Robot Self-Characterisation of Experience Using Trajectories in Sensory-Motor Phase Space

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Abstract

We describe sensorimotor phase-plots constructed using information theoretical methods from raw sensor data as a way for a robotic agent to characterise its interactions and interaction history. Measurements of the position and shape of the trajectories, including fractal dimension, can be used to characterise the agent-environment interaction.

1. Introduction

Taking a dynamical systems approach we view cognition as the development and activity of an embodied system in response to a history of interactions with its environment (including the social environment) (Smith and Thelen, 1993, Dautenhahn, 1996). Cognitive structures arise from the recurrent sensorimotor patterns that enable and scaffold increasingly complex perceptually guided action.

Our research approach starts with a robotic agent that possesses sensors and effectors coupled to basic reactive systems that allow it to act in the world. We then look at how cognitive structures might develop that can start to make sense of the world that the organism finds itself in, with a particular interest in how an experiential interaction history would be constructed and used from the robot's perspective.

This paper investigates a first step towards the dynamical construction of an experiential interaction history; that is, to establish a basis whereby an agent may characterise and identify behaviour using the experiential (sensor-motor) information available to it. A robot acting in the environment constructs trajectories in a reduced dimension space and characterises those trajectories in terms of their shape. We then examine how those characteristics vary with the behaviour executed.

2. Average Information Distance (AID)

Crutchfield's *information metric* (Crutchfield, 1990) gives a metric measure[1] of the distance between information sources X and Y, and is defined as $d(X,Y) = H(X|Y) + H(Y|X)$. The conditional entropies are calculated by estimating the joint probability distributions of sensor values from the τ most recent sampled values of the sensor across Q bins (Mirza et al., 2005).

The *average information distance* (AID) is defined for a group of sensors as the average of the information distance between all sensor pairs in the group. With our sensors separated into two groups loosely representing "environment" and "agent", we calculate the AID for each group and plot in two dimensions to get a representation of the relation between the two groups of sensors. This is done for successive time-steps over a fixed-sized moving window to get a trajectory representing, from the robot's perspective, how the agent-environment interaction is changing with time. We call this plot an *AID phase-plot*.

3. Characterising AID trajectories

It is our hypothesis that the postion and shape of an AID phase-plot trajectory can be used to characterise the agent-environment interaction. This would lead to a reduction in the amount of data needed to be kept in an interaction history. To test this, AID trajectories produced when the robot was executing known behaviours were analysed using simple measures and the ability of the measures to characterise behaviour assessed.

Three measures were considered, 1) *centre-of-gravity* - average of the positions of the points on the plot assuming unit-mass, 2) *sum-of-vectors* - sum of the directional vectors between successive points, gives a measure of the overall direction and magnitude of motion of the trajectory and 3) *fractal dimension* - a measure of the convolutedness of a trajectory. Each was calculated for a particular region or time-frame of an AID phase-plot.

[1] satisfying axioms of *symmetry*, *equivalence* and the *triangle inequality*

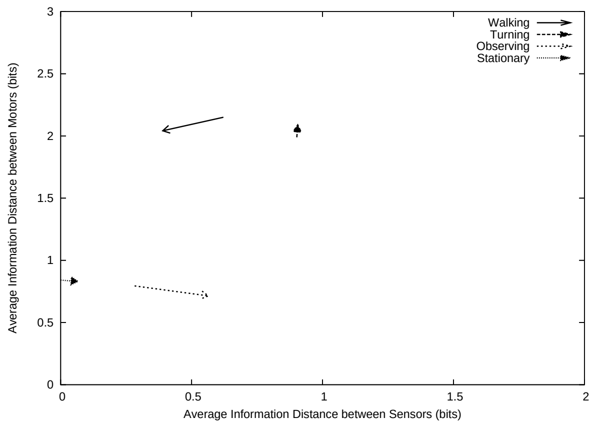

Figure 1: *AID trajectories. Summary of 24 experiments.* Arrows representing the summarised results for 11 *walking*, 7 *turning*, 5 *observing* and 1 *stationary* experiment. The arrows are positioned at the average of the centre-of-gravity and have length equal to the average of the sum-of-vectors.

We estimate fractal (capacity) dimension by counting the coverage of N^2 boxes dividing the plot area and iterating over N ("box-counting" method). The slope of a line fitted to a log-log plot of the results gives the fractal dimension. Fractal shapes have a dimension between 1.0 and 2.0, convolutedness increasing towards 2.0.

4. Results

Experiments were conducted using the SONY AIBO[2] robot. Sensory data was collected at regular intervals (on average 10 frames/sec.). The average information distance was calculated using $Q = 12$ bins for a moving time-window of $\tau = 20$ timesteps ($\simeq$2 seconds).

Three simple behaviours were studied; *walking*, *turning*, and *observing* (activity in the environment while the robot was stationary). Each was repeated a number of times with variations in, for example, the direction of walk or location of turn. A *stationary* behaviour was also studied as a reference.

The centre-of-gravity and sum-of-vectors results are summarised in Fig. 1 (see (Mirza et al., 2005) for details). Typical AID plots of the four types of behaviour are shown in Fig. 2, results for the fractal dimension are summarised in Table 1.

5. Conclusion

Fractal dimension was found to be a useful measure that, along with centre-of-gravity and sum-of-vectors, could be used to distinguish frames of experience from a robot's perspective represented by a trajectory in average information distance (AID) phase-space. A combination of shape measures can be used by a robot interacting with its environment to characterise experience and build an interaction history.

Future work will focus on social interactions and revisiting experience, moving along trajectories in the space described by experience. Learning how to move in this space presents a major challenge.

[2]AIBO is a registered trademark of SONY Corporation

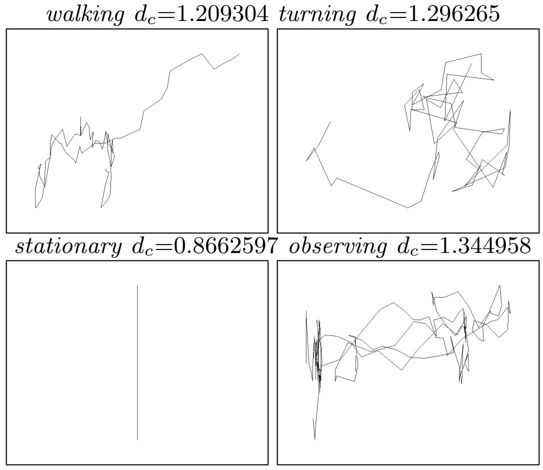

Figure 2: *Average Information Distance phase-plots.* Typical plots for each type of behaviour and the calculated fractal dimension d_c for each figure. AID for enviornment/sensor group on horiz. axis, agent/motor group on vert. axis.

Table 1: *Fractal dimension.* Summary of fractal dimension d_c calculated by the box-counting method for a robot conducting simple tasks.

Behaviour	mean d_c	min d_c	max d_c	Std Dev
walking	1.1886	1.1111	1.2521	0.04665
turning	1.3153	1.2600	1.3765	0.03985
observing	1.3133	1.2838	1.3450	0.02841
stationary[a]	0.8663	0.8663	0.8663	N/A

[a] $f_d < 1.0$ as the line does not extend over the entire area.

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