

Introduction to Interference Systems

Gerd K. Heinz

*Gesellschaft zur Förderung angewandter Informatik e.V.,
Rudower Chaussee 30, D-12489 Berlin, heinz@gfai.de*

Abstract

Asking for theoretical equivalencies between imagination 'pictures of thought' and speech recognition, between neural networks or fuzzy systems, global positioning system, radio antennas, optical lens systems and FIR-filters we find a hyperclass of networks. We will call them interference networks (IN). We need them to analyse structures that are for example projective (in the optical, not in mathematical meaning) and frequency responsible at the same time.

Understanding INs, the transfer response equation of a finite impulse response (FIR) digital filter can be expressed from the same viewpoint as a wave field equation of a projection system (optical, neural...). The paper¹ analyses, why INs can not distinguish between seeing and hearing.

Introduction

At hand of examples we will derive some properties of interference nets. A physical point of view will characterise temporal and spatial interference nets as digital filters and projective (image carrying) nets. The role of thresholds between linear superimposition, threshold logic, fuzzy systems and neural networks is discussed. We try to find out, why it is better to ask for the location of interference than to ask for the function of a neuron. We explore the role played by inhomogenities and the preferred role of spikes.

Realising functions of delay/weight-networks with delays only and weights only we find out typical properties between space and time. Last not least we will characterise neural networks as a mathematical abstraction of a special interference network type. We have to look for physical insufficient modelling properties of such nets.

The paper tries to introduce different discoveries concerning neural and nerve nets. The term interference net was introduced to characterise abstract physical and mathematical qualities of neural nets to become able to model nerve networks.

To compute actions of a digital unit, a fuzzy controller or a complex network means, to compute defined actions at defined time steps. Any change of time schedule between net nodes results in different actions of the total network -

mostly we characterize such changes as faulty behaviour. Investigating the errors we find importance of time for the solution of tasks in interference nets.

The algorithmical role played by space and time is observed. Thinking about time schedules in algorithms offers to think about discrete wave fields. When any time function on a water surface is part of a so called wave field, a time function at any node of any algorithmically working net can be seen by analogy as a part of a (discrete) wave field laying over the network. To understand the influence of space and time in neural nets, we observe properties between space and time functions.

Motivation: Projectivity

Things changes there face if we modify the physical level of modelling. In our case the same 'neural' network produces an opposite projection if we model with weights or at the other hand with spikes, signal delays and waves. What is the difference between wave-optical and neuro-mathematical projectivity?

An optical **wave projection system** projects a location over partial beams to a location, where the different waves come into (self-) interference again. A projection occurs at places, where a lot of partial waves lays (on the detector site) in the same phase relation, that means, where they have all the same delay relative to the source time function.

A **mathematical projection** is a relation between two sets of values: $P \Rightarrow P'$ etc.. If P and P' are vectors with elements p_1, p_2, \dots, p_n and p'_1, p'_2, \dots, p'_n we suggest normally a straight relation between p_1 and p'_1, \dots, p_n and p'_n . This is also the meaning in Neurocomputing sciences until now. But introducing the term this way we neglect the essential **mirroring property** of the wave-optical 'projectivity' [7].

However, in interference networks we will ask for wave properties, so we only can use the optical meaning of projectivity.

Introducing length proportional delays, suggested in all forms of nerve networks *to be the main key* for information processing I tried to open a larger entrance to neuronal networks research, so the title of my first manuscript in this field was "Neuronale Interferenzen"

¹ Invited plenary speech and regular paper 100027-01-GH-147 for the First International ICSC Congress on Neuro-Fuzzy Technologies, January 16-19, 2002, Havana, Cuba, <http://www.icsc-naiso.org/conferences/nf2002>

(Neural Interferences) [4]. But ever the same misunderstandings especially about 'projectivity' with experts of 'neuro-computing' research offered a reaction, provoked to create a new and different name for that research. So I'd like to use the term 'interference networks'. Now it seems, this was a good idea - students have no tolerance to accept that 1+1 sometimes is 2 and sometimes is -2 for example.

But it should be clear: it provokes a situation that is not simple: Up to now we use the term 'neural networks' to express a scientific field researching the effectiveness of pattern learning schemes with weights or of code-learning algorithms with delays.

Behind now we use the term 'interference networks' for modelling problems of wave networks *on a structural level*. So the IN-research asks for information computation in nerve nets with a very higher consequence, than neuro-computing can do. A time-delaying IN maps generally mirroring - while a weighted NN can only map non-mirroring in general.

What means the term Interference Net (IN)?

To reach projectivity in wave-theoretical sense we need following properties for INs:

- a) A net in space and time dimensions
- b) Each processing unit (neuron) has a place in 3D-space
- c) Each wire has all co-ordinates in 3D-space
- d) Each signal that bridges a distance has a delay
- e) Wiring delays are mostly length proportional
- f) Wires can have different velocity classes (colours)
- g) Neurons compute signals *in time and in space*

The Field of IN-Research

Any elementary interference circuit (Fig.4) can detect different sorts of information. At the one hand, between generator or detector fields appears **spatial correspondence** (projection of images or coupling of locations) using the 'Eigeninterferenz' (self interference) of time functions (channels). At the other hand the same circuit **corresponds temporal** (by behaviour, frequency, code) using 'Fremdinterferenz' (cross interference) properties. And third, we have to analyse **mixed behaviour**. For example: what influence has any input time function on the interference location map in a interference field? Which output time functions can be produced from a certain arrangement of generating locations?

Signal Correlations

Using bipolar and floating signals, any cross-correlation of more than two channels is only possible in non-uniform hierarchical computation or with special correlation schemes [4].

