Self-Adaptive Recurrent Neural Networks for Robust Spatiotemporal Processing: from Animals to Robots

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Abstract: The ability to quantify temporal information on the scale of hundreds of milliseconds is critical towards the processing of complex sensory and motor patterns. However, the nature of neural mechanisms for temporal information processing (at this scale) in the brain still remains largely unknown. Furthermore, given that biological organisms are situated in a dynamic environment, the processing of time-varying environmental stimuli is intricately related to the generation of cognitive behaviors, and as such, an important element of learning and memory. In order to model such temporal processing recurrent neural networks emerge as natural candidates due to their inherent dynamics and fading memory of advent stimuli. As such, here we investigate recurrent neural network (RNN) models driven by external stimuli as the basis of time perception and temporal processing in the brain. Such processing lies in the short timescale that is responsible for the generation of short-term memory-guided behaviors like complex motor pattern processing and generation, motor prediction, time-delayed responses, and goal-directed decision making. We present a novel self-adaptive RNN model and verify its ability to generate such complex temporally dependent behaviors, juxtaposing it critically with current state of the art non-adaptive or static RNN models.

Keywords: Recurrent neural networks, Adaptation, Self-organization, Information dynamics, Temporal memory

Taking into consideration the brain's ability to undergo changes at structural and functional levels across a wide range of time spans, we make the primary hypothesis, that a combination of neuronal plasticity and homeostatic mechanisms in conjunction with the innate recurrent loops in the underlying neural circuitry gives rise to such temporally-guided actions [1,2]. Furthermore, unlike most previous studies of spatiotemporal processing in the brain [3], here we follow a closed-loop approach (Fig.1). Such that, there is a tight coupling between the neural computations and the resultant behaviors, demonstrated on artificial robotic agents as the embodied self of a biological organism. Using a RNN model of rate-coded neurons starting with random initialization of synaptic connections, we propose a learning rule based on local active information storage (LAIS). This is measured at each spatiotemporal location of the network, and used to adapt the individual neuronal decay rates or time constants with respect to the incoming stimuli. This allows an adaptive timescale of the network according to changes in timescales of inputs. We combine this, with mathematically derived, generalized mutual information driven intrinsic plasticity mechanism that can tune the non-linearity of network neurons. This enables the network to maintain homeostasis as well as, maximize the flow of information from input stimuli to neuronal outputs [4]. These unsupervised local adaptations are then combined with supervised synaptic plasticity in order to tune the otherwise fixed synaptic connections, in a task dependent manner. The resultant plastic network, significantly outperforms previous static models for complex temporal processing tasks in non-linear computing power, temporal memory capacity, noise robustness as well as tuning towards near-critical dynamics. These are displayed using a number of benchmark tests, delayed memory guided responses with a robotic agent in real environment and complex motor pattern generation tasks. Furthermore, we also demonstrate the ability of our adaptive network to generate clock like behaviors underlying time perception in the brain. The model output matches the linear relationship of variance and squared time interval as observed from experimental studies.

Having achieved such a model of spatiotemporal information processing, we first demonstrate the application of our model on behaviorally relevant motor prediction tasks with a walking robot, implementing distributed internal forward models using our adaptive network [5]. Following this, we extend the previous supervised learning scheme, by implementing reward-based learning following the temporal difference paradigm, in order to adapt the synaptic connections in our network. The neuronal correlates of this formulation are discussed from the point of view of the corticostriatal circuitry, and a new combined learning rule is presented [6]. This leads to novel results demonstrating how the striatal circuitry works in combination with the cerebellar circuitry in the brain, that lead to robust goal-directed behaviors. Thus, we demonstrate the application of our adaptive network model on the entire spectrum of temporal information processing, in the timescale of few hundred milliseconds (complex motor processing) to minutes (delayed memory and decision making).

Overall, our results affirm our primary hypothesis that plasticity and adaptation in recurrent networks allow complex temporal information processing, which otherwise cannot be obtained with purely static networks.

[†] Sakyasingha Dasgupta is the presenter of this paper.

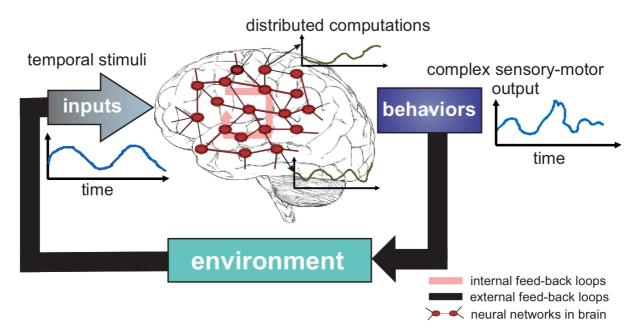


Fig.1 Closed-loop approach to temporal information processing. A constant barrage of time varying stimuli perturb the resting state of the brain leading to non-trivial, non-linear, and highly distributed computations in neuronal networks in the brain. Such computations also occur over a wide distribution of timescales. With learning and adaptation, cognitive behaviors and complex sensory motor outputs, requiring robust processing of the temporal information, can be obtained. Such behaviors typically lead to changes in the environmental conditions, which in turn change the incoming stimuli to the brain networks, thus closing the input-output loop.

Furthermore, homeostatic plasticity and neuronal timescale adaptations could be potential mechanisms by which the brain performs such processing with remarkable ease.

REFERENCES

[1] Dasgupta, Sakyasingha, Florentin Wörgötter, and Poramate Manoonpong. "Information dynamics based self-adaptive reservoir for delay temporal memory tasks." *Evolving Systems* 4.4 (2013): 235-249.

[2] Lazar, Andreea, Gordon Pipa, and Jochen Triesch. "SORN: a self-organizing recurrent neural network." *Frontiers in Computational Neuroscience* 3 (2009).

[3] Buonomano, Dean V., and Wolfgang Maass. "State-dependent computations: spatiotemporal processing in cortical networks." *Nature Reviews Neuroscience* 10.2 (2009): 113-125.

[4] Stemmler, Martin, and Christof Koch. "How voltage-dependent conductances can adapt to maximize the information encoded by neuronal firing rate." *Nature Neuroscience* 2.6 (1999): 521-527.

[5] Manoonpong, Poramate, Sakyasingha Dasgupta, Dennis Goldschmidt, and Florentin Worgotter. "Reservoir-based online adaptive forward models with neural control for complex locomotion in a hexapod robot." In *Neural Networks (IJCNN), 2014 International Joint Conference* on, pp. 3295-3302. IEEE, 2014.

[6] Dasgupta, Sakyasingha, Florentin Wörgötter, and Poramate Manoonpong. "Neuromodulatory adaptive combination of correlation-based learning in cerebellum and reward-based learning in basal ganglia for goal-directed behavior control." *Frontiers in Neural Circuits* 8 (2014).