Biology-Inspired Pulse Processing Neural Networks (BPN) for Neurotechnology

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1 Description of BPN Hardware

The development of artificial neural information processing systems has been significantly advanced by the incorporation of new functional concepts as derived from neurophysiological studies (Eckmiller, 1991; Harris-Warrick et al., 1992; Muhowald and Douglas, 1991; McKenna et al., 1992). Only recently, however, biology-inspired pulse processing neural net (BPN) hardware (as discrete circuit boards as well as chips) was developed to include the combination of adaptive weights as well as synaptic delays (Jansen et al., 1991; Richert et al., 1993).

This type of asynchronous BPN models temporal properties of biological neurons, such as transformation of impulses into EPSPs or IPSPs, slow potential integration as "membrane potential", as well as a threshold mechanism for impulse generation with subsequent absolute and relative refractory period in real time. The typical functional properties of a single BPN neuron (Fig. 1) can be briefly described as follows: incoming rectangular voltage pulses of 1 ms duration and 5 V amplitude reaching a synapse S, pass through a delay line T (representing the summed delays of a pulse signal in synapse, axon, and dendrite), before being weighted. Weight W determines the amplitude of the voltage pulse that is formed as output of S. Discrete values of adaptive synaptic weights W and delays T are stored digitally, but converted to analog values for real time processing. Special "learning inputs" at the synapses allow weight and/or delay changes. These weighted and delayed voltage pulses are subsequently summed up and low-pass filtered at the membrane circuit. Membrane potential \( u_m \) models the sum of EPSPs and IPSPs. If \( u_m \) reaches a threshold voltage \( u_T \), an output pulse of 1 ms duration is generated. During the pulse generation time, \( u_T \) is set to a saturation value and then decreases with a hyperbolic time function to its stationary value, \( u_{T0} \), until a new intersection with \( u_m \) occurs. The entire BPN system can be arranged into any net topology via computer-controlled switch arrays. Typical BPN applications for adaptive weights and adaptive delays have recently been published (Eckmiller and Napp-Zinn, 1993; Jansen et al., 1991).

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Fig. 1  Pulse processing of a single neuron with adaptive weights and delays

In the depicted example, a single impulse is processed simultaneously by three synapses and yields two delayed impulses at the neural output.
2 Neurotechnology

The emerging field of "Neurotechnology" deals with compensation of functional deficits of the human nervous system by means of novel computer and microsystems technologies. Accordingly, neurotechnology requires the development of adaptive BPNs, as well as novel multicontact neural interfaces (MNI) to allow for functional substitution of and bi-directional communication with specific parts of the nervous system in real time (Eckmiller, 1993). Thus, it is essential for technical neural systems (BPN) to be adjustable in response to signals from the implant-carrying patient as well as to encode and decode neural signals.

![Diagram of neurotechnology](image)

**Fig. 2** Two schemas for typical neuroprosthetic applications of neurotechnology

**Top:** Technical sensor system (prosthesis) supplies an adaptive neural computer as BPN (which serves here as neural encoder) with sensory signals. BPN generates corresponding encoded impulse trains as input (stimulation) for a sensory nerve via a multi-contact neural interface (MNI).

**Bottom:** Motor control signals, which are recorded as impulse trains from a motor nerve via a multicontact neural interface (MNI), are decoded by a BPN and fed into a technical motor system (prosthesis).
The aim of neurotechnology is the development of a new generation of prosthetic devices, such as novel cochlea implants, functional electrical stimulation (FES) systems, or retina implants as indicated in the two schemas of Fig. 2.

The top schema depicts a BPN as adaptive neural encoder to map signals from a technical sensor array onto (several hundreds) separate neural impulse trains, which are being connected with single nerve fibres by means of a MNI. In contrast, the bottom schema in Fig. 2 indicates the reverse situation of another MNI for recording of (several hundreds) separate neural impulse trains from human nervous tissue and a subsequent BPN as adaptive neural decoder to map the spike trains onto appropriate control signals for technical devices (e.g.: prostheses or monitors).

### 3 Concept of a Retina Implant

A large portion of visually impaired human subjects suffers from retinal defects (especially: retinitis pigmentosa (RP)), which typically begins with night blindness (loss of rod photoreceptors), deteriorates into tunnel vision and finally leads to total blindness (additional loss of all cone photoreceptors). However, significant portions of retinal ganglion cells and subsequent parts of the visual system remain intact (Stone et al., 1992). In a recent pioneering study (Humayun et al., 1993) it could be demonstrated that local electrical stimulation of the retinal ganglion cell layer in blind RP-patients yields localized visual sensations (see also: May, 1993).

We are currently developing components for a retina implant for RP-patients in cooperation with several partners from microelectronics-, microsystems- and retina surgery research centers. The conceived retina implant (Fig. 3) consists of a retina stimulator for ganglion cell stimulation and a retina encoder designed as neural net with flexible antagonistic receptive field properties (RF-BPN). The currently developed RF-BPN module, handling both slow potentials and impulse events, allows for modification of ten spatial and/or temporal parameters in order to adjust the RF-BPN to the desired receptive field properties of a given ganglion cell (Dacey and Petersen, 1992; Wässle and Boycott, 1992). Specifically, each RF-BPN module can be tuned in a learning process to the receptive field properties of a retinal X-cell type (about 60% of the total ganglion cell population in the primate retina) or a Y-cell type (about 25%) with regard to parameters such as RF center, time constants, etc. (Eckmiller, 1994).
The new generation of prosthetic retinal stimulators (PES) - a successor of Fig. 2.

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Fig. 3 Retina implant schema

Top: RF-BPNs consisting of photo sensors, bipolar cells, and about 500 ganglion cells as well as an implanted ganglion cell stimulator with about 5000 microcontacts

Bottom: Modifiable parameters of the receptive field properties of RF-BPNs
4 References


