

The Cognitive Symmetry Engine: An Active Approach to Knowledge

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Abstract

Knowledge acquisition and representation is an integral part of an active cognitive system, and such systems are continuously updating their knowledge of their own embodiment, the external world and the relation between the two. Given a stream of control commands and sensory data, we want to understand how the three types of knowledge are acquired. We propose that a core set of abstract symmetry theories constrain this process, and give an in-depth example for the case of autonomous agent sensorimotor reconstruction.

1. Introduction

Knowledge representation has been identified as a central issue for autonomous robot development. This involves questions like:

- What is robot knowledge?
- How is robot knowledge acquired?
- How is robot knowledge represented?
- How is robot knowledge shared?

However, this implies a somewhat static view of knowledge, whereas knowledge is just one aspect of a cognitive system. Cognition is an active process which attempts to produce the appropriate response in a given context. Note that this is very different from the common framework of simply producing a scene description given a set of percepts.

Cognitive knowledge includes:

- Self-knowledge; i.e., how the various actuators and sensors of the robot platform are related and act on the world,
- World knowledge; i.e., information about objects and properties of the world that exist independently of the autonomous agent, and

- Interaction knowledge; i.e., knowledge of the relation of self to the external world and the possible interaction modalities.

The question that we pose is:

Given a stream of control command values and sensory data, how can the three types of knowledge (self, world, self-world) be achieved?

We base the answer to this question on the following assumptions:

- Control (action) precedes perception during learning.
- Control results from perception during performance.
- Learning is on-going.
- Experiential knowledge is embedded in control-perception loops by maintaining appropriate invariants.
- Symbolic knowledge is derived from experiential knowledge by finding appropriate invariants.
- Inter-robot sharing occurs at the symbolic level, but requires shared experiential knowledge.
- Symmetry operators are key in all aspects of cognition, and in particular, for knowledge acquisition, representation and sharing.

Examples of previous work in this direction include Roy [12], Granlund [2], and Krueger et al. [7]. Roy proposes a method to ground language in action and perception. His agent schemas interpret signs (i.e., provide a computational semiotics) in order to guide action, and he posits specific processing channels that detect patterns. These schemas combine motor action and sensory processing to ground knowledge in terms of five types of projections of

beliefs, sensory input, action, and categorizers and intentions. Granlund describes a cognitive computer vision architecture that provides an interpretation by linking actions and percepts; that is, it relates percepts of objects to actions on them. He further argues that a more symbolic structure is appropriate for communication and is abstracted away from the specific motor-percept loop. This framework has strongly influenced our approach. Object Action Complexes (OACs) [7] are generalized from instantiated state transition fragments (ISTFs) observed during low-level execution. This allows the representation of actions and objects in tight correspondence. All these approaches include action as a key element of the learning process and the resulting knowledge representation. We demonstrate here how symmetry relations can constrain this learning process (and could be exploited in any of these approaches) and apply this to the acquisition of self-knowledge (sensorimotor reconstruction).

2. Symmetry

We propose to explore the thesis that symmetry theory provides key organizing principles for cognitive architectures. As described by Vernon et al. [13], cognition "can be viewed as a process by which the system achieves robust, adaptive, anticipatory, autonomous behavior, entailing embodied perception and action." Their survey considers two basic alternative approaches to cognition: *cognitivist* (physical symbol systems) and *emergent* (dynamical systems), where the cognitivist paradigm is more closely aligned with disembodied symbol manipulation and knowledge representation based on a priori models, and the emergent paradigm purports dynamic skill construction in response to perturbations to the embodiment. An important aspect of this discussion which concerns us here is that raised by Krichmar and Edelman [6]: "the system should be able to effect perceptual categorization: i.e., to organize unlabeled sensory signals of all modalities into categories without a priori knowledge or external instruction." We address this issue and propose that certain fundamental a priori knowledge about symmetries is vital to this function.

