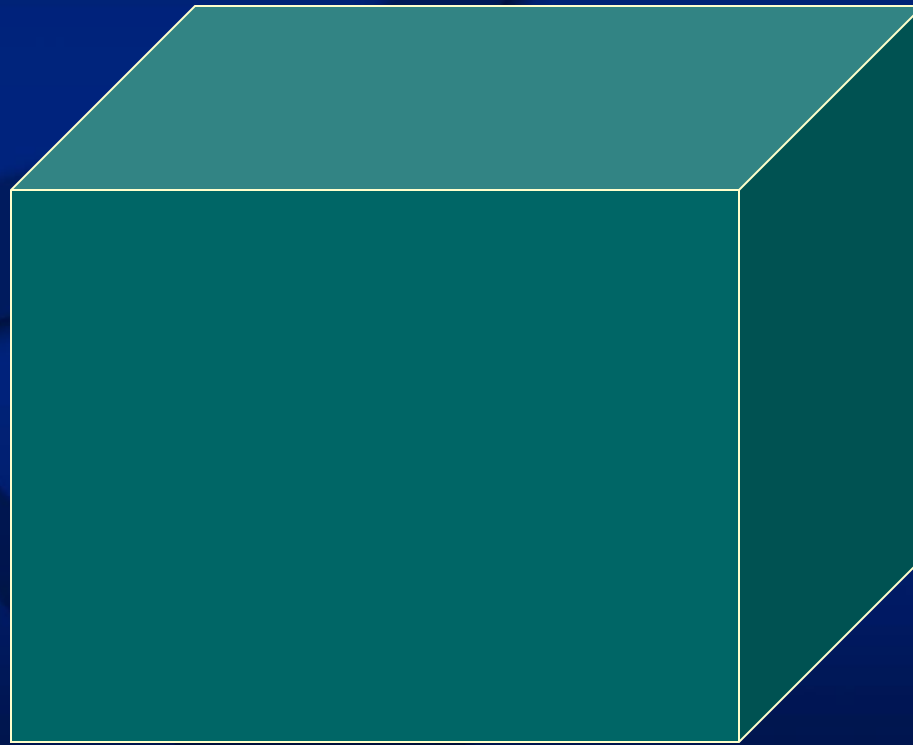
- (1) $F \rightarrow S^1 S^2 \{\mu_1 == \mu_2\}$
- (2) $U \rightarrow S^1 S^2 \{\mu_1 < \mu_2\}$
- (3) $D \rightarrow S^1 S^2 \{\mu_1 > \mu_2\}$
- (4) $C \rightarrow F$
- (5) $C \rightarrow CF \{\text{constant}(C) == \text{constant}(F)\}$
- (6) $B \rightarrow UD \{\text{slope}(U) \approx -\text{slope}(D)\}$
- (7) $B \rightarrow DU \{\text{slope}(D) \approx -\text{slope}(U)\}$
- (8) $W \rightarrow \text{any permutation}$
- (9) $P \rightarrow W^+ W^+ \{\text{attributes}(W^1) \approx \text{attributes}(W^2)\}$
- (10) $Z \rightarrow C \mid B \mid P$
- (11) $R \rightarrow UZD \{\text{slope}(U) \approx -\text{slope}(D)\}$
- (12) $R \rightarrow DZU \{\text{slope}(D) \approx -\text{slope}(U)\}$
- (13) $R \rightarrow FZF \{\text{constant}(F^1) \approx \text{constant}(F^2)\}$
- (14) $R \rightarrow URD \{\text{slope}(U) \approx -\text{slope}(D)\}$
- (15) $R \rightarrow DRU \{\text{slope}(D) \approx -\text{slope}(U)\}$
- (16) $R \rightarrow FRF \{\text{constant}(F^1) \approx \text{constant}(F^2)\}$
- (17) $S \rightarrow R \mid C \mid P$
- (18) $A \rightarrow U$
- (19) $A \rightarrow AU$
- (20) $E \rightarrow D$
- (21) $E \rightarrow ED$



