

# Interference Networks - a Physical, Structural and Behavioural Approach to Nerve System

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## Abstract<sup>11</sup>

Physical wave properties in nervous system offer new methodologies by contrast to artificial neural networks, especially to pattern handling networks.

All information inherent a nerve impulse is only the time point the first derivative crosses zero. To change physical distances, delays or arrangement in space means for net models, to vary the most significant value, to destroy the information.

It is somewhat surprising, that mathematics, medicine and neurocomputation years ago began simultaneous but different to use and to interpret the physical term 'projection'. In opposite to non-mirroring, mathematical vector- or matrix 'projections' ( $X \Rightarrow Y$ ) a *physical projection mirrors* the image between source and screen in general.

Neurophysiology speaks of 'projective' trajectories and maps. Known nerve maps, independent if they are feature-specific, anatomically or abstract seem to have mirroring properties.

There are lots of works about brain maps and *non-mirroring projections in neurocomputation*. Not realizing, that this is a dangerous, wave-interferential, physical category, the term projective is missused.

In neuro-physiology we find maps, that mirrors the representations between source and sink, between generator and detector field, so the well know 'Homunculus'. By analogy between neuro-physiology and physical meaning, physical wave properties in nervous system must be supposed.

## Introduction

The work will analyse the physical properties *delay* and *time* by contrast to *weigh*, *level* and *pattern* for better understanding the nature of spiking neural networks. Introducing space geometries, velocities and delays in 3-dimensional neural nets we find *mirroring(!) wave*

*interference projections*. Using inhomogeneous interference systems highly specialized interference locations reflect scenes.

Using physical approaches, the question is to ask for effective values, for high 'interference hills', for interference maxima to get imaginations and to find plausible abstractions, how nervous system can really work.

'Radial-basis-function (RBF) networks were introduced by Broomhead and Lowe in 1988. The RBF-network model is motivated by the locally tuned response observed in biologic neurons.' They can be found in several parts of the nervous system for example in the auditory system selective to small frequency bands or in visual cortex sensitive to bars orientation. (Palm, NC2000).

For the first time in [4] we find descriptions of simple wave interference networks, solving such RBF tasks. Later, a generalization occurred, so in [9] we find them again as 'dynamic basic functions of neural trees', solving tasks like code generation, code detection, level generation.

Analyzing cross interference overflow one can find pain-like behaviour [9] or cramp-like [4] excitments. Studying moving and zooming projections [9] we get imaginations of glia-function, the content of EEG-data streams and the task of local field potentials for informational tasks of nerve system.

The dynamic basic functions of neurons offer addresses and contents of serial or parallel interference data, of 'bursts' observed during invasive electrode experiments.

A view into physics of wave experiments lets examine parameters for transmissions of 'pictures of thought' between cell assemblies using spikes.

To be able to use the terms 'wave' or 'wave space' investigations had shown differences and analogies between 'homogeneous' and 'wiring' wave space. Optical basic equations for diffraction or reflection can be derived of wiring wave space equations [4]. The intention comes, homogeneous optical space is a subspace of (neural)

<sup>11</sup> Lecture hold at "Brain Inspired Cognitive Systems" (BICS), 29 Aug. - 1 Sept. 2004, University of Stirling, Scotland, UK, paper on conference CD as #1115.pdf

wave space.

Huygens wave front creation model gives the possibility to introduce interference integrals and wave equations. Delays and weights appear as two, very different sites of one coin.

Time-functions in bio-systems propagate very slowly, while wavelengths (product of pulse duration and propagation velocity) are very short. Any questions of information processing (where do the data come from, where do they go to, what is their content) is closely coupled to a slow movement of spikes and to interference locations [4].

While until now the question is: "What is the function?" wave interference informatics suggests a new question, that is: "Where is the location?"

Simple physical models generate interesting behaviour: *mirroring projections, moving, zooming, overflow* [4...9].

Simulation experiments with time-functions in space gave impressions about possible properties of neural assemblies.

An informational role of nerve delays can inspire a field '*Wave Interference Informatics*'. It seems the role of *delays* is more important as the rule of synaptic *weights*.

Not the less nature themselves gives the Lords fingertip: parameters of interference systems match parameters observable in nature, wherever we looked for (fast axons for transmission lines, rule of refracteriness, mirroring projections).

"The question, how the nervous system creates representations of its environment has fascinated philosophers and scientists since mankind began to reflect on its own nature." (Singer, 1993).

Although there is a large progress in analytical neurosciences at the one site and in neurocomputation at the other there are problems of general attention. While neurocomputation is one a way to become more and more a mathematical discipline far away from biological and physical circumstances, analytical neurosciences seem to get more and more knowledge in nameless details, trying to find powerful but realistic abstractions.

The lecture gives some impressions about wave interference systems trying to find bounds to pattern networks.

## Assumptions

The paper carries the following assumptions:

- a) A wire in nerve system has a very limited velocity ( $\mu\text{m/s} \dots \text{m/s}$ ).
- b) A nerve pulse has a typical geometrical pulse length in the range  $\mu\text{m} \dots \text{m}$  (geometrical wave length: product of pulse velocity and pulse duration).
- c) The nerve acts like a *wave conductor* with length to diameter dependend delay, not like an electrical node.

d) An electrical representation of nerve is a set of colored delay lines within a 3D-space.

e) We suppose networks with distributed parameters in general, no wire is without delay.

f) Short impulses and low velocities produce geometrical puls lengths in the range of  $\mu\text{m}$  to cm.

g) To calculate *meeting points* of pulses we calculate the nerve system in spatial, 3+1-dimensional representations.

h) While the possibility to excite a place is as much higher, as much closed *in time* different waves or impulses from different directions appear, we will ask for locations of superimposition or interference.

i) A nerve cell body has a non-zero size. Where is one cell body, there is not another. Thus, any signal flow bridges distances and needs (incremental small) *delay time to reach any destination*.

j) Following Hodgkin/Huxley, nerve velocity (and delay) is influenced by background (glia) potentials. Thus interference locations are influenced too. Observation of special cases result in the possibility to zoom and to move projections.

k) Like a tree a nerve branches out. Thus (ionic, molecular or cellular) information carriers, which we shall call 'impulses', split at possible places into very different directions and they meet again at other places.

l) Whether we consider the flow of chemical substances (e.g. leucin, acetylcholerase, mitochondric containers etc.) through nerves, or ionic mechanisms ( $\text{Na}^+$ ,  $\text{K}^+$ ), or the measurable electric representation of various transportation mechanisms, the nervous system can be seen as a system of different channels or an inhomogenous system of wires in real space dimensions and with real signal delays between computational nodes carrying different signals with different velocities (*colored flow graph* [9]). Gates stop or modify the information flow at certain places (i.e. at synapses). Each mechanism carries a time function with a certain velocity and a certain flow direction. Because different mechanisms work together, different signal carrier types (*colors*) flow with different velocities on a nerve. Independently of their type, signals can only go discrete ways, they only can flow through the nerves shape.

m) Neurons without axons, dendrite to dendrite or axon to axon coupling between nerves (Crick/Asanuma) suggest the idea of nerve system as inhomogeneous wave space (neuropile) with soft synaptical influences only. We will try to avoid the discussion about the locality of pulse excitments within the nerve cell.

n) We suggest, that a lot of information flows parallel through nerves. We have to observe wave front directions.

o) By analogy to so called 'neural networks' we use

comparable circuit structures. But we will avoid a state-machine like pattern processing of data introduced by McCulloch/Pitts 1943.

### States or pulses? Differences between pattern and interference networks

By conceiving physical networks with velocities, distances and delays however small we discover new classes of code-, frequency- and location-sensitive networks called 'interference networks' working in 4-dimensional (x,y,z,time) wave space respective in n-dimensional channel space. As a special characteristics, pattern carrying interference networks mirror any input-output field relation. By wave theoretical analogy with optical projections we call this behaviour 'projective'.

We find, that circuits of general attention in neurocomputation (pattern networks) mostly seem not to work in wave space environments (for example unsymmetrical nets like the net for concept formation, Amari 1977).

To make any data exchange between synchronized, machines, a clock period has to be slower than all inner delays. The signals can reach defined levels in each working step (state machine and pattern matching approach, see McCulloch/Pitts). For (pulsating) time-distributed systems things differ.

