Characterising Unconventional Computers using Novelty Search

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A growing interest in the neuro-inspired Reservoir Computing (RC) framework has led to new unconventional and physical computing systems. These include, optoelectronic and photonic computers (Appeltant et al., 2011; Vandoorne et al., 2011), quantum (Obst et al., 2013; Fujii and Nakajima, 2017), magnetic (Prychynenko et al., 2018), disordered (Dale et al., 2016) and memristor-based computing (Du et al., 2017).

However, no unifying framework exists to characterise the *quality* of substrates for RC, or assess how *faithful* the RC model represents the physical computational processes being exploited. Many systems can appear suitable but very few are characterised by the computational properties found to be essential for RC, often due to challenges involved in evaluating such properties.

Here we outline a three-phase substrate-independent framework we have developed and evaluated to characterise and exploit physical systems for RC.

Phase 1: We measure substrate "quality" by experimentally mapping the dynamical degrees-of-freedom the substrate can exhibit; with higher degrees suggesting more variety of realisable reservoirs in a single substrate. To map the space of dynamics, we use a minimalistic genetic algorithm with Novelty Search (NS) (Lehman and Stanley, 2008). The NS algorithm is well-suited as the substrate-dependent parameter space can often have complex and deceptive relationships to the substrates dynamical behaviour. Traditional objective-based search can be counter-productive here, leading to less global exploration and more local exploitation.

Phase 2: We select an appropriate reservoir for a given task based solely on the mapped dynamics. This is a nontrivial problem. We use a metaheuristic search to navigate the mapped dynamical space as an optimisation problem.

Phase 3: We evaluate the faithfulness of the model by predicting task performance of one system based on the similar dynamics of another. A faithful representation and measures imply high accuracy in task prediction across systems. This could allow rapid task evaluation on cheaper behaviourally equivalent systems and functional models when no physical models exist.

Through these combined phases the complex relationship between physical properties and reservoir performance is mapped, leaned and exploited. Leading to a better understanding of suitable RC substrates and a significant reduction in time and effort to verify suitability. Ultimately, freeing RC practitioners to focus more on substrate exploration and design.

References

Appeltant, L., Soriano, M. C., Van der Sande, G., Danckaert, J., Massar, S., Dambre, J., Schrauwen, B., Mirasso, C. R., and Fischer, I. (2011). Information processing using a single dynamical node as complex system. *Nature Communications*, 2:468.

Dale, M., Miller, J. F., Stepney, S., and Trefzer, M. A. (2016). Evolving carbon nanotube reservoir computers. In *International Conference on Unconventional Computation and Natural Computation*, pages 49–61. Springer.

Du, C., Cai, F., Zidan, M. A., Ma, W., Lee, S. H., and Lu, W. D. (2017). Reservoir computing using dynamic memristors for temporal information processing. *Nature communications*, 8(1):2204.

Fujii, K. and Nakajima, K. (2017). Harnessing disordered-ensemble quantum dynamics for machine learning. *Physical Review Applied*, 8(2):024030.

Lehman, J. and Stanley, K. O. (2008). Exploiting open-endedness to solve problems through the search for novelty. In *ALIFE*, pages 329–336.

Obst, O., Trinchi, A., Hardin, S. G., Chadwick, M., Cole, I., Muster, T. H., Hoschke, N., Ostry, D., Price, D., Pham, K. N., et al. (2013). Nano-scale reservoir computing. *Nano Communication Networks*, 4(4):189–196.

Prychynenko, D., Sitte, M., Litzius, K., Krüger, B., Bourianoff, G., Kläui, M., Sinova, J., and Everschor-Sitte, K. (2018). Magnetic skyrmion as a nonlinear resistive element: A potential building block for reservoir computing. *Physical Review Applied*, 9(1):014034.

Vandoorne, K., Dambre, J., Verstraeten, D., Schrauwen, B., and Bienstman, P. (2011). Parallel reservoir computing using optical amplifiers. *Neural Networks, IEEE Transactions on*, 22(9):1469–1481.