Symmetry as an Organizational Principle in Cognitive Sensor Networks

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Abstract

Cognitive sensor networks are able to perceive, learn, reason and act by means of a distributed, sensor/actuator, computation and communication system. In animals, cognitive capabilities do not arise from a tabula rasa, but are due in large part to the intrinsic architecture (genetics) of the animal which has been evolved over a long period of time and

depends on a combination of constraints: e.g., ingest nutrients, avoid toxins, etc. We have previously shown how organism morphology arises from genetic algorithms responding to such constraints[6]. Recently, it has been suggested that abstract theories relevant to specific cognitive domains are likewise genetically coded in humans (e.g., language, physics of motion, logic, etc.); thus, these theories and models are abstracted from experience over time. We call this the *Domain Theory Hypothesis*, and other proponents include Chomsky [2] and Pinker [11] (universal language), Sloman [16, 17] (artificial intelligence), and Rosenberg [13] (cooperative behavior). Some advantages of such embedded theories are that they (1) make learning more efficient, (2) allow generalization across models, and (3) allow determination of true statements about the world beyond those available from direct experience. We have shown in previous work how theories of symmetry can dramatically improve representational efficiency and aid reinforcement learning on various problems [14]. However, it remains to be shown sensory data can be organized into appropriate elements so as to produce a model of a given theory. We address this here by showing how symmetric elements can be perceived by a sensor network and the role this plays in a cognitive system's ability to discover knowledge about its own structure as well as about the surrounding physical world. Our view is that cognitive sensor networks which can learn these things will not need to be pre-programmed in detail for specific tasks.

1 Introduction

The development of effective mental abilities for cognitive systems is a longstanding goal of the AI and intelligent systems communities. The major approaches are the *cognitivist* (physical symbol systems) and *emergent* (dynamical systems) paradigms. For a detailed review of the relevant characteristics of cognitive systems and how these two approaches differ, see [18]. Basically, cognitivists maintain that patterns of symbol tokens are manipulated syntactically, and through percept-symbol associations perception is achieved as abstract symbol representations and actions are causal consequences of symbol manipulation. In contrast, emergent systems are concurrent, self-organizing networks with a global system state representation which is semantically grounded through skill construction where perception is a response to system perturbation and action is a perturbation of the environment by the system. The emergent approach searches the space of closed-loop controllers to build higher-level behavior sequences out of lower ones so as to allow a broader set of affordances in terms of the sensorimotor data stream. We propose to combine these approaches in order to exploit abstraction and specific cognitive domain theories to overcome sensor data analysis complexity. Our specific hypothesis is:

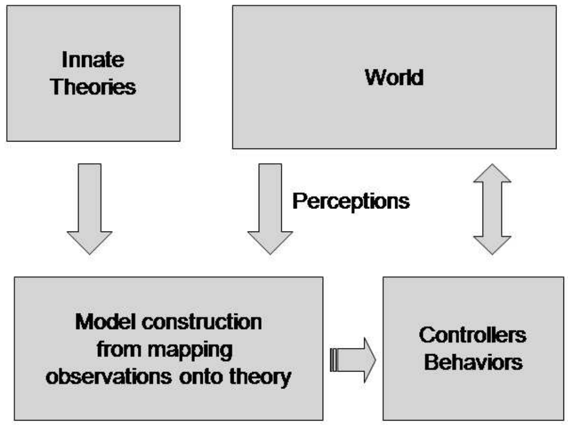

Figure 1: Innate Theory based Cognitive Architecture.

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

Sloman [16, 17] has argued for this from an artificial intelligence point of view, while Chomsky [2] and Pinker [11] have explored universal structures for human natural language, and Rosenberg [13] explores the genetic evidence for cooperative behavior among humans. We proposed a framework for intrinsic sensor-actuator behaviors [5], and recently have studied the hypothesis in the context of some standard AI and robotics problems [14]. In particular, we considered there the role that a theory of symmetry can play in various learning scenarios. When symmetry can be exploited in reinforcement learning, the time to learn the solution to the task should be proportional to the size of the set of asymmetric states (note that this may be characterized in terms of the quotient space of the associated group where it exists). Figure 1 shows the cognitive architecture for this approach.