In nervous system we find positive, spiking pulses with amplitudes near 100mV, parts of milliseconds wide, with velocities between 5µm/s and 120m/s. The geometrical impulse length (product between velocity and duration) vary typically between 50µm and 50 mm [4]. The information inherent a nerve impulse is only the time point the first derivative crosses zero. To remove physical distances, delays, graphs, 3-D-arrangements in net models means, to vary this value, to destroy it.

So state machine or pattern matching suggestions are dangerous for pulses, pulses have weather states nor levels.

### An introductory experiment

Starting wave interference research, I proved the relevance of assumptions for the human body. A simple experiment can be done using an two channel EEG-device. With a double-ring electrode we can stimulate the thumb while we observe the time functions at two nerves. We observe the relative delays in dependence of the thumb position a), b).

We find wave directions in form of delays between n.radialis and n.medianus (source: [6]) that correspond with theoretical assumptions in a) and b). Now we can try to construct a circuit that is able to interpret the information on both nerves. We will call this circuit 'interference circuit', and we characterise it to be

one-dimensional.

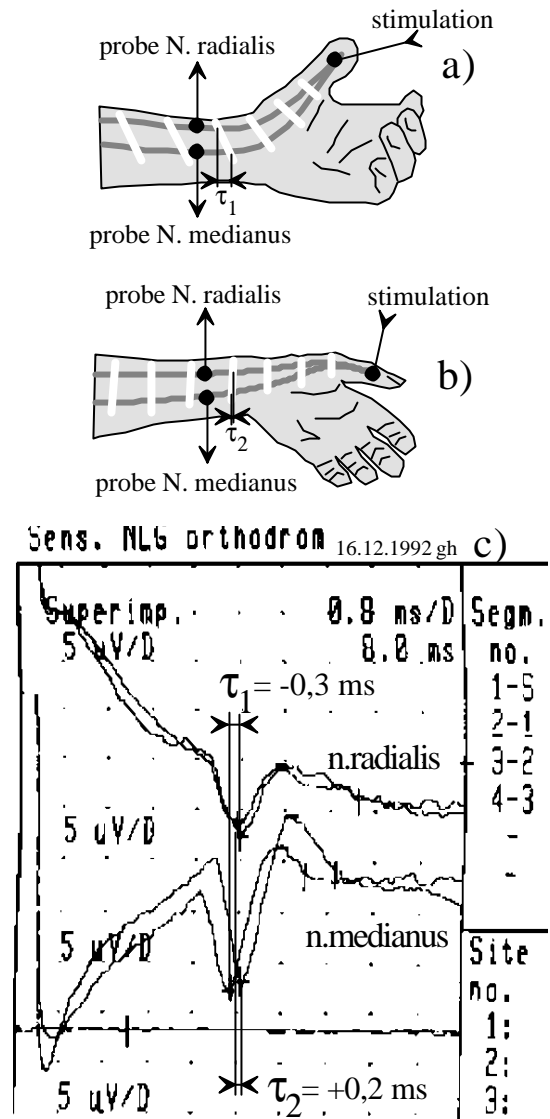
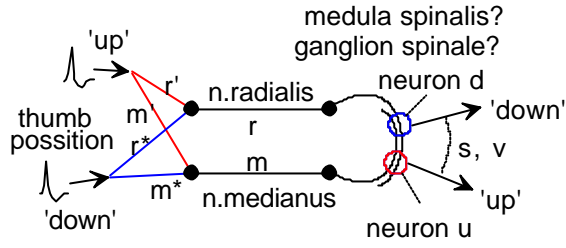


Fig. 1: EEG-experiment exploring delay differences between n.radialis and n.medianus in dependence of the thumb angle a), b). Resulting delay differences equivalent to wave fronts in Fig. c) .

We suppose, there is any closed mesh in ganglion spinale or in the medula spinalis. Each wire has a non-zero delay, depending of the velocities. Nerve velocities vary in a range between 5 µm/s and 120 m/s [4...9].



**Fig. 2: Circuit to interpret delay differences. Dependent of the position, a related neuron 'd' or 'u' gets a maximum interference value**

Independent if we compute, the position of maximum interference (the point, where both signals arrive at the same time) will vary between neuron d and neuron u. If we assume, that there is a velocity  $v = 10 \text{ m/s}$  within the ganglion, we can get the distance  $s$  between the interference locations:

- (1)  $s = v dt; \quad dt = \tau_2 - \tau_1$
- (2)  $s = 10 \text{ m/s} \cdot (0.2 - (-0.3)) \text{ms} = 5 \text{ mm}$

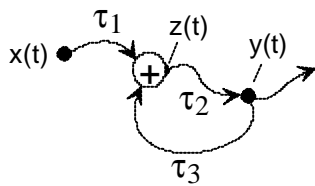
Varying the delays in the arrangement or the velocity  $v$ , we find variations between the points of interference, this inspired the ideas of 'zooming' and 'moving' projections, first documented in [4].

The interference circuit shows two details: the left side offers a tree-like, the right side a mesh-like arrangement. Both types can interact in different forms.

(The idea of interference circuits was born in september 1992, while studying optical and multichannel radar circuits.)

### Superimposition of time functions

Independent of the function type of a discrete (boolean) or floating data set of a time function we suppose functions are super-impositionable.



**Fig. 3: Example for the use of time functions**

A (data independent) interpretation of the Figure using time functions like spikes can be for example:

$$(3) \quad z(t) = x(t - \tau_1) + y(t - \tau_3); \quad y(t) = z(t - \tau_2)$$

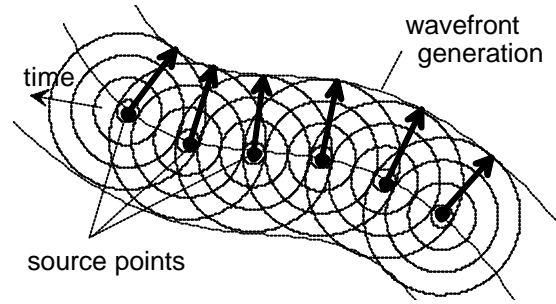
For pattern networks the writing looks different. Starting the work, McCulloch/Pitts introduced in their very first equations a state machine description, substituting the delays by integers. Although this was a revolution for

computer technology, the writing introduces abstraction for state machines and pattern networks. But it is not useful for the description of wave interference networks, it forms a too rough grid and removes the pulse's information: the time of occurrence.

### Wavefront generation

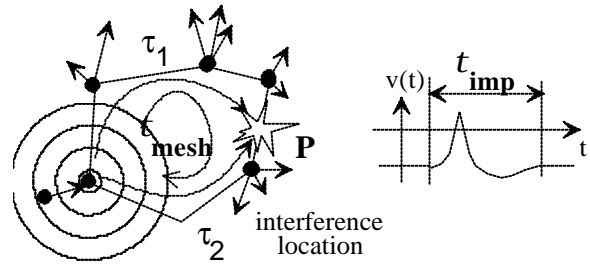
Huygens principle roughly says, that different elementary sources form a wavefront by superimposition. So, if we know any wavefront surface, the elementary sources can be found. A special set of so called *hyperbolic differential equations*, including the *wave equations*, base on Huygens principle.

For the following, we need a nerve layer, carrying signals in all directions (neuro-pile). Any impulse has only the opportunity to leave his dead- or refractoriness-zone, so a movement into the feeding direction begins.



**Fig. 4: Huygens wavefront generation in virtual, neural space (successive time steps drawn)**

If many pulses meet onto an (abstract) homogenous nerve plane, by superimposition a wavefront is generated.



**Fig. 5: Delay mesh (scheme)**

Supposed a nerve system consists of multiple coupled, closed delay meshes. To form a wavefront the refractoriness period stops backgoing partial impulses. Half the way, any pulse-half perishes in the refractoriness zone of the other pulse half. Independent of parameters, an interference location appears at point P.

$$(4) \quad P : \tau_1 = \tau_2 = \tau_{mesh}/2$$

**Case 1)** If the pulse duration  $\tau_{imp}$  (including the

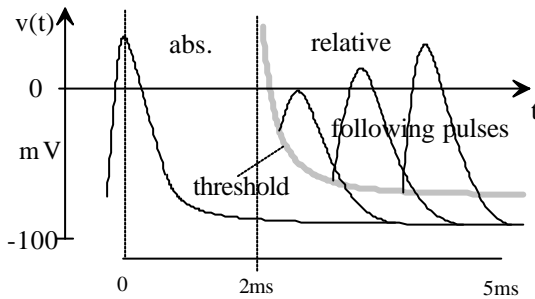
refractoriness zone) is shorter the half mesh delay ( $\tau_{\text{mesh}}/2$ ), single interference locations occur by external sources, or feedbacks can excite the circuit.