Finding Symmetries in 3D using the 3D FEP

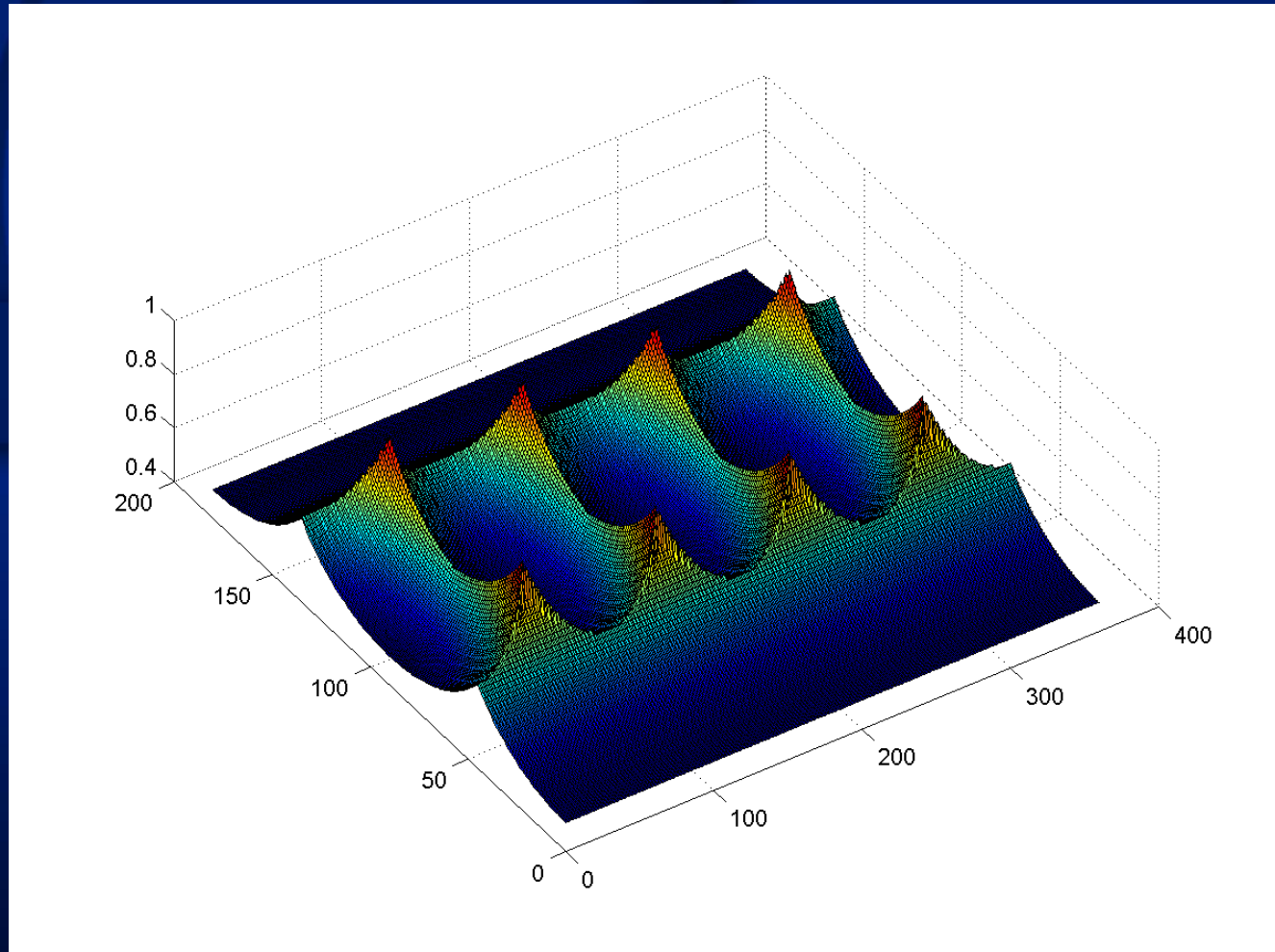
- Assume surfaces are known
 - E.g., Meshes from range data
 - Local density maxima
- Inside object at center of mass,
 - Rotate about x
 - Rotate about z

