EvoSpike: Evolving Probabilistic Spiking Neural Networks for Spatio-Temporal Pattern Recognition

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Participants:
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Background

Spatio- and spectro-temporal data (SSTD) are the most common type of data collected in many domain areas, including engineering, ,bioinformatics, neuroinformatics, ecology, environment, medicine, economics, etc. However, there is lack of methods for the analysis of such data, for the discovery of complex spatio-temporal patterns in it and for spatio-temporal pattern recognition (STPR). The brain functions as a spatio-temporal information processing machine and deals extremely well with spatio-temporal data. Its organisation and functions have been the inspiration for the development of new methods for SSTD analysis and STPR. The brain-inspired spiking neural networks (SNN), considered the third generation of neural networks, are a promising paradigm for the creation of new intelligent ICT for SSTD. This new generation of computational models and systems are potentially capable of modelling complex information processes due to their ability to represent and integrate different information dimensions, such as time, space, frequency, phase, and to deal with large volumes of data in an adaptive and self-organising manner.

Goals and objectives

The project develops novel methods and systems of SNN for SSTD analysis and STPR, namely evolving probabilistic spiking neural networks (epSNN) and evolving probabilistic computational neuro-genetic models (epCNGM). Software and hardware implementations and some pilot applications for audio-visual pattern recognition, EEG data analysis, and neurogenetic cognitive systems are also being developed.

Project development and current results

The epSNN are built on the principles of evolving connectionist systems [1], of eSNN [1-3] and of probabilistic neuronal models [4], previously developed by prof. Kasabov's group at KEDRI. The latter extend the widely used leaky integrate-and-fire spiking model by introducing some biologically plausible probabilistic parameters [4] (Fig.1). The epSNN are evolving structures that learn from and adapt to new incoming data. The research explores a range of approaches to creating epSNN for STPR, from a single neuron to 'reservoir' computing and neuro-genetic systems.

1. Novel epSNN models and systems for STPR

A single neuron is a complex information processing machine. A single neuronal model, namely Spike Pattern-Association Neuron SPAN [5-7], has been developed in this project. SPAN can be trained to capture SSTD patterns of hundreds and thousands of input spike trains and to generate in response a precise time spike sequence (Fig.2).

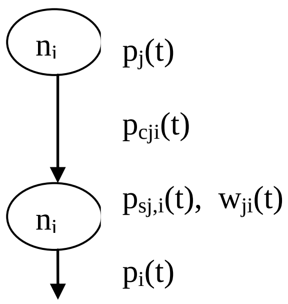
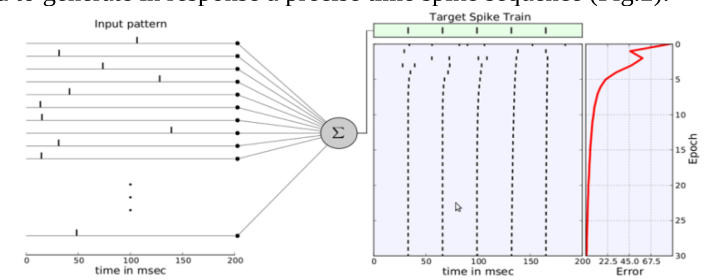


Fig.1



A single output neuron is trained to respond with a temporally precise output spike train to a specific spatio-temporal input.

Fig.2

Apart from the eSNN [1,2] and SPAN [5-7], the project explores other neuronal models and dynamic synapses, namely Fusi's model [8] implemented on the INI Zurich (www.ini.unizh.ch) SNN chip [9]. Two novel models have been developed that combine eSNN and SPAN with the dynamic synapse model from [8]. Improved accuracy for STPR have been achieved when address-event representation (AER) was used [10,11]. AER is implemented in the INI Zurich silicon retina chip (DVS camera) and the silicon cochlea chip (www.ini.unizh.ch).

The research explores further ensembles of probabilistic neuronal models and recurrent deep learning connectionist structures. These structures capture correlated spatial and temporal components from incoming data. The epSNN can learn data in an on-line manner using a frame-based input information representation, or alternatively AER. Some preliminary experiments on gesture- and sign language recognition [12], moving object recognition [13], sound recognition, EEG data recognition [14] (fig.3) have been conducted.