**Case 2)** A directed wave front forms out if the half mesh delay ( $\tau_{\text{mesh}}/2$ , two paths minimum) is shorter the total impulse duration  $\tau_{\text{imp}}$  including the refractoriness period, because further excitations cannot excite the circuit while the pulses travel, a plane of such meshes seems to be homogeneous:

$$(5) \quad \tau_{\text{imp}} \geq \tau_{\text{mesh}}/2 \text{ (wavefront generation)}$$

### The rule played by refractoriness

The excitement of a neuron  $u(t)$  causes a period of non-excitability, the so called period of refractoriness.



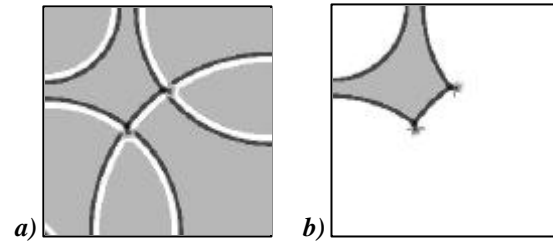
**Fig. 6: Absolute and relative refractoriness model following [18]**

To create learnability, any learning system is inspired to allow connections between all possible inputs (and outputs too), for example between eyes and feet to avoid dangerous movements. Supposed any pulse interference network with thousands of shortcuts and inner connections. Pulses can overflow the total network, especially if there is no spherical relation between in- and outputs, each place must be supposed to be an input or an output within the same time.

In opposite to water waves nerve refractoriness can delete crossing waves. (By the way this fact appears also as a limitation of superimpossibility.) A simple model can demonstrate the effect.

Waves seem to flow only in the direction of locations with highest interference, flowing to other regions they are removed. So we find refractoriness has different tasks:

- a) to reduce cross interferences by deletion of fast followers within the field, see [9], chapter 'pain';
- b) to 'clean' the field by the overlay of smaller sources;
- c) to remove possible cross-interferences outside coming from sources far away.



**Fig. 7: Superimposing waves of four sources: a) with small refractoriness zone, b) with wide refractoriness zone. Colors: refract.: white; peak: black; excitable: gray. Source: Heinz, 1996<sup>21</sup>**

So the measurement of cross interference-free field size can be calculated by the amount of refractoriness.

With other words: sources in a system sending contralateral waves can suppress the contrahents using this method. In summary, outer regions become cleaned, cross interferences become reduced, small pulse sources become removed. In case of conflicts the strongest sources with the highest fire rates are the winners.

Refractoriness seems one of the most interesting properties of wave interference systems. It seems to be the *basic for self-organisation of wave interference nets*.

### Movement trajectory examination

In nameless papers authors offer trajectory examination algorithms. By analogy to mathematical methods for trajectory examination there is a way using wave-interferences.

Supposed we have some in succession firing cells creating a line of any trajectory of a moving figure. In the case any interference location is near the end of the trajectory, the delays occurred by trajectory velocity might be in the range of the movement of the fire. Thus different interference locations detect different velocities within the trajectory.

Neurons on the trajectory may fire successive one each other by velocity  $v$ , interference maximum occurs in  $P$  for

$$(6) \quad \tau_1 = t_2 + \tau; \tau_2 = t_3 + \tau; \dots; \tau_n = t_{n+1} + \tau_n$$

For equal distances between firing neurons

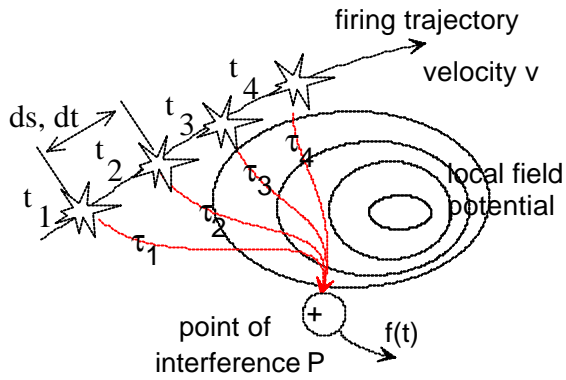
$$(7) \quad t_1 = t_2 = \dots = t_n = dt = \frac{d}{v} \text{ we get}$$

$$(8) \quad \tau_{n+1} = \tau_n - dt = \tau_n - \frac{d}{v} \text{ and with}$$

$$(9) \quad \tau_{n+1} - \tau_n = d\tau \text{ we find } d\tau = -\frac{ds}{v}.$$

Following Hodgkin/Huxley, the delay difference  $d\tau$  could be influenced by a local field  $E$  that controls the delays of nerve fibres. As first order dependency between  $E$  and  $d\tau$  we can introduce a proportionality constant  $k$

<sup>21</sup> For more see [http://www.gfai.de/www\\_open/perspg/heinz.htm](http://www.gfai.de/www_open/perspg/heinz.htm)



**Fig. 8: Movement trajectory examination by local field potential**

$$(10) E \approx d\tau; \quad E = k d\tau, \text{ it follows}$$

$$(11) \frac{E}{k} = -\frac{ds}{v}$$

The equation shows the possibility of a dependence between an ionic or electric field  $E$  influencing the nerve fibre delay versus for example glia potentials and the velocity  $v$  of the running fire. Thus in a certain range a running fire trajectory is detectable with a field. Or: maximizing (however) the interference in  $P$  we get a measurable field component as a representative for the velocity of the fire on the trajectory.

### Time functions in space, characteristic delay vector of a location

For introduction, the theoretical background is given.

Supposed that different impulses move within a dendritic tree to any neural soma from different directions with a low velocity. Supposed further, that a neural cell body receives waves over  $n$  different channels.

Enhancing [6] we introduce weights  $w_k$ , to provide the possibility to use inhibition cases.

The time function  $g(t)$  of  $n$  delayed time functions  $f_k$  that are able to excite the neuron is in time  $t$  and at location  $P(x_0, y_0, z_0)$  with interference function  $\Psi$  (sum, product...). We imply normalized function values  $f_k(t)$  in the range  $\{0, 1\}$  and relative weights between  $\{-1, 1\}$ . By analogy to pattern networks the interference sum/product  $g(t)$  can be written in the form:

$$(12) g(t) = \Psi \sum_{k=1}^n w_k f_k(t - \tau_k); k = 1 \dots n; \Psi = \Sigma, \Pi, \dots$$

The **effective value**  $g_{eff}$  of the **interference integral** of  $g(t)$  in the time interval  $T$  (pay attention to the positive time axis direction for an inverse delay vector) may be

$$(13) g_{eff} = \sqrt{\frac{1}{T} \int_{-T/2}^{T/2} g^2(t) dt}$$

The function values of  $g_{eff}$  are positive floating point numbers. Note, that times and delays are not to be regarded as integer values, as introduced by McCulloch/Pitts in 1943.

For **inhomogeneous spaces** (nerve cell assemblies) an exact measurement or modelling of delays  $t_k$  is necessary. For **homogeneous delaying spaces** there exists a well known correspondence between distance  $s$  ( $dx, dy, dz$ ), velocity  $v$  and delay  $t_k$

$$(14) \tau_k = \frac{1}{v} \sqrt{(x - x_0)^2 + (y - y_0)^2 + (z - z_0)^2}$$

Any tree at the cell body  $P$  has a **characteristic delay vector**  $M$  (*mask*) of wiring delays in relation to points  $K_i$

$$(15) M = \{\tau_1, \tau_2, \dots, \tau_n\}^T$$

where  $n$  is the channel number. Observing generating and receiving points  $P$  we find, the characteristic vector  $M^*$  of the location  $P$  of a *receiving tree* is the negative vector  $M^*$  of wiring delays  $M$  of a *generating tree* because

$$(16) M^* + M = \tau \{1\}$$

$$(17) M^* = \tau \{1\} - M$$

where  $\{1\}$  is the unity vector and  $\tau$  is the total delay of the arrangement.

The interference integral (the possibility to be exited) becomes maximized, if pulses over different partial paths between sending and receiving points reach the destination simultaneously.

Because the total delay mostly has no role, it is possible to simplify the equation sometimes to  $M^* = -M$ .