Example: The Cube

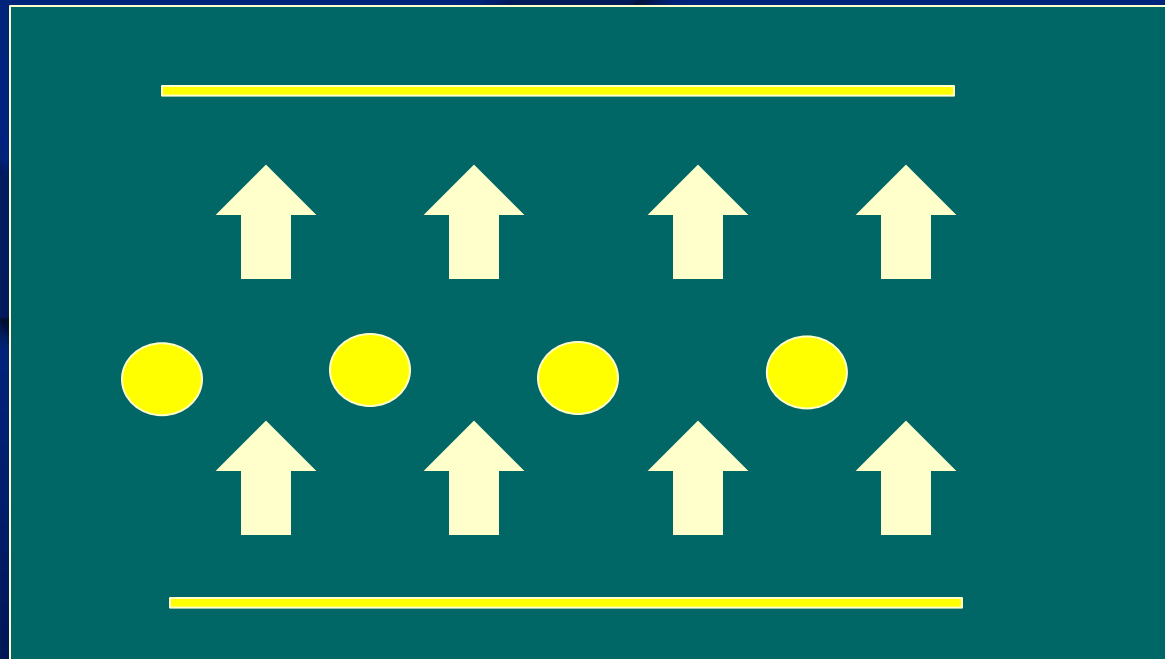


3D FEM Symmetry Detection

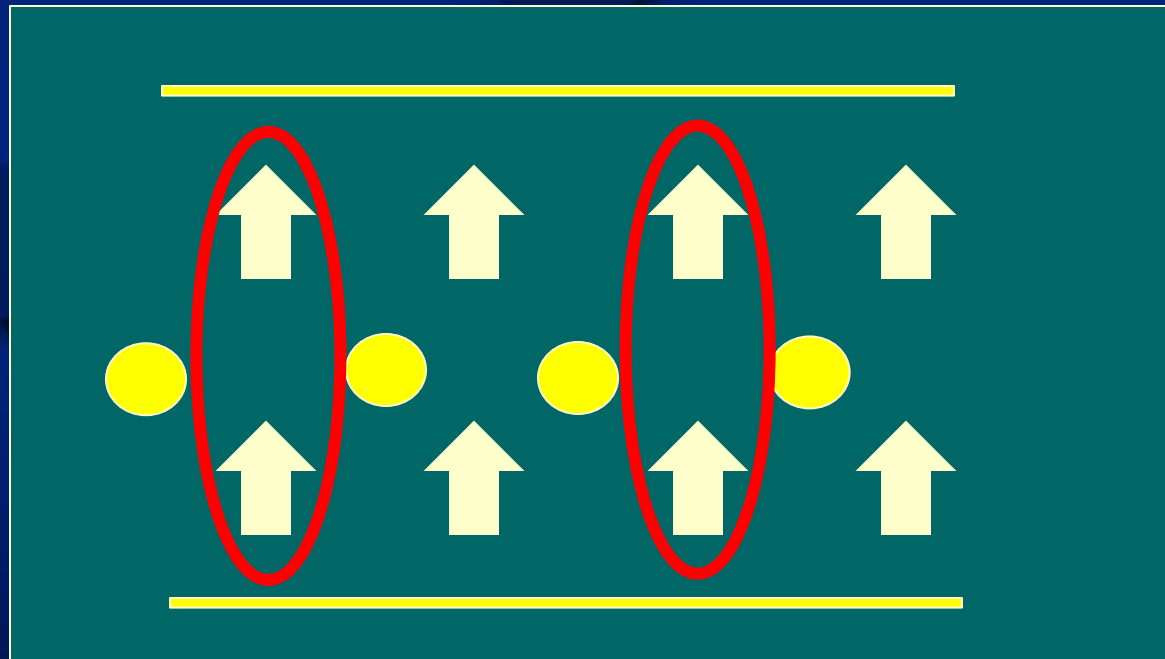
SCHOOL OF
COMPUTING



Peaks and Pits

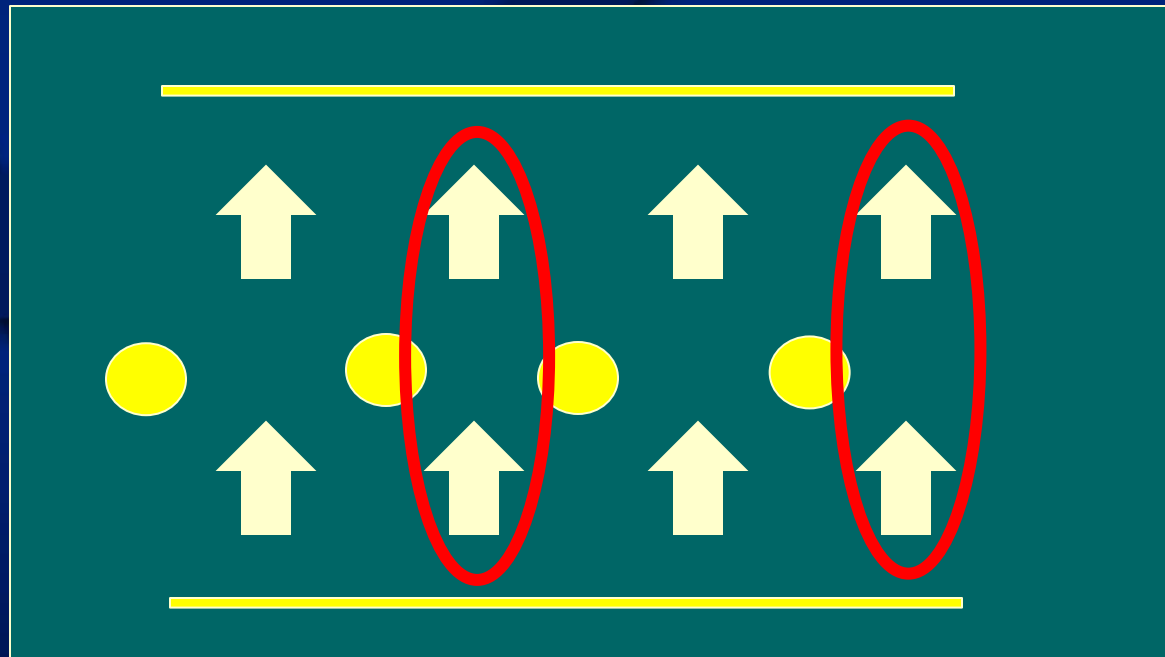


Peaks and Pits: Reflective Symmetry

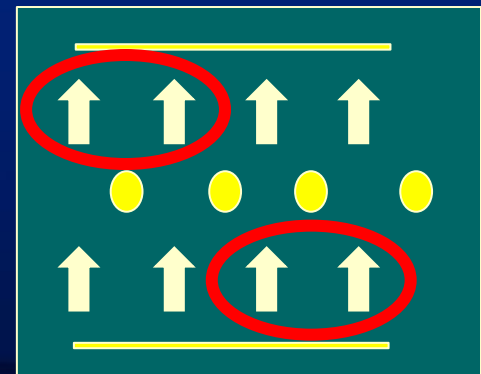
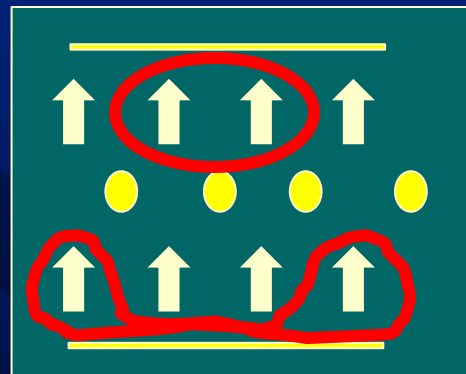
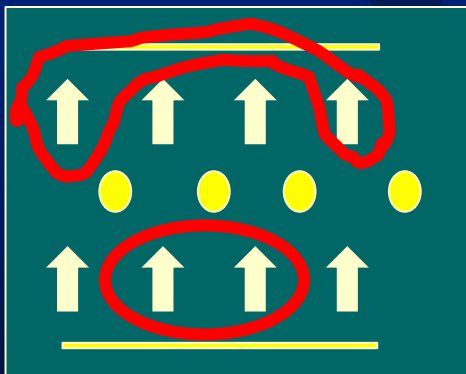