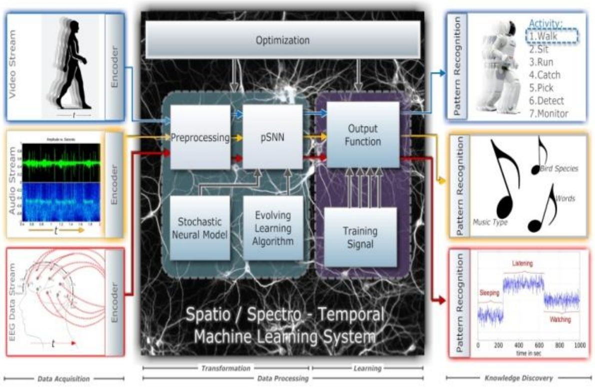


Fig.3

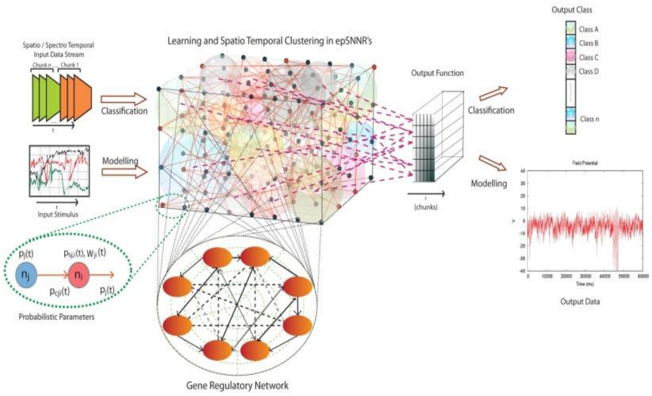


Fig.4

2. Computational neurogenetic models

A major issue in the EvoSpike model and system development is how to optimize the numerous epSNN parameters. Here we combine local learning of synaptic plasticity with global optimisation of probability and other parameters. Three approaches are being investigated that: evolutionary computation methods [12]; gene regulatory network (GRN) model [15,16] – fig.4, or using both together [15,16]. Linking gene/protein expression to epSNN parameters may also lead to new types of neuron-synapse-astrocyte models inspired by new findings in neuroscience. Neurogenetic models are promising for cognitive robotic systems and for the prognosis of neurodegenerative diseases such as Alzheimer's disease and for personalized medicine [16]. The research is expected to contribute to the fast developing area of neuromorphic engineering [17,18]. Future research is expected to continue through tighter integration of knowledge and methods from information science, bioinformatics and neuroinformatics [19].

Resulted publications form this project (highlighted in red)

1. N. Kasabov, Evolving connectionist systems: The knowledge engineering approach, Springer, 2007 (first edition 2002).
2. S. Wysoski, L. Benuskova, N. Kasabov, Evolving spiking neural networks for audiovisual information processing, Neural Networks, vol 23, 7, pp 819-835, 2010.
3. L.Benuskova and N.Kasabov, Computational neuro-genetic modelling, Springer, New York, 2007, 290 pages
4. N. Kasabov, To spike or not to spike: A probabilistic spiking neuron model, Neural Networks, 23(1), 16–19, 2010.
5. A.Mohemmed, S.Schliebs, S.Matsuda, N.Kasabov, (2011) Learning a neuron to associate spiking patterns, Proc. EANN 2011, Springer Verlag
6. A.Mohemmed,S.Schliebs,S.Matsuda,Kasabov(2011) SPAN: Spike Pattern Association Neuron for Learning Spatio-Temporal Sequences, Int. J. Neural Systems, submitted
7. A.Mohemmed,S.Schliebs,S.Matsuda,N.Kasabov(2011) Spike Pattern Association Neuronal Networks for Learning Spatio-Temporal Sequences, Neurocomputing, in preparation.
8. S.Fusi et al, Spike driven synaptic plasticity: Theory, simulation, VLSI implementation (2000), Neural Computation, 12, 2227-2258
9. G.Indivery et al, Neuromorphic silicon neuron circuits, Frontiers in neuroscience, vol.5, 1-23, May 2011.
10. N.Nuntalid, K.Dhoble, F.Stefanini, G.Indivery and N.Kasabov, Improved spatio-temporal pattern recognition for AER stream of data with eSNN and SDSP, Proc. WCCI 2012, IEEE Press, in preparation.
11. K.Dhoble, A.Mohemmed, N.Nuntalid, F.Stefanini, G.Indivery and N.Kasabov, Spike pattern association using dynamic synapses, Proc. WCCI 2012, IEEE Press, in preparation.
12. S.Schliebs, Hamed, H. N. A., Kasabov, N. (2011). A reservoir-based evolving spiking neural network for on-line spatio-temporal pattern learning and recognition. Proc. 18th Int. Conf. ICONIP, Shanghai, Springer LNCS.
13. N.Kasabov, Dhoble, K., Nuntalid, N., & Mohemmed, A. (2011). Evolving probabilistic spiking neural networks for spatio-temporal pattern recognition: A preliminary study on moving object recognition. Proc. ICONIP 2011, Springer LNCS.
14. N.Nuntalid, Dhoble, K., Kasabov, N. (2011). EEG Classification with BSA Spike Encoding Algorithm and Evolving Probabilistic Spiking Neural Network. Proc. 18th ICONIP, Shanghai, Springer LNCS.
15. N.Kasabov, A.Mohhemed, S.Schliebs (2011) Modelling the Effect of Genes on the Dynamics of Probabilistic Spiking Neural Networks for Computational Neurogenetic Modelling, Proc. CIBB 2011, Springer, LNBI
16. N.Kasabov, R.Schliebs, H.Kojima (2011) Probabilistic Computational Neurogenetic Framework: From Modelling Cognitive Systems to Alzheimer's Disease, *IEEE Trans. Autonomous Mental Development*, 3, No.3, Sept. 2011, 1-12.
17. G.Indiviery and T.Horiuchi (2011) Frontiers in Neuromorphic Engineering, Frontiers in Neuroscience, 5:118.
18. N.Kasabov et al, Spatio-and spectro-temporal pattern recognition with SNN, Neural Networks, 2012, in preparation.
19. N.Kasabov (ed) The Springer Handbook of Bio- and Neuroinformatics, Springer, 2012, in preparation

Invited/plenary talks: CIBB2011(Gargnano, Italy); Workshop IJCNN 2011(San Jose); Irish CICS 2011(Derry, UK); EANN2011 (Corfu); ICONIP2011 (Shanghai); WCCI2012 (Brisbane), IEEE IS 2012 (Sofia), EANN2012 (London).