Our goal is to advance the state of the art in embodied cognitive systems. The requirement for cognitive ability is ubiquitous, and its achievement is an essential step for autonomous mental development. At its root, a cognitive architecture is a structural commitment to processes and representations that permit adaptive control in an operating environment that cannot be modeled completely a priori. A cognitive agent optimizes its behavior to achieve an objective efficiently by finding models that resolve hidden state information and that help it to predict the future under a variety of real-world situations. These processes involve monitoring, exploration, logic, and communication

with other agents. It is necessary to create new theories and realizations for cognitive organization in complex, real-time systems that consist of interacting domain specific agents, each with rich internal state and complex actions in order to facilitate the construction of effectively organized cognitive infrastructure. The proposed technical basis for this is symmetry operators used in perception, representation and actuation. Our specific hypothesis is:

The Domain Theory Hypothesis: Semantic cognitive content may be effectively discovered by restricting controller solutions to be models of specific symmetry theories intrinsic to the cognitive architecture.

The *Domain Theory* predicates: (1) a representation of an innate theory and inference rules for the theory, (2) a perceptual mechanism to determine elements of a set and operators on the set, (3) a mechanism to determine that the set and its operators are a model of the innate theory, and (4) mechanisms to allow the exploitation of the model in learning and model construction.

Early on, Pierce [11] described an approach to learning a model of the sensor set of an autonomous agent. Features are defined in terms of raw sensor data, and feature operators are defined which map features to features. The goal is to construct a perceptual system for this structure. One of the fundamental feature operators is the *grouping operator* which assigns features to a group if they are similar. This work was extended to spatio-visual exploration in a series of papers [8, 11]. For a detailed critique of Pierce's work, see [4]. Olsson extended this work as well [9]. He used information theoretic measures for sensorimotor reconstruction, and no innate knowledge of physical phenomena nor the sensors is assumed. Like Pierce, Olsson uses random movements to build the representation and learns the effect of actions on sensors to perform visually guided movements. The major contributions are the analysis of information theoretic measures and motion flow. O'Regan and Noë [10] use the term *sensorimotor contingencies* and give an algorithm which can determine the dimension of the space of the environment by "analyzing the laws that link motor outputs to sensor inputs"; their mathematical formulation is elegant.

3. Symmetry in Sensorimotor Reconstruction

Symmetry [15] plays a deep role in our understanding of the world in that it addresses key issues of invariance, and as noted by Viana [14]: "Symmetry provides a set of rules with which we may describe certain regularities among experimental objects." By determining operators which leave certain aspects of state invariant, it is possible to either identify similar objects or to maintain specific constraints while performing other operations (e.g., move forward while main-

taining a constant distance from a wall). A symmetry defines an invariant. The simplest invariant is identity. This can apply to an individual item, i.e., a thing is itself, or to a set of similar objects. In general, an invariant is defined by a transformation under which one object is mapped to another.

Invariants are very useful things to recognize, and we propose that various types of invariant operators provide a basis for cognitive functions, and that it is also useful to have processes that attempt to discover invariance relations among sensorimotor data and subsequently processed versions of that data.

3.1. Symmetry Detection in Signals

Assume a set of sensors, $\mathcal{S} = \{S_i, i = 1 \dots n_S\}$ each of which produces a finite sequence of indexed sense data values, S_{ij} where i gives the sensor index and j gives an ordinal temporal index, and a set of actuators, $\mathcal{A} = \{A_i, i = 1 \dots n_A\}$ each of which has a finite length associated control signal, A_{ij} , where i is the actuator index and j is a temporal ordinal index of the control values.

We are interested in determining the similarity of sensorimotor signals. Thus, the type of each sensor as well as the relation to motor control actions play a role. It is quite possible that knowledge of the physical phenomenon that stimulates a sensor may also be exploited to help determine the structure of the sensor system and its relation to motor action and the environment [3].

We suppose that certain 1D signal classes are important and are known a priori to the agent (i.e., that there are processes for identifying signals of these types). The basic signals are: (1) *constant*: $y = a$ (for some fixed constant a), (2) *linear*: $y = at + b$ (function of time index), (3) *periodic*: has period P and the most significant Fourier coefficients C , (4) and *Gaussian*: sample from Gaussian distribution with mean μ and variance σ^2 . Thus, a first level symmetry is one that characterizes a single signal as belonging to one of these categories.

3.2. Sensorimotor Reconstruction

The sensorimotor reconstruction process consists of the following steps: (1) perform actuation command sequences, (2) record sensor data, (3) determine sensor equivalence classes, and (4) determine sensor-actuator relations. An additional criterion is to make this process as efficient as possible.