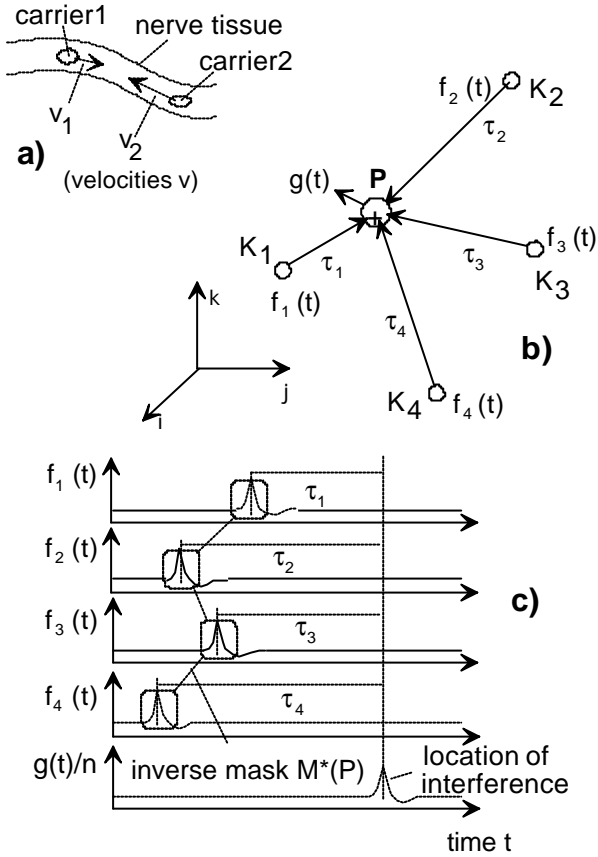
If the space dimension  $D$  is in relation to the channel number  $n$ , we call the system **'well conditioned'**

$$(18) D = n - 1$$

Observing inhomogeneous space geometries,  $D$  defines the dimension of an equivalent, homogeneous problem solving space.

### Dynamic basic functions of neural trees

Suppose two neurons coupled via fibre trees c). We get a substitute circuit Fig. d). We suppose an input time function  $x(t)$ , unity weights  $w_k=1$  and a summation point creating an summative output  $y(t)$



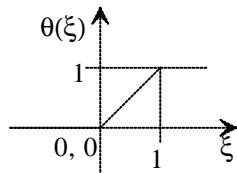
**Fig. 9:** a) Colored interference system, nerve tissue with two carrier types; b) time function  $g(t)$  of point  $P$  summing up four sources  $f_k(t)$ ; all wires imply distributed delays; c) maximum interference in  $P$  occurs if functions  $f_k(t)$  appear pre-delayed with the inverse delay vector  $M^*(P)$

$$(19) \quad y(t) = \theta(w_i x(t - \tau_i) + w_j x(t - \tau_j) + \dots + b)$$

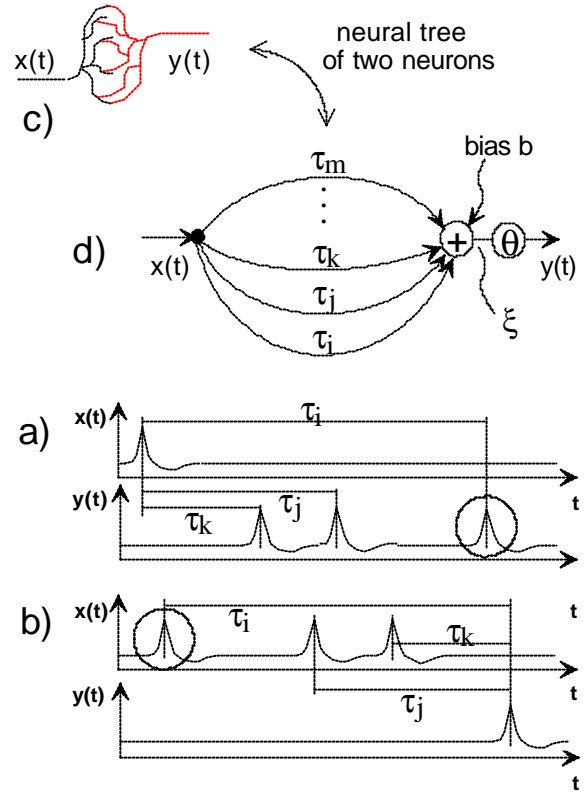
Depending on a bias  $b$  and a threshold function  $\theta$ , the neuron has different possible answers to any input.

Some special cases may be of interest. We use normalized time functions and weights. A simple, ramp-like threshold function  $\theta(\xi)$  is used in the range 0 to 1 with  $\theta(\xi)/d\xi = 1$ .

In case of a large bias (boolean OR-type) each single input impulse appears delayed at the output. So we call this case burst or *code generation* (a).



**Fig.:** Threshold function



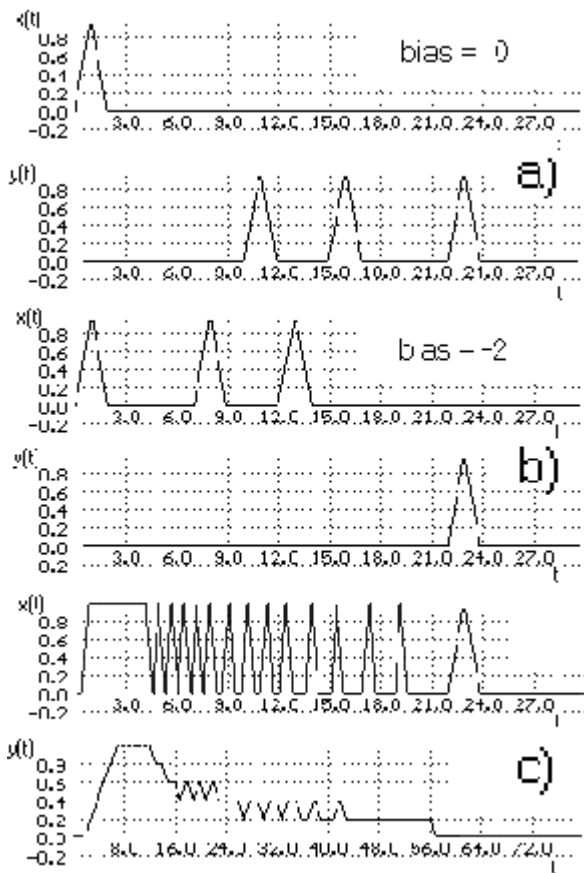
**Fig. 10:** Equivalence circuit d) of a coupling c) of neural trees acting as a) code or burst generator; b) code or burst detector

Using a small bias near the inverse sum of weights  $g_i(t)$  (boolean AND-type) all inputs of the adder have to have the level 'one' to reach any output. This case is called burst or *code detection* (b).

For a bias of zero, with a sum of weights near one and small delay differences, the circuit produces floating or *gating potentials* (c).

If the receiving mask differs from the incoming burst, according to Fig. b) the neuron is almost not excitable, the mask acts like a key. We call this case *dynamic inhibition* or delay vector inhibition (not drawn).

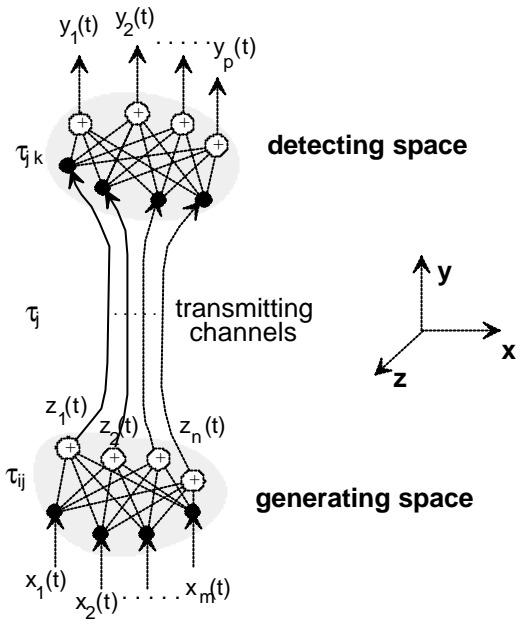
A special case of rule d) is that of *dynamic neighbourhood inhibition*. Suppose two symmetric, connected neuron trees 1 and 2. Both neurons may have an identical geometry with  $M = M_1 = M_2^*$ . For interference maximum, the delay vectors have to fulfil  $M_1 + M_2^* = t\{1\}$ ;  $2M = t\{1\}$ ;  $M = t/2\{1\}$ . So the firing of one neuron can excite the other only if all places of coupling (i.e. synapses) have the same delay radius around the cell soma.



