Evolving Spiking Neural Networks and Neurogenetic Systems for Spatio- and Spectro-Temporal Data Modelling and Pattern Recognition

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Abstract. Spatio- and spectro-temporal data (SSTD) are the most common types of data collected in many domain areas, including engineering, bioinformatics, neuroinformatics, ecology, environment, medicine, economics, etc. However, there is lack of methods for the efficient analysis of such data 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) are considered the third generation of neural networks and 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, and phase, and to deal with large volumes of data in an adaptive and self-organising manner. The paper reviews methods and systems of SNN for SSTD analysis and STPR, including single neuronal models, evolving spiking neural networks (eSNN) and computational neuro-genetic models (CNGM). Software and hardware implementations and some pilot applications for audio-visual pattern recognition, EEG data analysis, cognitive robotic systems, BCI, neurodegenerative diseases, and others are discussed.

Keywords: spatio-temporal data, spectro-temporal data, pattern recognition, spiking neural networks, gene regulatory networks, computational neuro-genetic modeling, probabilistic modeling, personalized modeling, EEG data.

1 Spatio- and Spectro-Temporal Data Modelling and Pattern Recognition

Most problems in nature require spatio- or/and spectro-temporal data (SSTD) that include measuring spatial or/and spectral variables over time. SSTD is described by a
triplet \((X,Y,F)\), where: \(X\) is a set of independent variables measured over consecutive discrete time moments \(t\); \(Y\) is the set of dependent output variables, and \(F\) is the association function between whole segments (‘chunks’) of the input data, each sampled in a time window \(d_t\), and the output variables belonging to \(Y\):

\[
F: \ X(d_t) \to Y, \ where: \ X(t) = (x_1(t), x_2(t), \ldots, x_n(t)), t=1,2,\ldots; \quad (1)
\]

It is important for a computational model to capture and learn whole spatio- and spectro-temporal patterns from data streams in order to predict most accurately future events for new input data. Examples of problems involving SSTD are: brain cognitive state evaluation based on spatially distributed EEG electrodes \([70, 26, 51, 21, 99, 100]\) (fig. 1a); fMRI data \([102]\) (fig. 1b); moving object recognition from video data \([23, 60, 25]\) (fig. 15); spoken word recognition based on spectro-temporal audio data \([93, 107]\); evaluating risk of disease, e.g. heart attack \([20]\); evaluating response of a disease to treatment based on clinical and environmental variables, e.g. stroke \([6]\); prognosis of outcome of cancer \([62]\); modelling the progression of a neurodegenerative disease, such as Alzheimer’s Disease \([94, 64]\); modelling and prognosis of the establishment of invasive species in ecology \([19, 97]\). The prediction of events in geology, astronomy, economics and many other areas also depend on accurate SSTD modelling.

![Fig. 1.](image)

The commonly used models for dealing with temporal information based on Hidden Markov Models (HMM) \([88]\) and traditional artificial neural networks (ANN) \([57]\) have limited capacity to achieve the integration of complex and long temporal spatial/spectral components because they usually either ignore the temporal dimension or over-simplify its representation. A new trend in machine learning is currently emerging and is known as deep machine learning \([9, 2-4, 112]\). Most of the proposed models still learn SSTD by entering single time point frames rather than learning whole SSTD patterns. They are also limited in addressing adequately the interaction between temporal and spatial components in SSTD.