Pinker previously proposed a schema for innate computational modules in humans; he also outlined the following tests for possible computational modules (what we call theories) in humans and gives some examples (pp. 436-438): (1) Does the theory help solve a problem that our ancestors faced in their environment (biological anthropology)? (2) When children solve problems for which mental modules exist, they should know things they have not been taught. (3) Neuroscience should discover that the brain tissue computing the problem has some kind of physiological cohesiveness (tissue or subsystem). Pinker also lists some possible modules, including: (1) Intuitive mechanisms: knowledge of the motions, forces and deformations that objects undergo, (2) Intuitive biology: understanding how plants and animals work, (3) Number, and (4) Mental maps for large territories. Here we explore theories of time, space, and motion in cognitive sensor networks.

In summary, 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 belief construction.

In previous work, we have developed many aspects of sensor networks: an object-oriented methodology called *logical sensors* for sensor networks, knowledge based multisensor systems, instrumented logical sensors, leadership protocols, simulation experiments, gradient calculation, reaction-diffusion patterns and computational sensor networks (see [7, 8]). Our most recent work on *computational sensor networks* emphasizes the exploitation of strong models of the sensed phenomena (e.g., the heat equation), and showed how inverse solutions to the model equations allows a solution to the mote localization problem, as well as estimates of sensor bias. Thus, models are very important for sensor networks, and the current work expands by demonstrating how models can be discovered.

A sensor network involves hardware, software, sensors, radios, and physical phenomena. In order to handle this complexity, models are exploited to allow abstract descriptions and a quantitative analysis of performance. For example, a sensor model usually describes the resolution, quantization, accuracy, and noise associated with the sensor data. R/F models describe a broadcast range and probability of packet reception. Models of the physical phenomena range from PDE's to finite state automata. With such models, it is possible to determine the performance capabilities of a sensor network, as well as to adapt the sensing, computation and communication to achieve more efficient operation. The major drawbacks with this approach include: (1) models must be constructed and exploited by human effort, and (2) models are usually static and may not be valid during execution. Thus, one of our goals is to develop methods to address these issues allowing the sensor network to become more cognitive by allowing it to: (1) learn models from its own observations, and (2) validate models during operation by comparing model predictions to sensed data.

To achieve these goals, that is, to achieve a cognitive sensor network, we propose to provide the sensor network with: (1) representations of innate theories and inference rules for the theories, (2) a perceptual mechanism to determine elements of a set and operators on those elements, (3) a mechanism to determine that the set and its operators are a model of an innate theory, and (4) mechanisms to allow the exploitation of the model in learning and belief construction. In [14] we demonstrated the last point by assuming that a theory of symmetry was available, and showed that reinforcement learning was made much more efficient on the Towers of Hanoi and the Cart-Pole Balancing problems. Here we address the first three points by examining how a theory of symmetry might be used to construct models of interest to a sensor network.

2 Symmetry Perception in Model Discovery

Symmetry plays a deep role in our understanding of the world in that it addresses key issues of invariance. 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 maintaining a constant distance from a wall). For an excellent introduction to symmetry in physics, see [3]. In computer vision, Michael Leyton has been a strong advocate of the exploitation of symmetry in computer vision [9]; we have shown how to use symmetry in range data analysis for grasping [4]. Popplestone and colleagues showed the intrinsic value of this approach, particularly in assembly planning problems [10], while more recently, Selig has provided a very technical basis geometric basis for many aspects of advanced robotics using Lie algebras [15].

In our work, we follow the formal development provided by Popplestone and Grupen [12]; they develop a formal description of general transfer functions (GTF's) and their symmetries. The basic idea is that a transfer function characterizes the input-output relationship of a system. This means that they are *functionals* which map from a specification of how the input to a system evolves over time to a specification of how its output evolves over time. Their key question is: "How do world symmetries relate to symmetries of transfer functions which are used to characterize reactive systems?" Their goal was to develop a set of elementary controllers that would span the space of behaviors of interest. See Appendix A for a summary of the propositions we use here to show how innate theories can be used by a cognitive sensor network to build models of its own structure.

We use their theory to allow expression of symmetries as transfer functions (i.e., input-output maps). Suppose we have a set of operators, S, their product, written as catenation, 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**: $\exists e \in S$ such that $a \in S \Rightarrow a + e = a$, and (4) **Inverse**: $\forall a \in S \exists a^{-1} \in S$ such that $a + a^{-1} = e$. Then S is a *group* of operators.