**Fig. 11: Testing dynamic basic functions<sup>31</sup> of a tree coupling of two neurons (example). a) code generation: weights  $g_1 \dots g_3 = 1$ , bias = 0, delays = 10, 15, 22 samples; b) code detection with inversive delay vector: similar to case a) but with bias = -2; c) gating potential: six inputs, all weights = 0.2; delays = 1, 2, 3, 4, 5, 6; bias = 0, (x-axis incompletely drawn)**

### Basic interference circuit

Cortical neurons have on average thousands of synapses. Neural space seems to be full of short circuits. Suppose we have two neural assemblies connected via some axons or pulse transmitting channels. The one neuropile may generate some impulses, waves interfere in the other. For simplicity, neural spaces may have delays proportional to distances in space (partial homogeneous spaces). All delays  $\tau_{ij}$ ,  $\tau_j$ ,  $\tau_k$  may depend on distances only,  $i = 1 \dots m$  (firing neurons),  $j = 1 \dots n$  (channel number),  $k = 1 \dots p$  (detecting neurons).



**Fig. 12: Two neuropiles connected via some axons as a basic interference circuit (all wires have wave properties with limited velocities)**

A signal crossing this circuit runs along all the different paths. Points of high interference are located in the opposite space, in contrast to *non-mirroring, synaptic projections* wave circuits of this type produce *mirroring projections* (comparable to optical projections). The higher the multiple self correlation of a signal is, the higher is the effective value of the interference integral. It seems to be of some interest, that while *transmitting channels* can have *high velocities* or delays near zero, *field velocities* have by contrast to be *very slow* for sharp interference locations, equal pulse durations supposed.

Only transmitting channels can have zero delays. In the most of following simulations delays of transmitting channels are supposed to be equal and zero. So the model become worthless, if the velocities within the generating and the detecting neuropiles become infinite. In fact we can find long myelinated axons to decrease reaction times, but myelinisation of neuropiles is not known. Also the model would be worthless if generator/detector velocities become infinite.

Observing the circuit, it seems to be comparable to neuroscience's synaptic circuits. What is the difference? Supposing *equal* synaptic weights, any such circuit is not able to transmit information without waves. Using pulses it works inverted. Now it can produce only *mirrored* projections instead of the *non-mirrored* projections of the synaptic type. Different properties of this circuit have

<sup>31</sup> Experiments with dynamic simulator 'Neuronet', Oct. 19-20, 1994; development: G. Schoel, P. Puschmann, FHTW Berlin



been studied<sup>41</sup> by the author between 1992 and 1998 . Because there is a bad chance to get analytical solutions for wave spaces, a special software PSI-Tools (PSI: **P**arallel and **S**erial **I**nterference) was developed to calculate simple wave fields. It uses the so called *H-Interference Transformation* (HIT) as a fast basic algorithm [6].

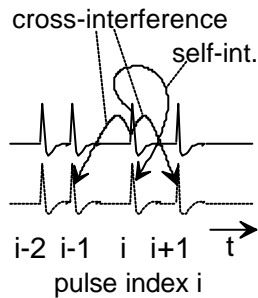
### Projection via reconstruction, overconditioning

Two tasks are of interest for the interpretation of time functions flowing through transmitting axons (channel data stream):

a) For technical purposes, the (non-mirroring) **reconstruction** of the excitement of a generating field is of interest. It can be realized by a propagation of the time-functions back to the generating space.

b) In nerve-simulations also the (mirroring) **projection**, the excitement of a detector field is of interest.

From a physical viewpoint, *reconstruction and projection are two sides of one coin*. Using comparable spherical coordinates only, the **time direction** of channel data stream decides between them c), d). Neural *projections* share the same problems as optical projections: depending on the degree of over-conditioning (channel number versus space dimension), interferences decline the more one moves away from the central axis<sup>51</sup>. Any *reconstruction* c) reasoned by perfect delay compensation reproduces the generators excitement scheme without distortion and over-conditioning problems in general. On the other hand, the *projection* in d), over-conditioned by one channel, do not reproduce the excitement scheme. While for example three channels reproduce all self interferences in 2D-space, higher channel numbers progressively suppress cross interference points.



### Parameters of pulse-interference systems

The **geometrical pulse width**  $l$  determines the sharpness of a pulse projection, it is defined by peak time  $t_{peak}$  and velocity  $v$

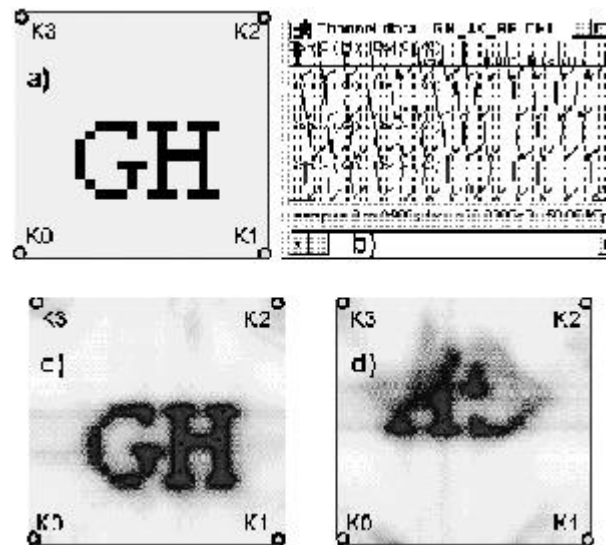
$$(20) \quad l = t_{peak} \cdot v.$$

Cross interferences can occur, if a next wave  $i+1$  comes into a field, while a wave  $i$  has not lost the field.

As smooth indicator acts the **cross interference distance**  $d$  with an average pulse distance  $t_{pause}$

(‘refractoriness period’)

$$(21) \quad d = t_{pause} \cdot v.$$



**Reconstruction and projection at the interference circuit of Fig. 4, over-conditioning system ( $n = 4, D = 2$ ). From left to right:**

a) generating field with firing neurons as black pixels (channel origins  $K0...K3$ ); b) channel data stream (four channels); c) reconstruction of the generating field with time-reversed channel data; d) projection into the detecting field (source: Heinz 1994; 1996)

Data: field sizes  $9 \times 9$  mm; velocity  $v = 3000$  mm/s; average pulse distance  $3$  ms  $\sim 9$  mm; time function length  $80$  ms; geom. pulse width  $= 0.1$  ms  $\sim 0.3$  mm; generator and detector field are set to identical coordinates.

It acts as the radius  $d$  between any interference location and a possible next interference location. Neurons fire one after the other depending on the pause. Channels are located at drawn positions with starting points in the generating layer and with ending points in the detecting layer.

To get detailed projections without **over- and under-conditioning** effects, there is an optimum number of channels  $n$  related to space dimension  $D = n-1$ .

To reduce cross interference we find the larger is the space dimension, the greater can be the cross interference distance.

### Cross-interference overflow

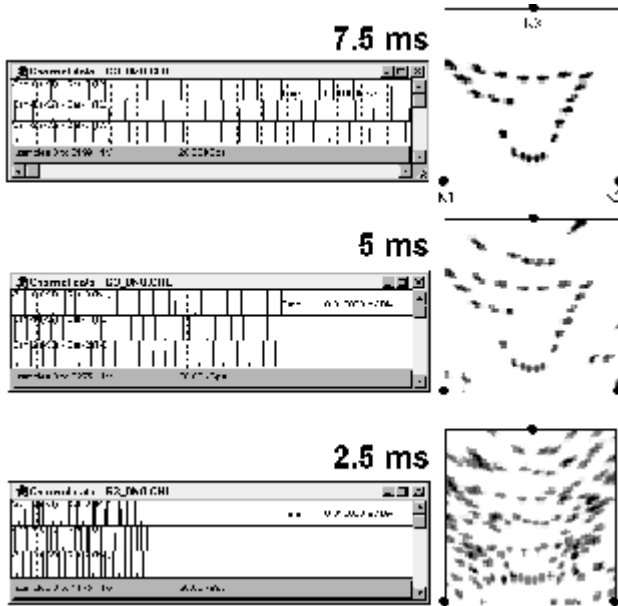
Let's observe the dependence of interference locations on pulse distances. Refractoriness shall be small in

<sup>41</sup> [http://www.gfai.de/www\\_open/perspg/heinz.htm](http://www.gfai.de/www_open/perspg/heinz.htm)

<sup>51</sup> [http://www.gfai.de/www\\_open/perspg/g\\_heinz/pressinf/bilder\\_d.htm](http://www.gfai.de/www_open/perspg/g_heinz/pressinf/bilder_d.htm)

relation to pulse distances.

