Information Processing in Biology-Inspired Pulse Coded Neural Networks

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Abstract Most current "artificial neural networks" reduce the function of a real neuron to that of a threshold logic element with weighted inputs and the function of a real neural system to that of a clock-controlled type of adaptive cellular automaton. In the light of abundant neurobiological evidence and new models in computational neuroscience, it becomes increasingly important to incorporate considerably more biological information processing features, in order to narrow the wide gap between the vast "computing power" of biological neural systems and that of current artificial neural networks. This paper briefly reviews characteristic properties of biological neural systems and describes the recent development of a biology-inspired pulse processing neural network (BPN) hardware. The BPN employs pulse processing, EPSP, IPSP, membrane potential, refractory period, adaptive synaptic weights, and adaptive time delays, as well as asynchronous pulse train communication in real time. Information is coded not only in the impulse rate but also in the time of occurrence of each individual impulse. A typical BPN application for adaptive recognition and subsequent tracking of discrete time event patterns using adaptive time delays and representation of the "learning rule" by means of special neurons and pre-synaptic events is presented. BPN systems may be particularly useful in the emerging field of "Neurotechnology", which deals with the repair or partial compensation of functional deficits of the human nervous system by means of coupling prosthetic devices (e.g. novel cochlea implants, FES-systems, retina implants) via multicontact single axon interfaces and BPNs with specific parts of the nervous system.

Computational Neuroscience In contrast to most artificial neurons, biological neurons communicate with one another via brief standard impulses at varying time intervals. The time delay T between impulse generation at a transmitting neuron and impulse arrival at a given synapse of a receiving neuron may vary from less than one millisecond to more than one second depending on the characteristic propagation velocity (typically ranging from less than 1 m/sec to more than 100 m/sec), the length of the connecting nerve fiber, and synaptic time properties. Generation of every single impulse requires a comparison between the current values of membrane potential and dynamic threshold, thus yielding an asynchronous sequence of impulses with changing discrete time intervals.

Various neuroscientific studies emphasized the possible relevance of phase or time information in pulse processing systems regarding coincidence detection (Harris-Warrick et al., 1992; McKenna et al., 1992), time-comparison (Carr et al., 1986), or cooperative information processing in small neural ensembles (Gerstein and Aertsen, 1985). Other studies

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discussed the generation of neural activity time courses (Eckmiller, 1991; Friesen and Stent, 1978; Kien et al., 1992), which typically require proper use of impulse timing information. More recent neurophysiological experiments suggest an important role of timing (phase) information of neural activity, at least for stereo audition (Konishi, 1991), which requires a time delay resolution of less than 100 nsec in bat (Simmons, 1990) and for visual signal processing (Eckhorn et al., 1988; Gray et al., 1989). Furthermore, the exact time structure of impulse sequences in afferent visual single unit activity has been recently associated even with the encoding of certain visual stimulus features (Lestienne and Strehler, 1987; Optican and Richmond, 1987).

It is generally accepted that the function of biological neural systems is largely based on the continuous evaluation of amplitude, time course, and discrete time of occurrence of numerous neural signals as impulses or post-synaptic potentials. Whereas biological systems establish the unique information processing features of a given neural subsystem by means of combining genetic, ontogenetic, and adaptive mechanisms (in interaction with the environment), technical biology-inspired pulse processing neural nets (BPN) have to replace genetic and ontogenetic mechanisms by pre-defined structures. On the other hand, adaptive mechanisms in BPNs can represent neurobiologically described as well as computationally desirable events by means of adaptation of various parameters such as: synaptic weights, neural growth or pruning, and time delays.

By replacing the simple synchronous weighted sum algorithms of the popular McCulloch & Pitts type models by asynchronous pulse processing and embedded learning mechanisms, BPNs capture essentials of the neurobiological code and emphasize the experimental dimension of neuroinformatics, however, at the expense of quick theoretical break throughs. It is hoped that BPN research (back to back with computational neuroscience) will bring neuroinformatics considerably closer to neuroscience for the benefit of both disciplines.

For the emerging field of "Neurotechnology" (Eckmiller, 1993), 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 to or from specific parts of the human nervous system, be it the auditory or visual nerve a peripheral nerve, or even part of spinal cord or cerebrum. In combination with novel multicontact single axon interfaces, BPNs could allow to compensate functional deficits of the nervous system and to form a new generation of prosthetic devices, such as novel cochlea implants, functional electrical stimulation (FES) systems, or retina implants.