Now let's consider how this framework can be applied so that a sensor network can learn models of sensed phenomena as well as its own structure. Suppose that we have a set of sensor elements (*SEL*'s), and that each *SEL* is equipped with an intensity sensor and a microphone. Moreover, the sensor at each *SEL* produces sequences of data which can be collected and analyzed. Each sensor, S, is viewed as a map from the integers to the reals: $S : I \rightarrow \Re$ (i.e., we assume that time steps are equal and just use the ordinals). Thus, operators on $\Re$ can be extended to act on sensor functions as described after Definition 1. Thanks to Propositions 1 and 2, we are allowed to treat the symmetry operators on sensor data as a group. Proposition 5 allows us to restrict our attention to translations on the integers due to our time indexes.

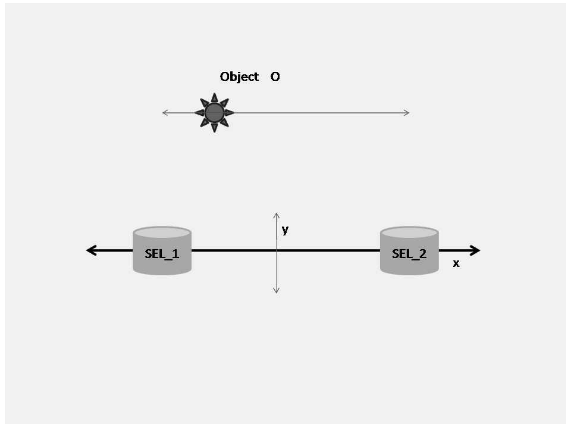

Figure 2: Sensing Scenario for Moving Object with 2 *SEL*'s.

Assume we have theories for certain subgroups of S_R, the symmetric group on $\Re$ (i.e., the set of all one-to-one mappings from $\Re$ to $\Re$). Let $I(\Re)$ be the group of isometries on $\Re$; that is, $I(\Re)$ is the subgroup of elements of S_R which preserve distance:

$$\sigma \in I(\Re) \Leftrightarrow (\sigma \in S_R) \wedge \forall a, b \in \Re, d(a, b) = d(a\sigma, b\sigma)$$

If $\sigma \in I(\Re)$, then $r\sigma = \epsilon r + 0\sigma$ where $\epsilon = \pm 1$. More specifically, $r\sigma = r + a$ moves the real line a units to the right, while $r\sigma = -r + a$ inverts about the origin and then translates a units to the right. (See [1] for details.)

2.1 Discovering Sensor Models

We now show how symmetry in the sensor data can be used to determine which sensors are similar (i.e., sense the same phenomenon). First, the signals are correlated, then the maximum correlation is used to determine the possible translation isometry coefficient, and finally, the transformed data are compared.

Suppose now that the sensor network has two *SEL*'s located at $[-5; 0]$ and $[5; 0]$ on the x-axis. See Figure 2. Moreover, assume that an object moves at a constant velocity along a line parallel and at distance 5 from the x-axis, and that the object emits light and a ramp noise (i.e., a signal whose amplitude goes from 0 to 30 DB in steps of 5). Now let these data sequences taken by the two *SEL*'s be considered as elements to be analyzed by the network. The goal is to cluster these into similar sensor sets.

We propose as one set of building operator the correlation coefficient between shifted ver-

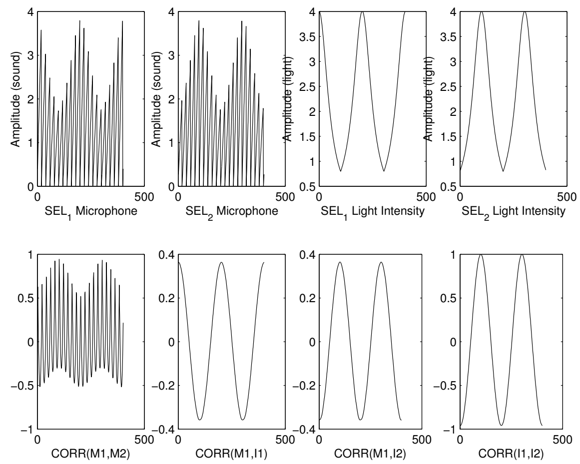

Figure 3: Data from 2 *SEL*'s in Moving Object Scenario.

sions of the signals. The top row of Figure 3 shows the intensity and audio data recorded by the two *SEL*'s (in simulation) for a two-cycle trip by the object. The bottom row shows the correlation results among various pairs of signals. As can be seen, the linear, constant velocity motion of the object results in translational symmetries in the data.