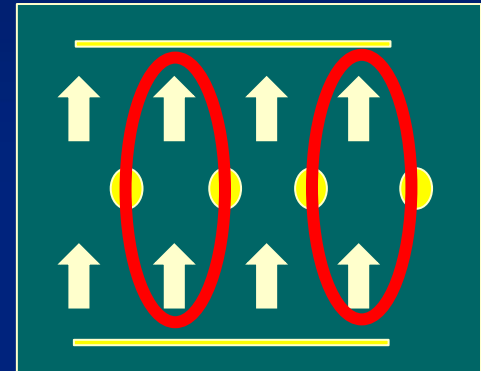
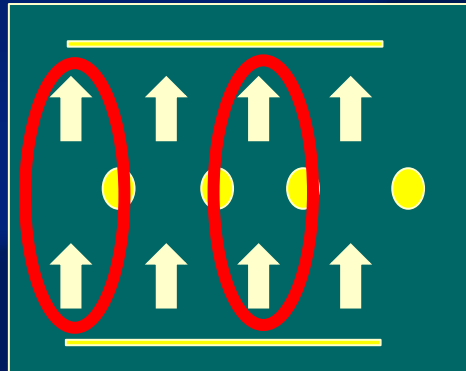
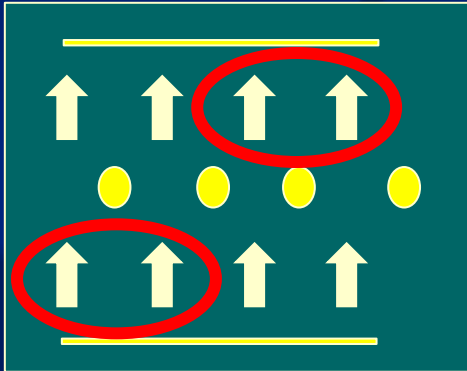


Pairs define a line and the two lines define a plane

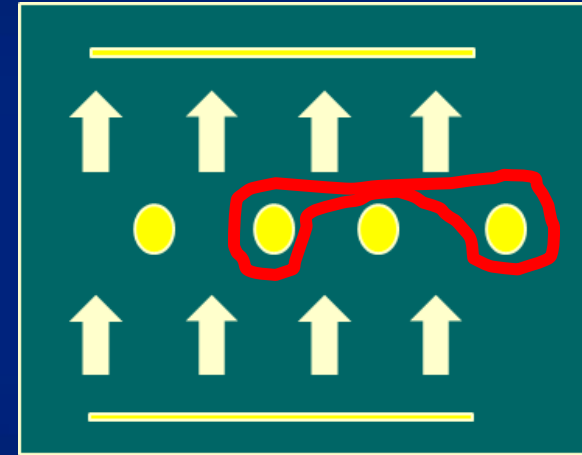
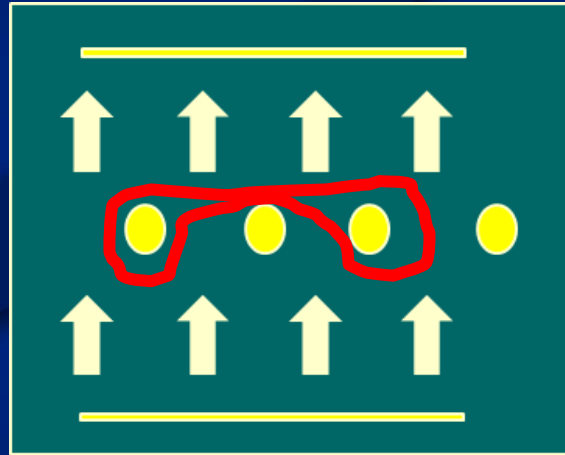
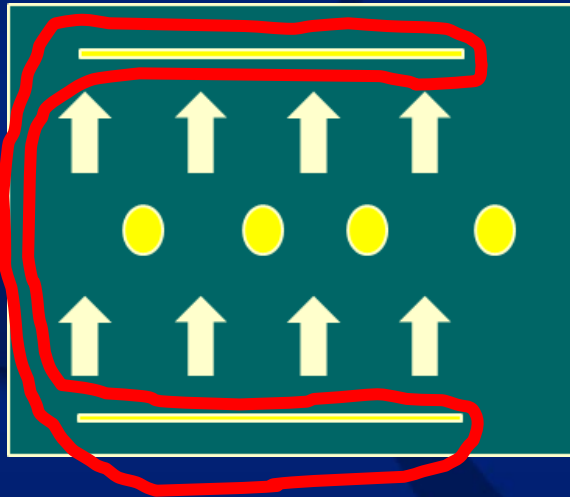
Peaks and Pits: Reflective Symmetry