Olsson, Pierce and others produce sensor data by applying random values to the actuators for some preset amount of time, and record the sensor sequences, and then look for similarities in those sequences. This has several problems: (1) there is no guarantee that random movements will result in sensor data that characterizes similar sensors, (2) there is

no known (predictable) relation between the actuation sequence and the sensor values, and (3) the simultaneous actuation of multiple actuators confuses the relationship between them and the sensors.

To better understand sensorimotor effects, a systems approach is helpful. That is, rather than giving random control sequences and trying to decipher what happens, it is more effective to hypothesize what the actuator is (given limited choices) and then provide control inputs for which the effects are known. Such hypotheses can be tested as part of the developmental process. The basic types of control that can be applied include: none, impulse, constant, step, linear, periodic, or other (e.g., random).

Next, consider sensors. Some may be time-dependent (e.g., energy level), while others may depend on the environment (e.g., range sensors). Thus, it may be possible to classify ideal (noiseless) sensors into time-dependent and time-independent by applying no actuation and looking to see which sensor signals are not constant (this assumes the spatial environment does not change). Therefore, it may be more useful to not actuate the system, and then classify sensors based on their variance properties. That is, in realistic (with noise) scenarios, it may be possible to group sensors without applying actuation at all.

Consider Pierce's sensorimotor reconstruction process. If realistic noise models are included, the four types of sensors in his experiments (range, broken range, bearing and energy) can all be correctly grouped with no motion at all. (This assumes some energy loss occurs to run the sensors.) All this can be determined just using the equals symmetry operator (identity) and the means and variances of the sensor data sequences.

3.3. Exploiting Actuation

Of course, actuation can help understand the structure of the sensorimotor system. For example, consider what can be determined by simply rotating a two-wheeled robot that has a set of 22 range sensors arranged equi-spaced on a circle. Assume that the control signal results in a slow rotation parallel to the plane of robot motion (i.e., each range sensor moves through a small angle to produce its next sample) and rotates more than 2π radians. Then each range sensor produces a data sequence that is a shifted version of each of the others – i.e., there is a translation symmetry (of periodic signals) between each pair. The general problem is then:

General Symmetry Transform Discovery

Problem: Given two sensors, S_1 and S_2 , with data sequences T_1 and T_2 , find a symmetry operator σ such that $T_2 = \sigma(T_1)$.

3.4. Symmetry-based Sensorimotor Reconstruction Algorithm

Using the symmetries described above, we propose the following algorithms.

Algorithm SBSG: Symmetry-based Sensor Grouping

1. Collect sensor data for given period
2. Classify Sensors as Basic Types
3. For all linear sensors
 - a. Group if similar regression error
4. For all periodic sensors
 - a. Group if similar P and C
5. For all Gaussian sensors
 - a. Group if similar variance

This algorithm assumes that sensors have an associated noise. Note that this requires no actuation and assumes the environment does not change. Finally, the similarity test for the above algorithm depends on the agent embodiment.

Algorithm SBSR: Symmetry-based Sensorimotor Reconstruction

1. Run single actuator and collect sensor data for given period
2. For each set of sensors of same type
 - a. For each pair
 - i. If translation symmetry holds Determine shift value (in actuation units)

This determines the relative distance (in actuation units) between sensors. E.g., for a set of equi-spaced range sensors, this is the angular offset.

4. Comparison to Pierce’s Work

A set of simulation experiments are described in Chapter 4 of Pierce’s dissertation [11]. The first involves a mobile agent with a set of range sensors, a power level sensor, and four compass sensors. The sensors are grouped and then a structural layout in 2D is determined. The second experiment concerns an array of photoreceptors. Here we examine the first experiment, and in particular, the group generator.

4.1. Symmetry-based Grouping Operator

Any simulation experiment should carefully state the questions to be answered by the experiment and attempt to set up a valid statistical framework. In addition, the sensitivity of the answer to essential parameters needs to be examined. The question to be answered is: **Grouping Correctness**: What is the correctness performance of the proposed grouping generator? This requires a definition of correctness for performance and we propose the following (for more details, see [4]):