Consider now the translation operator described above. Since the maximum correlation between I_1 and I_2 occurs at $t = 100$, we have that the translation operator is defined by $0\sigma = 100$. This means that $I_1\sigma = I_1(t + 100) = I_2$. There is then a translational symmetry between the two signals. This allows the sensor network to perform several control operations: (1) Turn off redundant sensors to minimize energy usage, (2) Select a sensor to minimize noise, (3) Use the sensor data at one sensor to predict the signal at another sensor in order to detect bad data (e.g., drift, hysteresis, etc.), and (4) Use relations between the sensor symmetries to solve the localization problem (e.g., where the sensors are located with respect to a given coordinate frame). This very simple example demonstrates how a theory of symmetry may be exploited by a sensor network to build effective models of its own structure.

We have performed experiments with SunSPOT motes to corroborate the results found in simulation. The experimental setup is shown in Figure 4. The two motes record intensity data as a light emitting object moves along a line directly above the motes. Figure 5 shows the data recorded from the two motes on a 2-cycle trip by the object. The symmetry discovered in the data allows the transformation between the data of the two sensors to be discovered as shown in the second row.

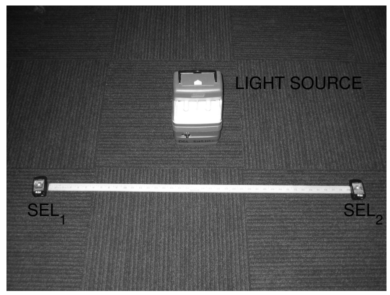

Figure 4: Experimental Setup with Two SunSPOT Motes.

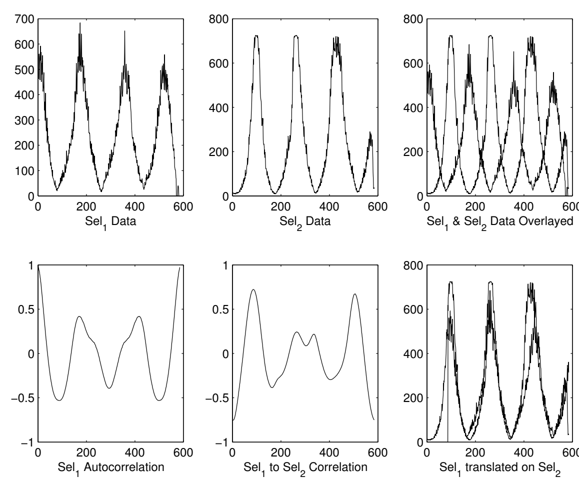

Figure 5: Experimental Data from 2 *SEL*'s in Moving Object Scenario.

3 Conclusions and Future Work

We have shown here that the exploitation of a simple theory of symmetry can allow a sensor network to build models of its environment and its own structure. However, even broader advantages arise. For example, given an appropriate theory, true statements can be discovered (by syntactic inference or semantic truth analysis) which are beyond the phenomena observed by the sensor network. Moreover, such theorems will be considered true and need not have a probabilistic structure. Where competing theories exist in a single cognitive sensor network (perhaps due to alternative axioms), it is possible to represent and entertain contradictory conclusions (e.g., believe A and $\neg A$ simultaneously), but without falling into inconsistency since the source of the inconsistency can be referenced.

Another key question that arises is for which domains such theories might exist, as posed by Pinker above. This gives rise to a vigorous future research agenda: (1) Which domains are significant for cognitive sensor networks? Clearly, time space and sensor data are important; but this also includes network and communication resources, energy, and some sort of internal goals, (2) What theories are appropriate for which domains? (3) How can theories be represented in the cognitive sensor network? (4) How can observations be mapped to the appropriate theory (i.e., how are models created)? (5) How can such models be exploited to improve learning? (6) How can such models be exploited to arrive at new knowledge? These questions can be studied in animals as well as artificial cognitive agents, including sensor networks, and give rise to deep questions about brain form and function, as well as to the possible genetic coding of innate theories.