The 6 Diagonal Reflective Symmetries

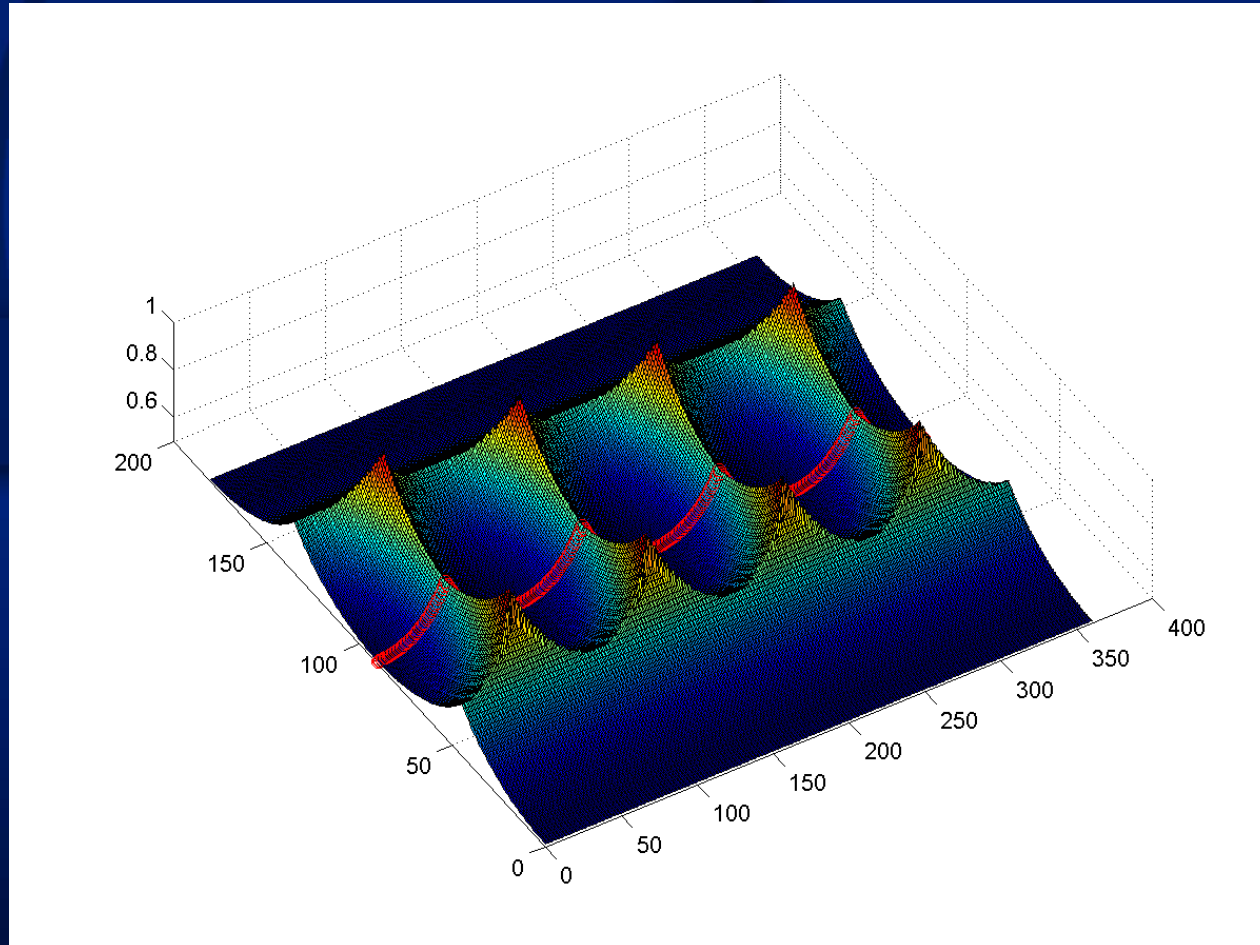


The 3 Orthogonal Reflective Symmetries

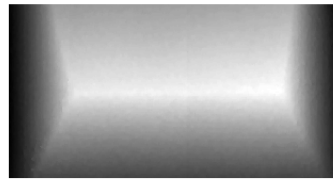


These pairs determine 2 lines which define a plane

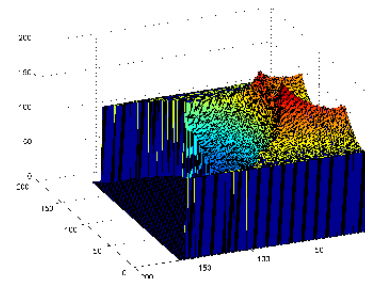
Possible Symmetry Found by Curve Made of Minima



