Dynamic Memory for Robot Control via Delay Neural Networks

Francis Jeanson Carleton University 1125 Colonel By Dr. Ottawa, Ontario francis jeanson@carleton.ca

ABSTRACT

We present a procedure to decode spatio-temporal spiking patterns in delay coincidence detection networks with stable limit cycles. We apply this to control a simulated e-puck robot to solve the t-maze memory task. This work shows that dynamic memory modules formed by coincidence detection neurones with transmission delays can be effectively coupled to produce adaptive behaviours.

Categories and Subject Descriptors

I.2.0 [ARTIFICIAL INTELLIGENCE]: General—Cognitive simulation; I.2.6 [ARTIFICIAL INTELLIGENCE]: Learning—Connectionism and neural nets; I.2.9 [ARTIFICIAL INTELLIGENCE]: Robotics—Autonomous vehicles

Keywords

Dynamic Memory, Transmission Delays, Coincidence Detection, Spiking Neural Networks, Embodied Cognition

1. INTRODUCTION

A unique form of neural behaviour referred to as coincidence detection (CD) was introduced in the early 80's by Moshe Abeles. Rather than behaving uniquely as frequency integrators, neurones will respond to near-synchronous input exclusively under specific dynamic constraints. Combined with biologically realistic propagation delays on the axon and dendritic trees, the coding and information capacity of these networks via spatio-temporal patterns is potentially greater than integration alone [5]. While this contemporary interest in coincidence detection and transmission delays has led to a number of interesting findings with respect to stability criteria [1] and timing dynamics [3], few methods have been developed to control them for dynamic memory function and adaptive behaviour. The present work extends this area of research by demonstrating how specific spiking network properties can be used as dynamic memories for behavioural control.

2. SPIKING NETWORK MODEL

Recent work by Jeanson & White, showed that networks of uniformly inter-connected neurones via delay coincidence

Copyright is held by the author/owner(s).

Anthony White Carleton University 1125 Colonel By Dr. Ottawa, Ontario arpwhite@scs.carleton.ca



Figure 1: Left: Unstable spiking for 60% connectivity. Right: Stable spiking for 100% connectivity.

detection (DCD) exhibit strong synchronous firing for narrow delay distributions and complex firing in broad delay conditions [4]. Recently, we found that narrow delays induced a state of high synchrony making the network response indistinguishable between different input conditions. In the broad delay condition, however, we found that these networks responded via a continuously changing chaotic state under lower degrees of connectivity yet converged to a limit cycle attractor in the case of high degrees of connectivity. Figure 1 illustrates the sustained spiking activity in both the lower connectivity case (60%) and high connectivity case (100%). Fundamentally, a memory mechanism must exhibit a differential response with respect to recall cues and produce *reliable* patterns with respect to what a decoder can discriminate. We here demonstrate that DCD networks can be organized to exhibit both of these features. We show how stable spatio-temporal limit cycles can be decoded into spatial spiking activity to inhibit a sensorimotor reflex circuit for a behaviour based memory task.

2.1 Architecture

We developed a three network model to control a robot in a t-maze memory task as depicted in Figure 2. The linearcamera sensor of a simulated e-puck robot stimulated five sensory neurones in the sensorimotor (SM) network for each left and right visual fields. Spikes then propagated to the contra-lateral motor area in a many-to-many fashion to four motor CD neurones for each of the two wheels. Narrow delays between 10ts and 20ts in SM promoted effective wall avoidance behaviour using this network alone [4]. Four regions in an intermediary inhibitory (INH) network of 72 cells inhibited these motor neurones if their level of activity was sufficiently high. The INH network projected to SM in a many-to-many scheme with random narrow delays between 10ts and 20ts. The third memory (MEM) network consisted of a fully connected network of 25 excitatory cells with a broad range of transmission delays between 20ts and 40ts. Full connectivity ensured stable spatio-temporal dynamics

GECCO'13 Companion, July 6–10, 2013, Amsterdam, The Netherlands. ACM 978-1-4503-1964-5/13/07.



Figure 2: Illustration of the overall network model with all three Memory, Inhibitory, and Sensorimotor networks.