Correctness Measure: Given (1) a set of sensors, $\{S_i, i = 1 : n\}$ (2) a correct grouping matrix, G , where G is an n by n binary valued matrix with $G(i, j) = 1$ if sensors S_i and S_j are in the same group and $G(i, j) = 0$ otherwise, and (3) H an n by n binary matrix which is the result of the grouping generator, then the grouping correctness measure is:

$$\mu_G(G, H) = \sum_{i=1}^n \sum_{j=1}^n [(\delta_{i,j})/n^2]$$

$$\delta_{i,j} = 1 \text{ if } G(i,j) = H(i,j); 0 \text{ otherwise}$$

4.1.1 Sensor Grouping with Noise (No actuation)

Assume that the sensors each have a statistical noise model. The real-valued range sensors have Gaussian noise sampled from a $\mathcal{N}(0, 1)$ distribution (i.e., $v_{sample} = v_{true} + \omega$). The binary-valued bearing sensors have salt and pepper noise where the correct value is flipped $p\%$ of the time. Finally, the energy sensor has Gaussian noise also sampled from $\mathcal{N}(0, 1)$. (The broken range sensor returns a constant value.)

Based on this, the grouping correctness results are given in Figure 1. Sensor data sampling time was varied from 1 to 20 seconds for binary noise of 5%, 10% and 25%, and Gaussian variance values of 0.1, 1, and 10. Ten trials were run for each case and the means are shown in the figure. As can be seen, perfect sensor grouping is achieved after 20 seconds without any actuation cost. Previous methods required driving both wheels for a longer time and they cost about $30k_{a/s}$ more in energy than our method ($k_{a/s}$ is the actuation to sensing cost ratio).

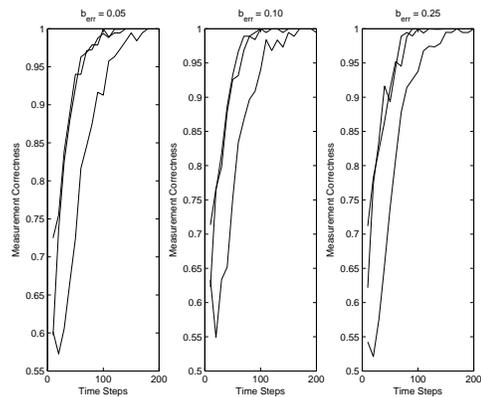


Figure 1: Grouping Correctness vs. Number of Samples; left to right are for binary salt and pepper noise of 5%, 10%, and 25%; curves for 0.1, 1.0, and 10.0 variance are given in each plot.

4.1.2 Sensor Grouping (Actuated)

Given a set of sensors that characterize the group operation nature of an actuator (in this case rotation), the sensors can be grouped based on the fact that similar sensors produce data that has a translation symmetry along the temporal axis. Figure 2 shows representative data for the range and compass sensors. The simple determination of a translation symmetry between signals allows both grouping (i.e., the signals match well at some time offset), and the angular difference between the sensors (given by the t_{offset} at which the symmetry occurs); t_{offset} is proportional to the angle between the the sensors in terms of actuation units.

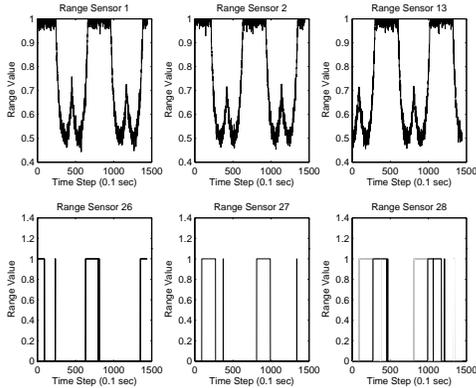


Figure 2: Sensor data showing translation symmetry: Row 1 shows sensors 1, 2, and 13; Row 2 shows compass sensors 27,28, and 29.

5. Physical Experiment

We have performed experiments with physical sensors to validate the proposed approach. Data was taken for both the static case (no actuation) and the actuated case (camera rotation).

5.1 Unactuated Experiment

Two sensors were used in this experiment: a camera and a microphone. The camera was set up in an office and a sequence of 200 images was taken at a 10Hz rate. Figure 3 shows one of these images. The 25x25 center set of pixels from the image comprise a set of 625 pixel signals each of length 200. An example trace and its histogram are given in Figure 4. As can be seen, this is qualitatively a Gaussian sample. Figure 5 shows a 200 sequence signal of microphone data, and its histogram which also looks Gaussian.