Example: For an average pulse distance (refractoriness) of 20 ms and an detector velocity of 0,5 m/s what is the maximum radius of the self interference space? With a cross interference distance  $d = t_{\text{pause}}$  it is approximately 10 mm. This is the maximum region of topologic projections without cross interference pattern (Lashley's holographic memory) and without self-holography (see also 'moving projections', case g with  $v = 10$ ).



**Fig. 13: Cross-interference overflow as function of three different firing rates/pulse distances (average in milliseconds). Firing neurons of the generator arranged in form of the character 'G'; three channels feed the fields (K1, K2, K3)**

Data: pulse distance variation 7.5 to 2.5 ms; field size 1x1 mm; velocity 200 mm/s; pulse peak ca. 0.1 ms ~ 20  $\mu\text{m}$ ; cross interference distance varies between 1.5 and 0.5 mm, channel feeding points located on the detecting field

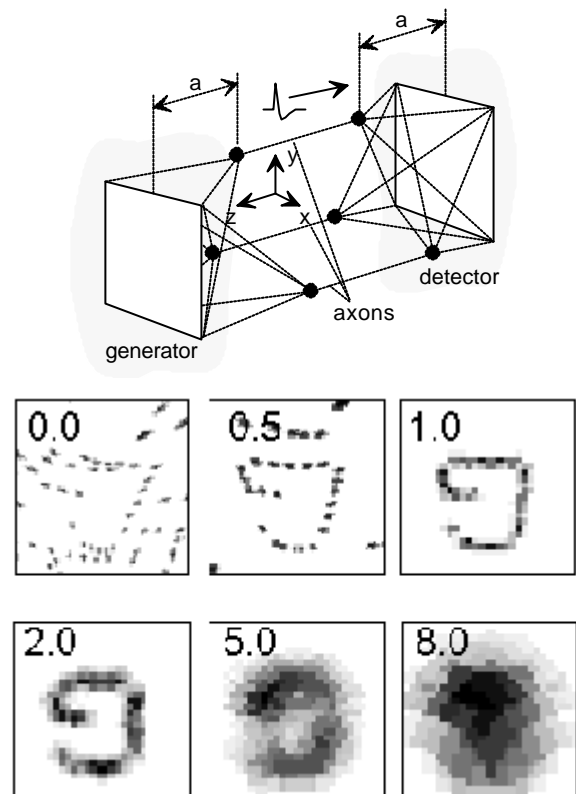
The suppression of cross-interference improves as more channels are used. By contrast, interference circuits with low channel numbers only work, when time functions are spike-like. Nevertheless over-conditioning effects increase as more channels are used.

In some situations the cross-interference distance becomes unbalanced, for example in the case of injuries. Generating neurons begin to fire with very high rates. Cross interference distances shrink. When the density of generating impulses is increased, more and more cross interferences appear in the detecting field. From a physical point of view this could be classed as "pain"<sup>61</sup>.

<sup>61</sup> see also [http://www.gfai.de/www\\_open/perspg/g\\_heinz/sim/pain/pain.htm](http://www.gfai.de/www_open/perspg/g_heinz/sim/pain/pain.htm)

## Influence of projection distance

Is the relative distance between sensing and sourcing points relevant for a projection? To answer the question, we tried further experiments, Fig. 7. Varying the distance 'a' between source points and the field produces different projection qualities. While short distances promote cross interference, large distances destroy the image.

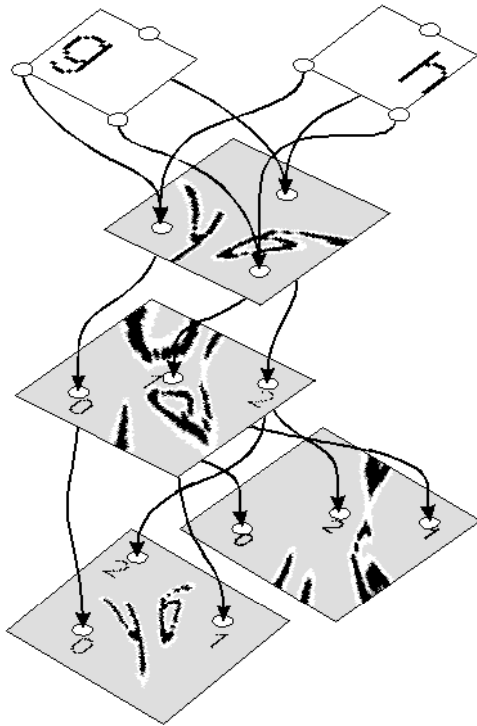


**Fig. 14: Variation of the distance  $a$  between feeding points and fields. We find different projection qualities. Parameter is  $a$  in mm (Heinz 1996)**

Data: field size 1x1 mm, velocity 200 mm/s; pulse peak ca. 0.1 ms ~ 20  $\mu\text{m}$ ; average pulse distance 4 ms, cross-int. dist. ~0.8 mm

## Topomorphism and scene interaction

In our imagination it is possible, to overlay images or impressions without problems. Are there theoretical grounds for such behaviour? To test this, we overlay two channel data streams.

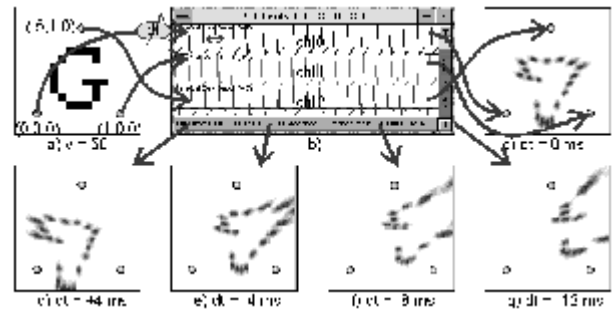


**Fig. 15: Overlay of two fields. Topomorphic projections with different channel source points<sup>71</sup>. Channelwise overlay (addition) of two 3-channel data streams, generated from independent source fields 'g' and 'h' (source: Heinz, 1996)**

We suppose, that all channels have the same channel number and project into a comparable space or field. Using two generator fields, the firing neurons are arranged in the form of an 'g' in the first and in the form of an 'h' in the second. We add or append the generated time functions sample by sample and channel by channel. Projections into different detector fields show, Fig.8, that both generator images have been combined. If channel source points are moved in the detector field, the projections become distorted. But the projections of 'g' and 'h' maintain in a *topomorphic relation*. It is not possible to separate them.

### Field influence by channel delay

In our mind, imagination suggests images as the word itself confirms. Our brain seems to work with the natural world of images, movement and sound. Abstract thinking with numbers, for example, appears as a hard task, if one tries to do it without the help of imagination. Up till now, we did not know a technical systems able to produce floating images or movies without of the use of picture-series.



**Fig. 16: Moving projection produced by a single, delaying axon in ch10. a) generator field; b) generated time functions; c)...g) detector field; c) no channel delayed; d) K0 delayed by 4 ms; e)...g) negatively delayed (source: Heinz 1996)**

Suppose that one channel is delayed by a parametric change  $dt$  of any connecting axon between generator and detector field occurred by local fields. Then the interference locations change in such a way that impulses meet each other at shifting places, Fig. 9. So, images become 'floating' according to an amount of a single channel delay variation!

### Field influence by background velocity

Over large areas of cortex one can measure weak local field potentials (LFPs) known as EEG or ECoG.

Already in Hodgkin/Huxley's model any volume potential change varies indirectly the propagation velocity of a neural path.

Let us suppose, that the background velocity changes within all neurons in the detector space influenced by such a glia-potential.

We find, that velocity changes  $v$  in the detecting field, for example reasoned by the influence of glia, have a zooming effect on the projection, Fig.10.

