Towards Adaptive Sensorimotor Autonomy: Developing a system that can adapt to its own emergent and dynamic needs

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Egbert and Barandiaran (2014) present a model of sensorimotor autonomy (Di Paolo et al., 2017), demonstrating how a pattern of sensorimotor activity can reinforce the mechanism that produces it. Subsequent investigation (Egbert, 2018) evaluated the adaptability of these autonomous sensorimotor 'habits', showing that they were robust to some perturbations, but not capable of adapting to changes to their own viability limits (Ashby, 1952) as has been demonstrated in other autonomous systems (Egbert and Pérez-Mercader, 2016).

This paper presents a new model intended to capture a more adaptive form of sensorimotor autonomy: the VIability-Sensitive Sensorimotor Autonomy (VISSA). VISSA plays the role of a 'brain' in an agent; it produces, from the sensorimotor state, a motor output and is itself transformed by its history of sensorimotor states. It interacts with a dynamic environment through a body's motors and sensors and through these interactions, self-sustaining patterns of sensorimotor behaviour emerge. This abstract provides an overview of VISSA and the first experiments that we are performing to evaluate its adaptability.

VISSA is a node-based sensorimotor-to-motor map (Woolford and Egbert, 2020) similar to the Iterant Deformable Sensorimotor Medium (IDSM) presented in (Egbert and Barandiaran, 2014; Egbert, 2018), in that it consists of a collection of 'nodes' that describe how the robot's motor activity is to change for any given sensorimotor state. Each node is a tuple: $N = \langle N_{\boldsymbol{p}}, N_a, N_{\boldsymbol{VA}}, N_{\boldsymbol{VB}} \rangle$, where $N_{\boldsymbol{p}}$ indicates the node's sensorimotor 'position,' i. e. region of sensorimotor space for which it determines the motor output; N_a is the node's 'age', a scalar value that approximates how long it has been since that node has been active; and $N_{\boldsymbol{VA}}$ and $N_{\boldsymbol{VB}}$ are the node's 'motor vectors'—ways that the node can change the system's motor output. Like in the IDSM, behaviours and the collections of nodes that generate them are 'precarious' (Di Paolo, 2009; Egbert, 2018)—when nodes are not used for an extended period of time, they cease to exist. This 'use it or lose it' dynamic means that only patterns of behaviour that maintain themselves by causing their own repetition can persist in the long term. Unlike previous architectures, VISSA includes an adaptation mechanism whereby each node adapts its influence so as to increase the likelihood of moving the sensorimotor state toward other nodes. We aim to investigate if this local 'learning' process can enable a more holistic form of adaptation whereby a cyclic collection of nodes adapts to sustain itself.

Implementation. At any given time, the 'active node,' $N^\star$, i. e. the node that is closest to the sensorimotor state, determines the change in motor output. Every iteration, the active node switches which of its motor vectors it uses to determine its output. So, if on the previous iteration $\frac{\delta m}{\delta t} = N^\star_{\boldsymbol{VA}}$, then on the current iteration $\frac{\delta m}{\delta t} = N^\star_{\boldsymbol{VB}}$, and vice versa.

After every iteration a score, S, is calculated that quantifies how well the most recently used motor vector performed at causing the sensorimotor state to approach all of VISSA's nodes,

$$S = \sum_{N^i \neq N^\star} \alpha(N^i_a)\Big(\phi(N^i_{\boldsymbol{p}}, \boldsymbol{x}_{t=t}) - \phi(N^i_{\boldsymbol{p}}, \boldsymbol{x}_{t=t-\delta t})\Big)$$

where the weight of each node, $\alpha(N_a) = \max\left(0, 1 + \frac{N_a - \mathrm{a}_{\max}}{\mathrm{a}_{\max} - k_{\text{thresh}}}\right)$, is a truncated linear function of the node's age, that gives more weight to nodes that have been visited less recently and zero weight to nodes that have been visited very recently. The function $\phi(N_{\boldsymbol{p}}, \boldsymbol{x}) = \frac{1}{1+(20|N_{\boldsymbol{p}} - \boldsymbol{x}|)^2}$ describes a non-linear proximity of the sensorimotor state ($\boldsymbol{x}$) to the position of the node in sensorimotor space ($N_{\boldsymbol{p}}$), sampled at the current ($t = t$) and previous iteration ($t = t - \delta t$).

Scores for the two most recent uses of $N^\star_{\boldsymbol{VA}}$ and $N^\star_{\boldsymbol{VB}}$ are then used to update the active node, using a (1+1) Evolutionary Strategie (Droste et al., 2002) adjusting the motor velocities to improve at moving the sensorimotor state toward other nodes within the network, with a preference for nodes visited less recently. As the sensorimotor state changes, the active node changes and so as time passes, an adaptive self-maintaining network of nodes emerges, where each node is in a loop adapting so as to better enable the next node in the loop. At least, that is the idea! Experiments are ongoing to evaluate how this local adaptation rule might produce an emergent collective of nodes that can also adapt in a way that prolongs its existence.