**Description of the BPN Hardware** Progress in the development of artificial neural information processing systems has been significantly advanced by incorporation of new functional concepts as derived from neurophysiological studies. For example pattern recognition (Fukushima, 1990; Hartmann, 1992) as well as hardware implementations could be clearly improved. Incorporation of both time information of discrete impulse events and impulse rate information, as used in biological neural systems, is gradually receiving more attention in the design of biology-inspired pulse-processing neurons (Mahowald and Douglas, 1991). Only recently, however, biology-inspired pulse processing neural net (BPN) hardware was developed to include the combination of adaptive weights as well as synaptic delays (Beerhold et al., 1990; Canditt and Eckmiller, 1990; Jansen et al., 1991; Schwarz et al., 1991).
The fully parallel, asynchronous BPN, which was designed in analog hardware by our group, 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. More details will appear in another publication (Napp-Zinn et al., 1993). 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 in 8 bit counter / memories, but converted to analog values for real-time processing. Special "learning inputs" at the synapses allow weight and delay changes by the impulses of special "learning rule" neurons. These weighted and delayed voltage pulses are subsequently summed up and low-pass filtered at the membrane circuit. Membrane potential $v_m(t)$ models the sum of EPSPs and IPSPs. If $v_m(t)$ reaches a threshold voltage $V_T$, an output pulse of 1 ms duration is generated. During the pulse generation time $V_T$ is set to a saturation value and then decreases with a hyperbolic time function to its stationary value, $V_{Th}$ until a new intersection with $v_m(t)$ occurs. The entire BPN system, consisting of 32 neurons and 64 synapses can be arranged into any net topology via PC-controlled arrays of analog and digital switches. For further details see: Beerhold et al., 1990. Typical BPN applications for adaptive weights and adaptive delays have recently been published (Jansen et al., 1991).

**Recognition and Tracking Task for BPN** The task for the BPN in the "recognition mode" is to classify a discrete event pattern, which is being handled by the assumed event allocator (Fig. 2). The aim is to distinguish this impulse triplet pattern from all others: i.e. after a learning period output neuron A generates a pulse, only if the previously learned pulse pattern occurs at the input. For this goal the BPN topology gradually changes during the learning phase in order to cause a membrane potential $u_m$ maximum. The corresponding threshold for neuron A is set sufficiently high to be reached only by the $u_m$ maximum. In the "recognition mode", the condition inputs for synaptic delays are constantly set to "true", so as to stay independent of the output of neuron C.

**Learning Rule for Adaptive Delays** Output neuron A of BPN (Fig. 2) receives the three single pulses of P1, P2, and P3 via separate inputs after being delayed in the synapses S1, S2, and S3 of the delay layer with neurons V. Only coincidence between the three EPSPs causes the required maximum potential $u_m$ on the membrane of neuron A. This can be achieved by a gradual adaptation of the delay values during the training period. The learning rule is embedded in the net topology rather than being calculated by an external algorithm. During the adaptation coincidences between the EPSPs of these pulses on the membrane of the output neuron A are gradually produced by delaying P1 and P2 in the synapses S1 and S2 of the delay layer neurons V1 und V2. The neurons D1+ and D1- (D2+ and D2-, respectively) control the delay adaptation by detecting the neuron, V1 vs. V3 (V2 vs. V3) that generates a pulse earlier than the other.

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Fig. 1: Pulse processing of a single neuron with adaptive weights and delays
Simulation results showed that the initial membrane potential time course gradually changed to the adapted stage within about 120 iterations (Event presentation every 250 ms). Event patterns could be distinguished with good selectivity: variation of $t_2$ (time interval between second and third impulse) by a 1/50 ms (best case) to 1/20 ms (worst case) of a given previously learned pulse pattern already caused non-recognition.

In the "tracking mode", the BPN can be used as a tracking filter for slightly changing input patterns. The aim here is to continuously adjust the tuning of the BPN to a previously learned event pattern, which now gradually changes its time interval $t_2$. "Condition-neuron" C, which has the same membrane potential but a lower stationary threshold than neuron A, is used to assure that only the changing recognized pattern rather than any random pattern yields corresponding delay adjustments. In this "tracking mode", the synaptic delays had to be adapted in both synapses S1 and S2, while $t_2$ is modified according to a sinusoidal function.

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**Fig. 2:** Topology of the BPN system as recognition and tracking filter for triple event patterns
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