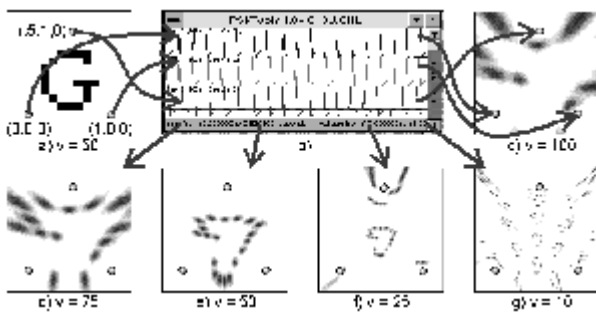
From this viewpoint it seems, EEG/ECoG-probes can be interpreted as measurements of zooming/moving control potentials only, reproducing a mathematical difference between a memorised code, image or function and a projection of any real input. In case of abstract figures we can imagine what zooming means. But what is zooming in relation to sensory interactions? Is it possible, that moving and zooming operations define the boundaries between sensory fields for example of the finger-representation in cortex?

### Distributed memory: the neural hologram

Lashley (Lashley 1950, Pribram 1974) studied the formation of memory by lesioning various parts of rat brains. Large areas could be removed, but animals were

<sup>71</sup> see also [http://www.gfai.de/www\\_open/perspg/g\\_heinz/pressinf/bilder\\_d.htm](http://www.gfai.de/www_open/perspg/g_heinz/pressinf/bilder_d.htm)

still able to reproduce the learned behaviour. In the section 'cross interference distance' we discussed and in Fig.10g) we demonstrate a comparable behaviour. In case of low velocities  $v$  or large field areas, waves come into cross interference within the field, because the **cross interference distance** will become smaller as the field size. Wave  $i$  interferes with followers  $i+k$  and with previous waves  $i-k$  of the other channels. A kind of 'holographic' projection (better: **cross-interference projection**) happens with reference waves coming from the other channels. Note, that the hologram is not perfect: while the center figure is complete and self-interferential, the outer figures are cross interferences and in our case incomplete!



**Fig. 17: Zooming and cross-interference replication produced by varying field velocities. a) generator field; b) channel data stream; c) and d) increasing sizes for higher velocities; e) projection with original field velocity  $v = 50$ ; f) and g) reduced sizes for low velocities: cross-interferences in g) appear self-replicative (source: Heinz 1996)**

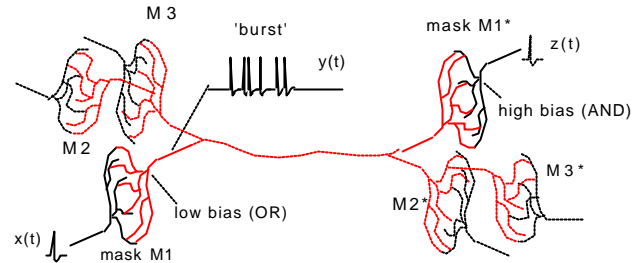
Data: field size 1x1 (cm);  $v_{gen} = 50$  cm/s;  $v_{det} = 10...50...100$  cm/s; average pulse width 1ms; pulse wavelength 0.1...0.5...1 mm; average pulse distance 20 ms  $\sim$  2...10...20 mm; 10 kS/s

We will call this general behaviour of interference systems *self-holographic*. Because every impulse has following and preceding pulses or waves, interference systems can be seen as self-holographic in general if delays between sourcing points are higher the pulse-distances.

### Neural address and sender-receiver relations

Let us return to the basic functions of a neuron. We have seen, that coupling trees are able to produce a burst. To reproduce a single impulse at a neurons output it is necessary, to use the inverse characteristic delay vector, the 'mask'. Detection is possible if the tree uses the complementary mask. Suppose different trees, we find, that each neuron on the left side (Fig. 11) communicates *only* with special trees on the right side. In the example, masks  $M_x$  and  $M_x^*$  are inverted. The neuron with mask  $M_1$  communicates with  $M_1^*$ ,  $M_2$  with  $M_2^*$  and  $M_3$  with

$M_3^*$ . So bursts can be seen as (parallel or serial) neural addresses, allowing any communication between different neuron trees across a (single or multiple) axonal path. It may be of some interest that this kind of communication can work in both directions. Theoretically neurons this way can talk bi-directionally if the bias can be modified.



**Fig. 18: Bursts can be seen as neural addresses to transmit different data streams on single axons (equivalence circuit see Fig. 2)**

The **burst** acts vice versa: it encodes both the *sender address* and it also encodes the *address of the receiver*. It is not possible to break this relation. Both addresses depend only on a single sign: the **direction of the time axis**. Supposed we have the 3-dim. nerve graph, if the time flows *forward*, we get the *projection*, the receiver address. If the time flows *backwards*, we get the *reconstruction* - the sender address or location - all with the same channel data stream!

### Serial and parallel interference

A cerebral neuron in average has 7400 synapses. The level of excitement appears as higher, as more closed the impulses appear in the soma. In the case of projections the pulses reach on different ways - but time synchron - the cell soma. Time synchrony is also possible using delayed pulses and a delaying net, compensating the delays of the time differences between pulses. So a spiking network *does not differ in general between parallel and serial interference* signals, the neuron cannot decide wheather a source is a sequential data stream 'to hear something' or a parallel projection 'to see something'.

### Colored interference systems

Untill now we implied electric measureable representations (pulses) as carriers of information. Behind thousands of nerve fibres are lots of interacting substances without electric representation carried by a so called mixed nerve. For example we know that radio-active marked leucin flows - comparable to ionic pulses - with very slow velocity ( $5\mu\text{m/s}$ ) and contralateral to pulses through nerve. So it seems necessary to view nerve to be

only the geometric carrier of different pulse-like informations, nerve is to suppose as carrier of different 'colored' signal flows, interacting together.

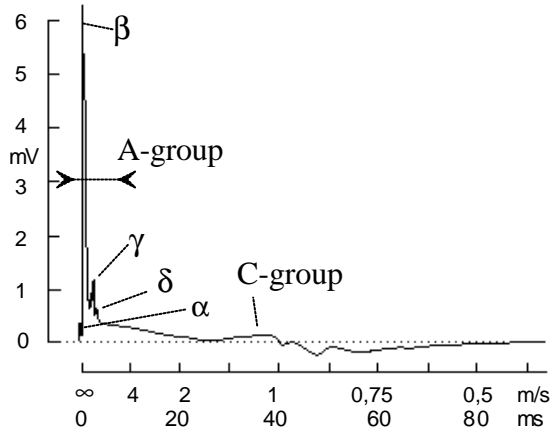


Fig. 19: Extracellular action potential of a mixed nerve [18]

### Learning in wave interference networks

Learning in each network is closed to interference, to a highest grade of time-synchrony between different events at certain locations, to a high correlation of time functions: to ask for the possibility of learning in spiking networks means to understand possible mechanisms of interference first.

### Separation problem in wave space

Minsky and Papert analysed the problem of linear separability of perceptrons. Any input space divides into two halfspaces. In consequence, two layer nets are necessary to solve XOR-like separation problems. In spiking systems the problem is more complex. Any pulse interference wave can only excite something. It is not simple to define the opposite to 'excite something'. We need indirect inhibitory mechanisms for wave interference nets, for example a wave interference can excite an location within an inhibitory plane, controlling other planes. Thus comparable to the XOR separation problem also interference nets need layers to excite or to inhibit something if we suppose an inhibition can not create an (exciting) wave.

### Scene reflection by highly specialized neurons

There are two different ways to realize a pulse projection: we find a image like projection of the optical type or we use an abstract projection type, characterised by a free interference of time functions in space.

Trying that, we consider different meshes in

$n$ -dimensional delay space ( $n$ -dimensional means, the information can flow on  $n$  independent paths between source- and interference point). Each path is a composited of different partial delays. For all paths the sum of delays has to be equal.

$$(22) \quad \forall: \quad \sum_{i=1}^p \tau_i = \sum_{j=1}^q \tau_j = \dots = \sum_{k=1}^r \tau_k = const.$$

If it is possible, to find for each point of an arrangement (neurons in form of GH for example) a path to a single interference point in  $n$ -dimensional space, so this interference point represents the information of the whole configuration, a single neuron is representing a complete scene. Asking for a good possibility, we find we need inhomogeneous delay spaces with very different velocities and connections.