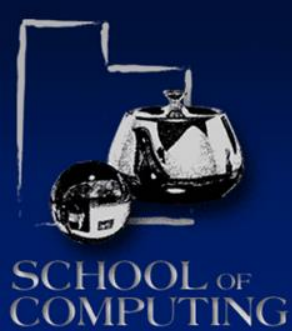
3D Kinect Data of Cube



Two Corner Kinect Data



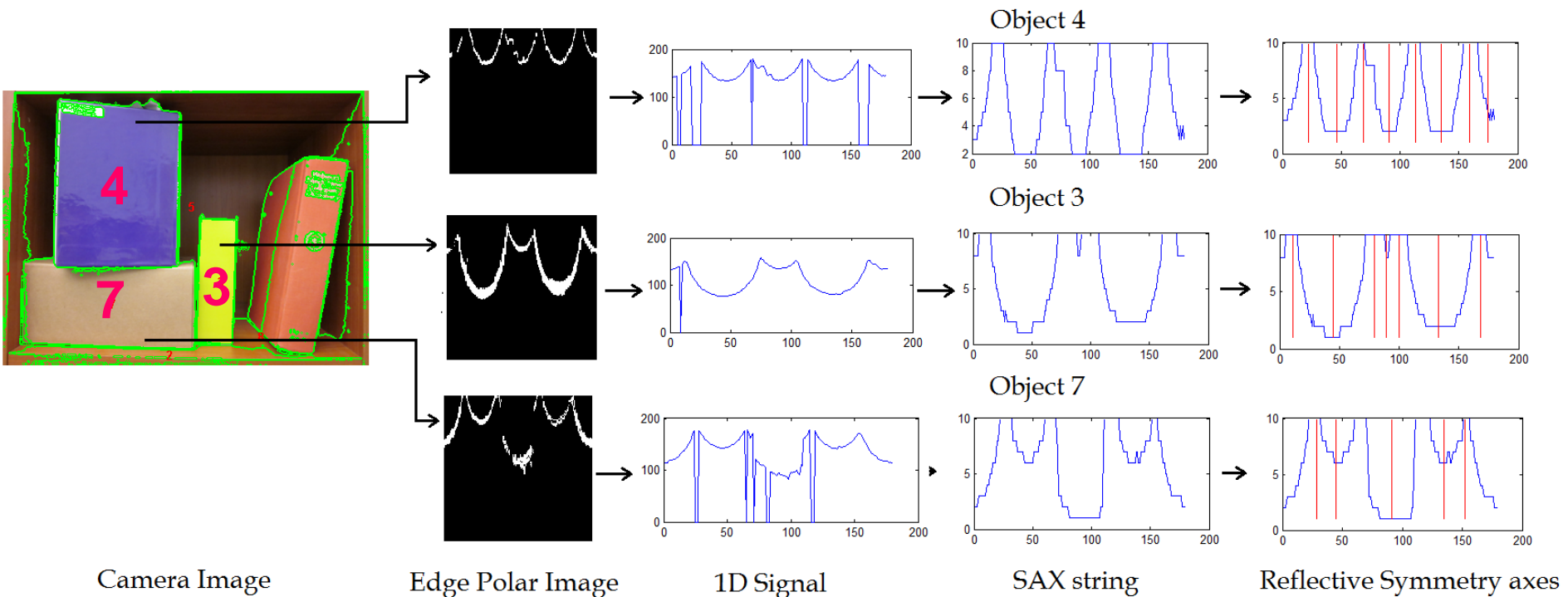
Two Corner Peaks in FEM Data



Some Lemmas; e.g.:

Lemma 1: Given a frieze expansion pattern at the center of mass of a 2D shape with reflective symmetry, then the orientation of the reflective axis corresponds to a min or max of the FEP of the boundary curve.

Concept Formation

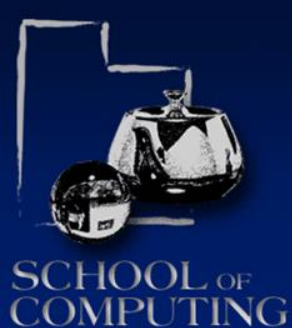


Concept Formation

<i>Object 3 Symmetry Type</i>	<i>Start Index</i>	<i>End Index</i>	<i>Basic Length</i>	<i>Symmetry Measure</i>
periodic	1	270	90	0.5000
reflective	2	20	9	0.3497
reflective	2	88	43	0.4241
reflective	68	90	11	0.4152
reflective	2	176	87	0.4627
reflective	90	110	10	0.6862
reflective	87	179	46	0.4759
reflective	157	179	11	0.6412

Concept Formation

<i>Object 4 Symmetry Type</i>	<i>Start Index</i>	<i>End Index</i>	<i>Basic Length</i>	<i>Symmetry Measure</i>
periodic	1	270	90	0.6000
reflective	2.0000	42.0000	20.0000	0.5902
reflective	2.0000	90.0000	44.0000	0.6079
reflective	36.0000	102.0000	33.0000	0.4067
reflective	3.0000	179.0000	88.0000	0.6802
reflective	62.0000	164.0000	51.0000	0.3894
reflective	91.0000	179.0000	44.0000	0.4098
reflective	139.0000	179.0000	20.0000	0.5495
reflective	171.0000	179.0000	4.0000	0.5698