Exp. #1 A minimal demonstration of local adaptation. With a single motor variable and no sensory variables, the sensorimotor state is just a motor state, represented by a single scalar value, $m \in \mathbb{R}$. Three nodes are placed evenly in sensorimotor space and assumed to fit within a larger collection, where movement from N^0 to N^1 to N^2 eventually results in a return (via other nodes $N^3 ... N^n$, which are not simulated, back to N^0. Given this assumption, motor activity that causes motion in the positive direction (i. e. from N^0 to N^1 to N^2) is considered 'adapted' as it causes the nodes in the network to be regularly revisited and thus is good for the overall persistence of the collection. In my talk, I will describe the simulations that show that the middle node, N^1 is indeed capable of adapting its velocity vectors in a way that that would improve the overall persistence of the collection and from a variety of initial conditions.

Exp. #2: An adaptive autonomous collective? I simulate a robot situated in a 1D periodic environment. Its position $r \in (0, 1]$ changes as a function of its motor state ($\frac{\mathrm{d}r}{\mathrm{d}t} = m$) and determines the state of its sensor, $s = \exp(-40|r - 0.75|^2)$, where $|r - 0.75|$ is the distance between the robot and the peak stimulus location. The robot is controlled by VISSA which now operates in a 2D sensorimotor space. To initialize the nodes I simulate a brief training phase, where the robot is initially placed at $r = 0.6$ and its motor is externally controlled as a function of time $m = \frac{3\sin(2t)}{4}$. This causes the robot to move back and forth close to the stimulus—a cycle in sensorimotor space involving positive and negative motor states with high and low stimulus levels. Every 10th iteration (the time step, $\Delta t = 0.01$) a node is added with its position, N_p set to the current sensorimotor state of the robot; its N_{VA} set to the current rate of motor change; its N_{VB} set to a 'wrong value' (i. e. a negative fraction of N_{VA}, $N_{VB} = -0.1 N_{VA}$); and $N_a = 0$.

After training ends, the nodes adapt to correct their wrong values to those that reproduce a cycle of behaviour. The behaviour that emerges appears to be robust (Figs. 1 & 2): with a sensorimotor loop similar to that driven during training repeated many times, but with variations. Some of the variations are minor, but four times during the trial, there is a significant divergence from portions of the main loop. I will discuss these results and the additional experiments that are needed to probe the limits of the robustness and adaptability of the VISSA-based behaviour.

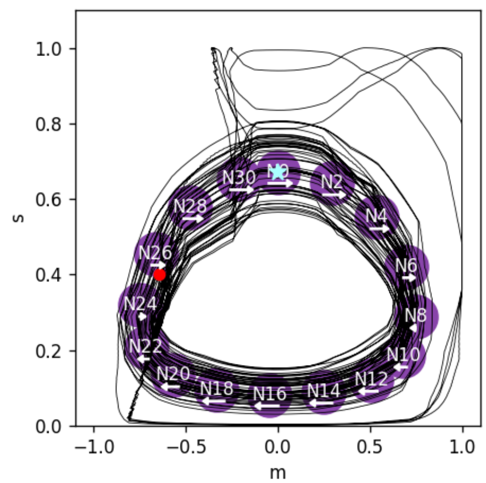

Figure 1: Node positions and sensorimotor trajectory of the robot in Exp. 2. Arrows indicate the N_{VA} values for each node at end of training. The blue star shows the sensorimotor state at the end of the training phase, and the red circle shows the sensorimotor state at the end of the trial.

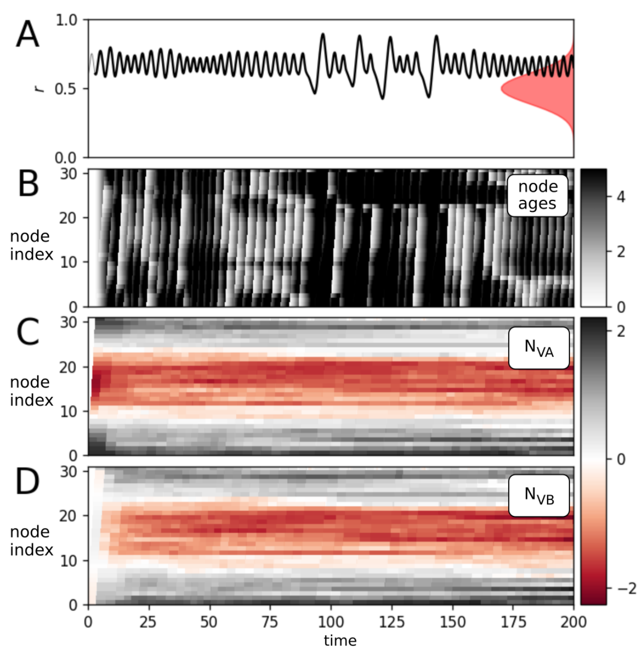

Figure 2: Exp. #2, showing (A) the position of the robot, with the the training phase indicated in a thinner line, and the stimulus associated with each location in space shown in red; (B) node ages; (C & D) node motor vectors.

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