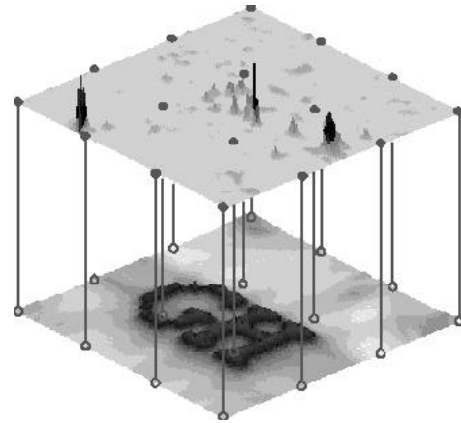


Fig. 20: 16-channel pulse projection as a scene reflection by specialized neurons. Heinz, 1996

One can arrange for example two wave fields in opposite to each other. In the following figure, two interference maps project counterwise over 16-channels. One field represents the direct opposite of the other. Connecting wires have equal delays. The two projective areas are supposed to be homogeneous wave conductors (like a water surface) in the example. Although the example arrangement is far away to be  $n$ -dimensional or clear inhomogeneous, we observe an information reduction: We find three neurons in the upper map representing the GH-arrangement of the bottom map nearly complete.

The upper three places correspond in wave interference view with dozens of neurons of the GH arrangement. Using wave interference, the circular wave nature themselves searches for points with high interference value. A 'scene reflection by highly specialized neurons' occurs in inhomogeneous nets automatically.

This scene reflection has an holographic feature: using only a view neurons of the GH as a 'key', it is possible to get the main places of interference, representing the complete GH. Thus, the circuit works like a holographic

memory. The key reproduces the recollection of the arrangement. In consequence, the network can not decide, if all GH-neurons have fired, or only some key-neurons. To recognize the total arrangement, the threshold  $\Theta$  of recognizing neurons must have the value of the number  $n$  of elements characterizing the delay vector  $M$  of the neuron, the mask.

$$(23) \quad \theta = n \quad (\text{recognition})$$

For the case, that the threshold  $\Theta$  is lower the interference number  $n$ , the network gets recollecting properties.

$$(24) \quad \theta < n \quad (\text{recollection})$$

Any key excites the recognizing neuron, implying the scene is complete. By contrast to boolean or threshold realizations with *basic functions* (AND, OR, NOT) our network is not deterministic. Supposed, any delay value occurs more times in a mask, the recognizing neuron can only decide the delay is there or is not there. So, the other identical delays are not missed, the source excitements can be still, nevertheless the recognition neuron is excited.

### Selective connections between assemblies

In informatics thinking selectivity means nothing more than one more exciting or inhibiting input to built any result, use  $n+1$  instead of  $n$  inputs.

There is a way to built selective connections also in wave interference systems. First, the complete scene must be recognized by one or a couple of specialized 'scene'-neurons representing the scene and the selection in parallel and in serial (including the selecting inputs). Next the 'scene'-neurons act as inputs for the next higher level, to create higher scenes. There is no new quality necessary to reach this. The problem is a clear practical one: How to avoid any excitement of 'scene'-neurons at a higher level by excitements of any lower level? It seems, to reach this, the only possibility is a clean decomposition in locality. One have to subdivide the net into different districts, reachable only for interferences of the demanded type. As higher the subdivision is, as higher scene levels can be observed, as more complex scenes can be recognized.

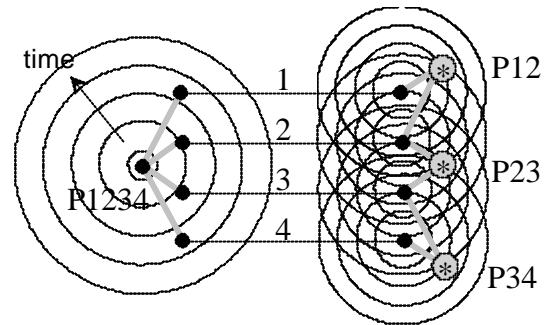
### Binding by synchrony in spiking systems

Information processing is possible, if the necessary informations appear at the same time (synchron) at the same place. This is also true in case of interference systems. Wave interference has the strongest demands for synchrony.

Measuring two points between any data exchange systems (for example rider and horse) we will find mostly a high cross-correlation of the signals, although the two systems work totally independent of each other. It seems to be the character of any data exchange to work partially

synchronous with high cross-correlations.

Global synchronization of wave interference systems is impossible, if we can not suppose a central, delay-free clock distribution. In fact, to any time-distributed interference system we can add a clock generator. But we have problems to distribute the clock! Because of the different delays of the clock lines to different places, synchrony in interference systems only can occur *event driven* (also the source can be a clock, however). This seems to be an important characterization of bio-systems.



**Fig. 21: Scene composition. Changing the dimension of an interference projection. The 3D-scene ( $n=4$ ) P1234 corresponds for example to 1D-scenes ( $n=2$ ) P12, P23, P34**

### Conclusions

As an alternative to different approaches we investigated the role played by delays coupled to nerve lengths and distances in physical wave spaces.

We studied pulse interference projections between two short-circuit neuro-piles avoiding the use of synaptic weights. The parameters varied were delays, velocities of pulses, pulse duration, pulse distance and coordinates of feeding and sensing points in spatial arrangements.

Introducing the characteristic delay vector (mask) of a location we find *new dynamic basic functions* of neuron connections or neural trees.

We find *mirroring projections* in a detecting field and *non-mirroring reconstructions* on the generating field. The only difference between projection and reconstruction is the *time-flow direction* of the time functions (channel data). One of our experimental arrangements consists of two short-circuit subspaces connected via some wires (axons). On changing the field velocity, projections begin to *zoom*. For small channel numbers we find *cross-interference replication* in simulation, supposed by Lashley in 1949. Modifying axonal delays, projections *move* across the detecting field.

**Table: Typical properties of PN and IN**

Pattern Network	Interference Network
<b>learning:</b> modify weights	modify delays
<b>information carrier:</b> level	relative time
<b>abstraction level:</b> discrete time step	continuous in time
<b>layer to layer transfer:</b> non-mirrored	mirroring only
<b>adaptability:</b> artificial	moving, zooming
<b>number of layers:</b> typ. 2...3	no bounds
<b>selforganisation:</b> see Kohonen	extinguished waves by refractoriness
<b>information flow:</b> clock driven	event driven
<b>spherical order:</b> matrix norm	3D-model

For the calculation of interference locations the velocity diagram of a neuropile is important to know.

Projections can be overlaid and *remain topomorphic*. Moving the axonal source points over the field, projections become distorted but remain topomorphic. Because every impulse has following and preceding waves, interference systems can be seen as self-holographic in general.

Fast firing into a field we find increasing cross-interference overflow, implying *pain-like behaviour* of animals.

Behind other parameters any distance variation between axons and fields changes the *projection quality*.

Interference circuits can help to analyze the role of *myelinization of long axons* and slow neuro-pile velocities in combination. While animals in biologic evolution need short reaction times to improve their chance of survival, pulse-propagating nets need the opposite: neural communication, data addressing and information processing couples to a slow flow of information in interference regions, resulting in small geometrical pulse-widths. Only the connecting channels between generator and detector spaces (axons) can be infinitely fast without influencing the information processing. In fact we also find axons with

myelin-insulation that propagate pulses at highest velocities over long distances.

As a result, physical network simulations of simple neural assemblies can reproduce different known, higher brain functions, in particular an *image-like information processing* on uncertain, inhomogeneous but uniform neural subspaces.

If neural delays and codes depend on space distances, neural functions are *coded by locations* in space and thus *by the geometry of the neural tissue* independent of weights and thresholds. Space-dependent delays appear as the 'coding institution', the code is the location, space codes the timing and so the neural tissue dominates the coding of the behaviour.

Bursts appear as neural data addresses. Different neurons can communicate over single axons.

Over-conditioning problems appear if the channel number is greater than the space dimension plus one. Interference locations become indifferent for high channel numbers in homogeneous space. Using inhomogeneous, wired interference spaces over-conditioning disappears. Because nerve fibres have different velocities and chaotic connectivity schemes, neural delay space can be regarded as higher dimensional.

If we compare static-synaptic and dynamic wave interference aspects, any multi-channel, neural network tends from the static, synaptic behaviour to a *non-mirroring* data transmission, from the dynamic or wave interference aspect to a *mirroring* data transmission.

## Acknowledgements

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