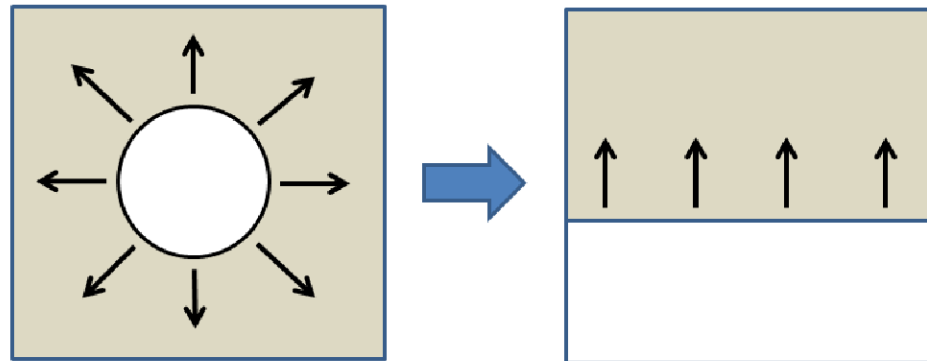
Structural Bootstrapping

- These concept structures allow for tree representations
- There exist group representations that allow for understanding symmetries on trees
- Can substitute symbols at various levels to bootstrap knowledge

Symmetry Bundles

Bundle Definition:

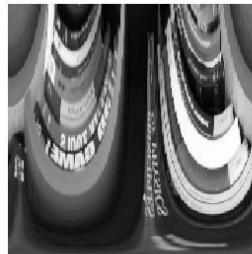
- Actuation
→ Translation
- Perception
→ columnar translation in FEP



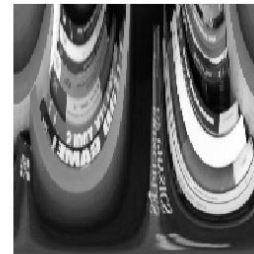
Symmetry Bundles

Bundle Detection:

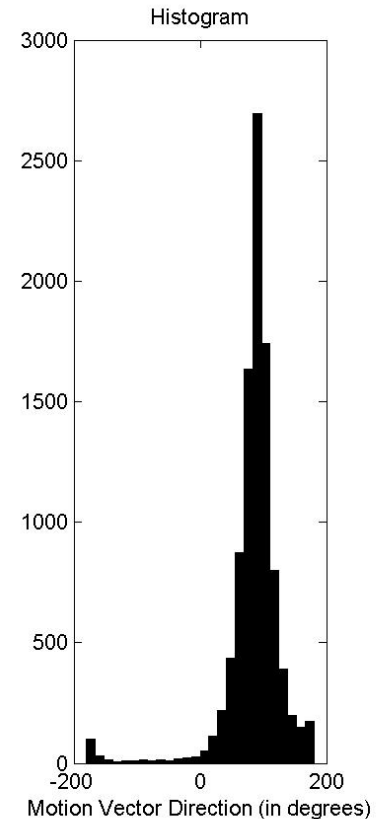
- Actuation
→ Apply signal
- Perception
→ histogram
translation
direction
(90 degrees)

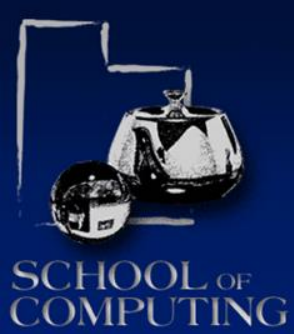


Polar Form of Image 1



Polar Form of Image 2

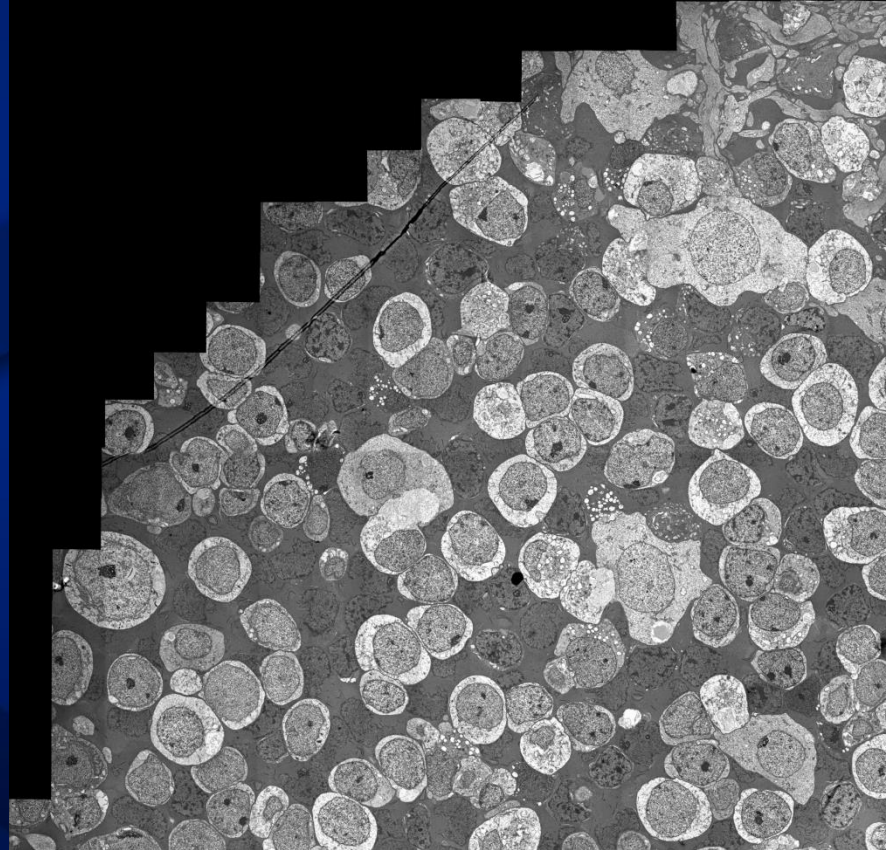


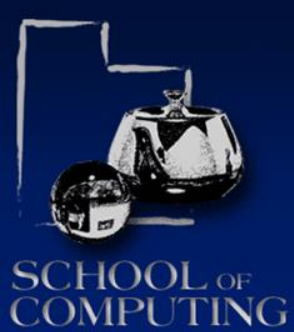


Questions?

