Commentary on the target paper by Ichiro Tsuda: TOWARDS AN INTERPRETATION OF DYNAMIC NEURAL ACTIVITY IN TERMS OF CHAOTIC DYNAMICAL SYSTEMS

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Puzzle of Chaotic Neurodynamics

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Abstract

The experimental evidence and mathematical/computational models show that in many cases the regime of chaotic, nonregular oscillations is adequate to describe the dynamical behaviour of neural systems. Further insights should be developed to understand the meaning of this dynamical regime for modelling of information processing in the brain.

Generally speaking, the models of mathematical/computational neuroscience could be categorised into the following sub-classes:

- Stochastic models. A neural activity is described by stochastic process and a multi-dimensional stochastic process with interactive components is a typical representative of such models (see, for example, Cottrel & Turova 2000).
- Deterministic model. This model is based on the axioms of dynamical system (with discrete or continuos time) and time dynamics is completely defined by initial values of the variables and boundary conditions (see, for example, Ermentrout 1998).
- Deterministic model with stochastic component (influence of noise). Usually the noise is eliminated by special filtering or averaging procedures to reduce the model to some deterministic system (see references in the target paper).

The author of the target paper considers the deterministic models with complex behaviour and he has stressed out that the oscillatory activity is an important feature of neural activity and experimental evidence confirms this statement. In general, the deterministic (dynamical) system demonstrate the following types of oscillatory dynamics:

- Regular oscillations. In this case, a stable limit cycle is the attractor. The system shows one-frequency oscillations nearby this attractor.
- Quasi-periodic oscillations. In this case, a stable torus is the attractor. The system shows two-, or three-, or many- frequency oscillations.
- Chaotic (complex, nonregular) oscillations. In this case, a strange attractor exists in phase space of the system. A power spectrum consists of many frequencies with similar power values.

To generate the chaotic neurodynamis, Tsuda considers the influence of chaotic network to the neural oscillator consisting of excitatory and inhibitory neural populations (see Fig. 8 of the target paper). Another natural way to generate chaotic neurodynamics is described by Borisyuk et al. (1995). Irregular chaotic oscillations appear in the system of two coupled neural oscillators with inhibitory to excitatory connections. Strange attractors of different types appear in the phase space under variation of the coupling strength with different scenarios of transition to the chaotic behaviour.

Despite the fact that the importance of complex dynamics for description of neural activity has been recognised in many papers (see the list of the target paper references), the following question is still very actual. “Is the chaotic dynamics an artefact relating to different kind of noise sources in neural tissue or this kind of dynamics is a necessarily component for information processing?” If we agree that the chaotic dynamics is not an artefact then we should put forward some hypothesis about the role of chaotic neurodynamics for the information processing and explain the advantages/disadvantages of such approach.

The author of target paper suggests the new concept of chaotic itinerancy in high-dimensional system that is different from conventional cases with dynamics in terms of simple transitions between low-dimensional attractors. However, it is not clear why transitions between strange attractors are more useful for neuroscience than transitions between equilibrium points or between limit cycle. Also, it is not clear what are advantages (if any) of the Milnor attractor and Cantor coding to compare with other attractors and coding schemes.

The idea of using transitions between attractors for memorising sequences of events has been exploited by many authors. For example, Baird (1990) has used the bifurcation theory for programming of fixed and oscillatory attractors for memorising of sequences. Freeman (1991) has suggested a brilliant example of using chaotic dynamics for modelling of olfactory system. The model describes a process of odour recognition as iterative movement along the strange attractor assembled with many wings relating to different odours. The odour recognition means that the system passes the corresponding wing more often then others. Kryukov et al. (1990) suggested that the attractors of neural dynamics are represented by metastable states that are characterised by stabilisation of average activity and increasing of variance to prepare the system for transition to another metastable state. Different applications of this metasbility approach for modelling of memory, attention, and other brain functions are considered.

From mathematical point of view, the process of itinerancy of neural activity might be described by dynamical system with time-dependent coefficients. We can imagine the evolution of the activities from zero time onwards as the movement of some “representing point” (current point) of the system in a multi-dimensional phase space relating to system variables. The representing point travels through the phase space under influence of neighbouring attractors. Being in the basin of some particular attractor, the representing point begins the waltzing along the attractor. The attractor is formed by sub-set of “principal” variables (usually, the number of principle components is small) which describe the dynamics of the system during a limited time period. Coefficients of the dynamical depend on time and it is possible that the stability of attractor will decrease and the attractor will disappear. After that, the representing point moves to another attractor which is governed by another subset of “principal” variables, etc.

The global dynamical behaviour of the system is non-stationary. Nevertheless, the travelling of representing point nearby of some attractor might be considered as more or less stationary dynamics during some limited period of time. Thus, the information processing in the nervous system is represented by a complex spatio-temporal dynamics in multi-dimensional space. At each moment of time, there is a set of principle variables, which form the attractor and govern the system dynamics during some time, and new attractors appear and one of them takes the initiative. The crucial point of this consideration is the mechanism for controlling of the system by variation of coefficients. There are several possibilities of such control: stimulus-dependent control; adaptation of coefficients according to behavioural “goals” or learning rules (cost function optimisation); control from the higher level structure, central executive, etc. For example, Kazanovich & Borisyuk (1994; 1999) studied the oscillatory networks with a central element and the applications of this network for modelling of attention focus formation. The mechanism for controlling the system dynamics is based on synchronisation of neural activity and the regime of partial synchronisation is very promising for description of neurodynamics. In this regime, some oscillators work synchronously with the central element forming a temporally existing attractor. Makarenko & Llinas (1998) have applied the synchronisation principle to study a phase synchronisation of chaotic systems and model the activity of inferior olivary neurons.

Conclusion. The chaotic neurodynamics looks as a very intriguing and promising mathematical technique. Further developments should be done in mathematics and neuroscience to understand the meaning of chaotic dynamics for modelling of information processing in the brain.

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