Figure 3: Derivation of deltas for pattern AY (red dots) with period $\lambda = 11ts$. Crossed dots correspond to collision spike times which are ignored.

as described above. MEM received input to 6 distinct cells from a context stimulus (A or B) followed by a cue stimulus (X or Y) after 350ts. Importantly, projections from MEM to INH were explicitly determined prior to experimental trials such that delays could decode the spatio-temporal pattern in MEM so to stimulate selective spatial regions in INH to produce desired turning behaviours in the robot. We called this process *delay mapping*.

2.2 Delay Mapping

We began by identifying the limit cycle period λ in MEM under each of the four stimulus pairs (AX, AY, BX, and BY) following input and a sufficient transient period. We chose $st_o = 1400ts$ as the start of a recording region. We then derived a list of spike times st_i for each cell i in the time window $st_o + \lambda$ for each of these stimulus pairs. To favour unique decoding of the patterns we performed 'collision removal' by removing spike times which occurred at the same time between lists. To assign delays from MEM to INH we derived the spike time 'delta' differences $\Delta_i^{\rho} = ts_r - st_i^{\rho}$ for pattern ρ by using a reference spike time ts_r within the window as see in Figure 3. Delays from each cell in MEM to each cell in INH were computed as $d_{ij} = \Delta_i^{\rho} + d_{base}$ using a base delay $d_{base} = 20ts$ such that it was above the refractory period of cells and half the period λ . For the reflectivity period of certs and that the period λ . For example, from Δ_{24}^{AY} and Δ_{23}^{AY} in Figure 3 we would ob-tain delays $d_{24jAY} = 2 + 20 = 22$ for cell 24 and obtain $d_{23jAY} = -2 + 20 = 18$ for cell 23. Finally, because target INH neurones had coincidence thresholds of 8, collision removal could render some patterns non-decodable. Hence neurones removed due to collisions were 'reinstated' by setting delays for these connections to some arbitrary value (here 10ts) in order to increase decodability while limiting ambiguity.



Figure 4: T-maze with solution to the AX condition.

3. EXPERIMENT

We ran 100 trials for 10 random memory networks to determine the effectiveness of dynamic memory storage using the proposed delay mapping method to control an e-puck robot on the t-maze task. Between trials, random delays for INH and SM connections were also reset leading to slight behavioural variations. As a performance measure, we independently counted the number of correct left turns when AX was presented (25% of trials) and the number of correct right turns when all three other stimuli pairs were presented (75% of trials). Simulation results showed that correct left turns were performed on 82% of AX trials and correct right turns were performed on 84% of AY, BX, and BY trials leading to an overall average success rate of 83%. An agent with no memory will have equal chance of turning left or right at the end of the maze which would lead to a 50% success rate. Similarly an agent biased towards left or right turns only will also have an overall success rate of 50%. Hence agents performed the t-maze task more effectively with the dynamic memory system than without any memory.

4. CONCLUSION

These results demonstrate an effective mechanism for decoding spatio-temporal spiking patterns into spatial patterns of firing cells for robot control. Here however, decoding ambiguities could still occur between stimulus pairs. This is primarily due to an unsystematic way of determining the coincidence threshold of the decoding cells in INH. In the future, we aim to improve this estimate as well as provide a more thorough investigation into the memory capacity and noise tolerance of these networks.

5. **REFERENCES**

- S. Arik. Stability analysis of delayed neural networks. In *IEEE Transactions on Circuits and Systems*, volume 47, pages 1089–1092. IEEE, 2000.
- [2] J. Cowan. Stochastic models of neuroelectric activity. In S. Ricce, K. Fread, and J. Light, editors, *Statistical Mechanics*, pages 181–182. University of Chicago, 1972.
- [3] E. M. Izhikevich. Polychronization: Computation with spikes. *Neural Computation*, 18:245–282, 2006.
- [4] F. Jeanson and A. White. Evolving axonal delay neural networks for robot control. In T. Soule, editor, Proceedings of the fourteenth international conference on Genetic and Evolutionary Computation Conference (GECCO '12), pages 121–128. ACM, New York, 2012.
- [5] H. Paugam-Moisy and S. Bohte. Computing with spiking neuron networks. In G. Rozenberg, T. Back, and J. Kok, editors, *Handbook of Natural Computing*. Springer Verlag, 2011.