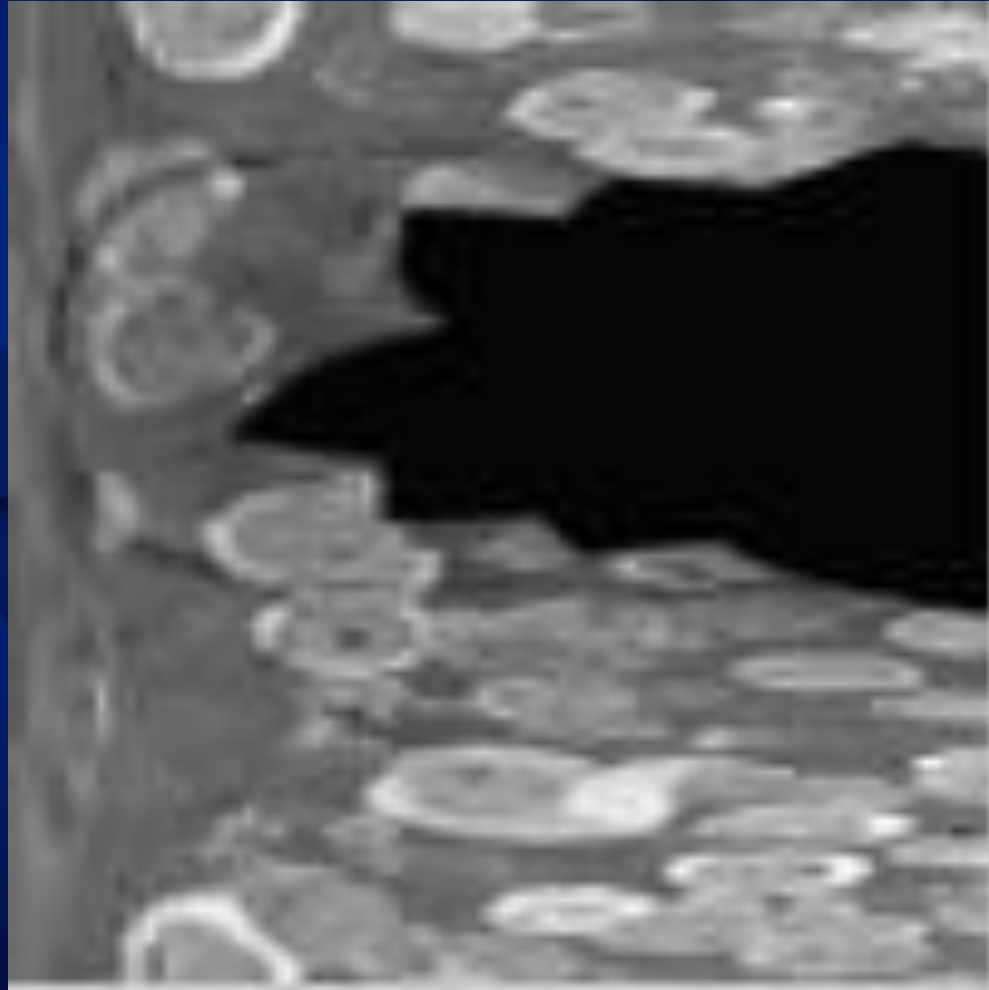
Moving through FEP's

Given a section
of neurons



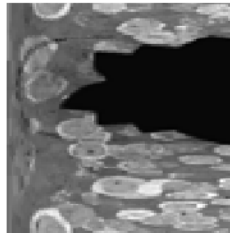


Move through to Find Centers

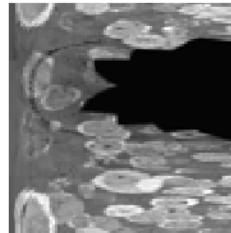


Still Sequence

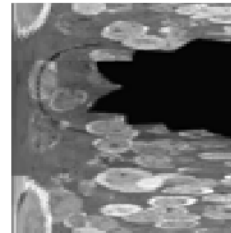
Step 5



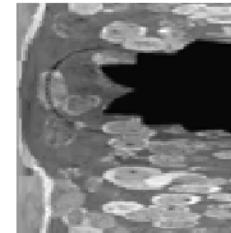
Step 16



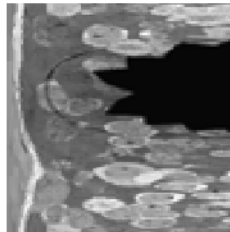
Step 21



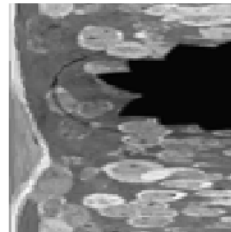
Step 27



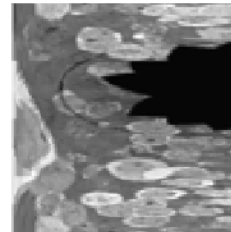
Step 34



Step 40



Step 45



Step 51