The application of our symmetry detectors classified all pixel and microphone signals as Gaussian signals, and

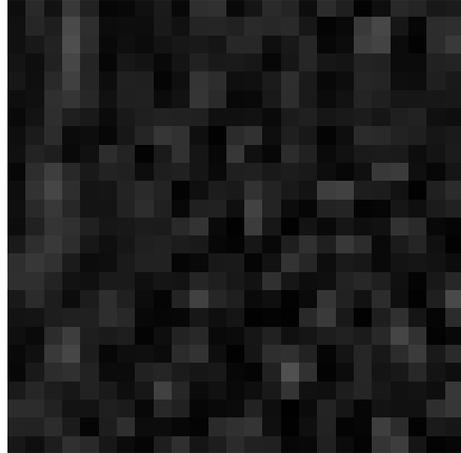


Figure 3: One of the 200 Static Images.

grouped the pixel signals separately from the microphone due to the difference in their variance properties.

5.2 Actuated Experiment

We also took a set of images by rotating the camera by one degree for 360 degrees. Domain translation symmetry allows the identification of all the pixel signals along a row as similar to each other (i.e., they are all in the plane of the rotation). Due to the translation amount, the offset between the signals is also discovered.

6. Conclusions and Future Work

We propose symmetry theory as a basis for sensorimotor reconstruction in embodied cognitive agents and have shown that this allows the identification of structure with simple and elegant algorithms which are very efficient and result in grounded self-knowledge. The exploitation of noise structure in the sensors allows unactuated grouping of the sensors, and a simple one actuator rotation permits the recovery of the spatial arrangement of the sensors. This method was shown to hold for physical sensors as well.

Next steps include the acquisition of world knowledge and self-world interaction knowledge. In addition, the abstraction of this knowledge to allow sharing is also necessary. We intend to explore these in the framework of Object Action Complexes.

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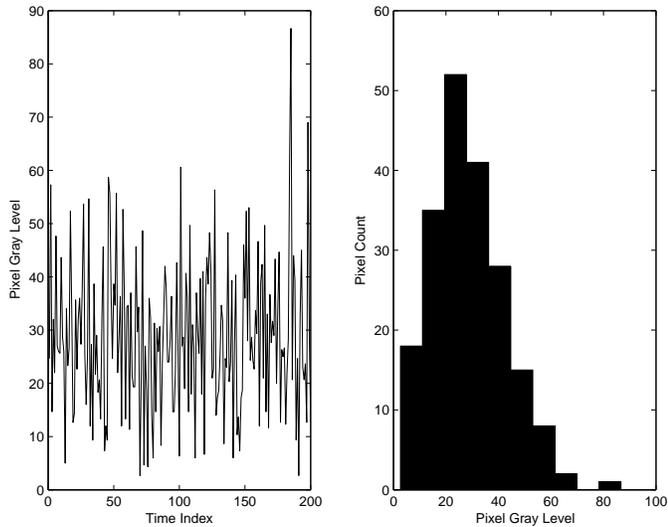


Figure 4: Trace and Histogram of the 200 Pixel Values of the Center Pixel of the Images.

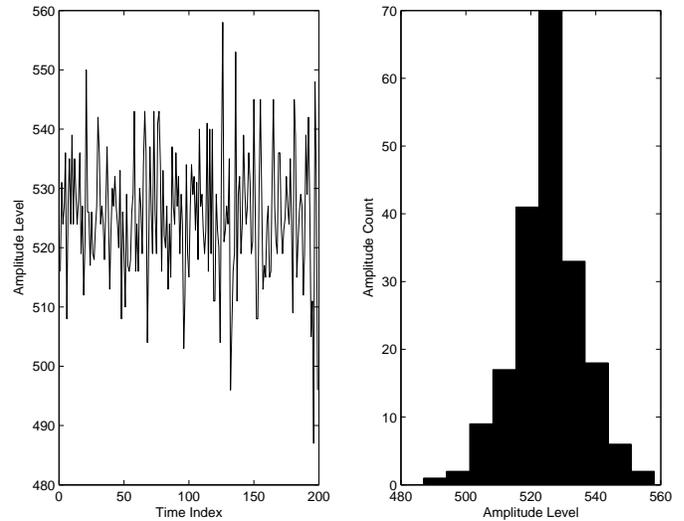


Figure 5: Trace and Histogram of the 200 Amplitude Values of the Microphone Data.

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