These also give rise to certain predictions concerning the exploitation of symmetry in humans and some requirements on cognitive sensor networks: (1) Cognitive sensor networks should be able to perceive symmetry. That is, sensor data analysis mechanisms should exist which respond to symmetric stimuli (as demonstrated here). (2) Mechanisms should exist to exploit symmetric relations during learning. (3) Using symmetry should reduce the size of the search space during learning (e.g., we have seen an order of magnitude reduction in some problems).

Appendix A

Proposition 1 *Let T be a GTF with input domain U_{in} and output domain U_{out} and preset domain P. Let Σ be a set of operators acting on these domains. Then the set of full symmetry operators on T form a group.*

Proposition 2 *The product of transfer functions is associative, with the identity transducer as its identity.*

Proposition 5 *Let* $\Sigma' \subset \Sigma$ *be a group of full symmetries of a transfer function* T *whose input space is* U*, whose output space is* X *and whose preset space is* P*. Let* $\theta = 1/\Sigma'$*. Then the function* T/Σ' *defined by* $(T/\Sigma')(u.\theta, p.\theta) = T(u,p).\theta$ *is a GTF.*

References

[1] B. Baumslag and B. Chandler. *Group Theory*. McGraw-Hill Book Company, New York, NY, 1968.

[2] N. Chomsky. Biolinguistic Explorations: Design, Development, Evolution. *International Journal of Philosophical Studies*, 15(1):1–21, March 2007.

[3] J.P. Elliott and P.G. Dawber. *Symmetry in Physics*. The Macmillan Press, London, UK, 1979.

[4] R. Grupen and T.C. Henderson. Apparent Symmetries in Range Data. *Pattern Recognition Letters*, 7:107–111, 1988.

[5] R. Grupen and T.C. Henderson. Autochthonous Behaviors: Mapping Perception to Action. In *Proceedings of the NATO ARW Workshop on Traditional and Non-Traditional Robotic Sensors*, pages 285–312, Maratea, Italy, 1989.

[6] T.C. Henderson and A.A. Efros. Evolutionary Teleomorphology. *Journal of Robotics and Autonomous Systems*, 19(1):23–32, 1996.

[7] T.C. Henderson, E. Grant, K. Luthy, and J. Cintron. Computational Sensor Networks. In *Proceedings of the IEEE Conference on Intelligent Robots and Systems*, San Diego, CA, 2007.

[8] Thomas C. Henderson. *Computational Sensor Networks*. Springer Verlag, New York, NY, 2009.

[9] M. Leyton. *Symmetry, Causality, Mind*. MIT Press, Cambridge, MA, 1992.

[10] Y. Liu and R. Popplestone. A Group Theoretic Formalization of Surface Contact. *International Journal of Robotics Research*, 13(2):148–161, 1994.

[11] Steven Pinker. *The Language Instinct*. Harper Collins, NY, NY, 1994.

[12] R. Popplestone and R. Grupen. Symmetries in World Geometry and Adaptive Behaviour. In *Proceedings of the Workshop on Algebraic Frames for the Perception Action Cycle*, pages 269–283, Kiel, Germany, 2000.

[13] A. Rosenberg. Will Genomics Do More for Metaphysics than Locke? In P. Achinstein, editor, *Scientific Evidence*, pages 186–205, Baltimore, MD, 2005. The Johns Hopkins University Press.

[14] F. Sawo and U. Hanebeck. Bayesian Estimation of Distributed Phenomena. In T.C. Henderson, editor, *Computational Sensor Networks*, pages 165–198, Berlin, 2009. Springer-Verlag.

[15] J.M. Selig. *Geometric Fundamentals of Robotics*. Springer Verlag, New York, NY, 2004.

[16] A. Sloman. Architectural and Representational Requirements for Seeing Processes and Affordances. In D. Heinke and E. Mavritsaki, editors, *Computational Modelling in Behavioural Neuroscience: Closing the Gap between NeuroPhysiology and Behaviour*, London, UK, 2008. Psychology Press.

[17] Aaron Sloman. The Well Designed Young Mathematician. *Artificial Intelligence*, 172(18):2015–2034, December 2008.

[18] D. Vernon, G. Metta, and G. Sandini. A Survey of Artificial Cognitive Systems: Implications for the Autonomous Development of Mental Capabilities in Computational Agents. *IEEE Transactions on Evolutionary Computing, Special Issue on Autonomous Mental Development*, to appear, 2008.