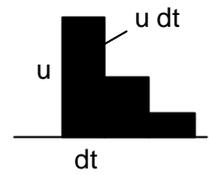
Effective Value, Linear Superimposition

Remembering electric circuit theory, we find the effective value of a signal over the square root :

$$(1) u_{eff}^2 = \frac{1}{T} \int_{-T/2}^{T/2} u^2(t) dt$$

$$(2) u_{eff}^2 = \frac{1}{N dt} \sum_{n=1}^N u^2(n dt) dt$$

$$(3) u_{eff}^2 = \frac{1}{N} \sum_{n=1}^N u^2(n dt)$$



Is the effective value relevant to recognise interference systems? Yes it is. It acts comparable to a correlation in case of unipolar signals.

For example, we have two pulses, each one sample long and one unit high. Observing two cases, first, the pulses reach our destination not in synchrony, we find a time series (we have 5 samples):

$$(4) u_1(t) = \{0; 1; 0; 1; 0\}$$

The effective value is $\text{SQRT}\{(0+1^2+0+1^2+0)/5\}=0,63$

Next, the two pulses meet at the same time sample with additive interference:

$$(5) u_2(t) = \{0; 0; 1+1; 0; 0\}$$

The effective value is $\text{SQRT}\{(0+0+2^2+0+0)/5\}=0,89$

That means, the closer the time correlation of time functions is, the higher is the effective value at this location.

This is a main idea of interference circuits in general. Remark: Note that the linear average value in both cases is 2/5.

What is the linear interference result if the two pulses interfere with different signs?

$$(6) u_1(t) = \{0; 1; 0; -1; 0\}$$

The effective value is $\text{SQRT}\{(0+1^2+0+(-1)^2+0)/5\}=0,63$

In case of interference within one sample we find:

$$(7) u_2(t) = \{0; 0; +1-1; 0; 0\} = \{0; 0; 0; 0; 0\}$$

The effective value is $\text{SQRT}\{(0+0+0+0+0)/5\}=0$

That means, a wave with different sign deletes another wave at the place of (highest) interference.

May be, this can help to understand the signal theoretical role played by inhibiting substances.

Non-linear Superimposition

Multiplication of n time functions (channels) with changing signs produces a result with changing sign. Using monopolar signals, this mistake is lost, the technique can be used for correlation. We call this type non-linear interference. We remember nerve signals to be asymmetric and monopolar.

Considered an n-channel interference at on location and the same time. While linear superimposition reproduces the shapes independent of the number of interfering

signals, *non-linear interference reduces the time function shapes* [4], see following chapters.

Wave Field of a Procedure

To give an idea, why IN-research corresponds closest to wave theory research, we will discuss the terms 'wave' and 'wave field' at hand of a simple procedure net.

Supposed we use any time function $f(t)$ and location functions $f(x)$. Delay elements T may produce different time functions at following nodes. At locations x we draw the values over each net node (Fig. 1). For the locations x_1 to x_3 we can note the time functions in traditional writing:

$$(8) \quad x_1: \quad f(x_1, t) = f(t)$$

$$(9) \quad x_2: \quad f(x_2, t) = f(t-T)$$

$$(10) \quad x_3: \quad f(x_3, t) = f(t-2T)$$

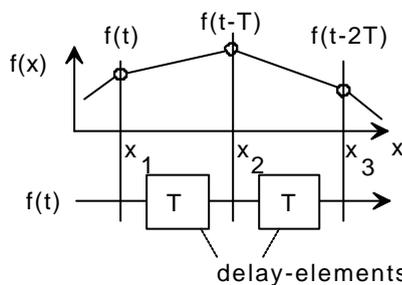


Fig. 1: Discrete wave field of a 1dim-net (example)

We find duality between time and space. When we connect the time functions marked by circles with lines or splines, we get the suggestion of a continuous wave field over the net. Thus we will call the space-time function set (eqns. 8...10) *discrete wave field of the procedure or net*. For a better imagination, we now can observe the function of the net at hand of the waves flowing over the surface.

We can summarise, that any function that is changing in time at any node of any computational array or network can be seen as a discrete wave field expression of this location.

Needless to say, that normally wave fields of mathematical nets, arrays or schedules are inhomogeneous, non-steady or not sinus-like. In our case, we need only limited values in the height.

So, we will call a wave carried by a single location a **zero-dimensional wave**. A wave, carried by a line of locations we will call **one-dimensional**, a wave carried by an 2-dim. array of values we will call two-dimensional wave field and so on.

To observe a simple wave field, see²¹

²¹ http://www.gfai.de/www_open/perspg/g_heinz/sim/s_waves.avi

Properties of IN

Observing INs show *spatial (to see)* and *temporal (to hear)* properties. The problem is, that different sciences observe different sites very independent. So opticians know a lot about spatial properties of interference systems while acousticians know the temporal site more.

The *spatial* property concludes research relating the transfer of interference locations within any 3D-space arrangement. Speaking about *temporal* properties means, we are interested to observe the relations of time functions between different (interfering) locations.

To work out, that both categories are one and the same thing, we start with a temporal interpretation of an IN using delays and continue with a spatial interpretation of a comparable net.

Simplest IN

Fig.2 shows the simplest interference network. Using as input a time function $e(t)$, the signal will move on different branches $1...n$, passing different delays $T_1 ... T_n$.

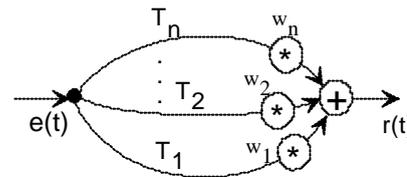


Fig. 2: Interference network (IN) with delays T_i and weights w_i

The signals may be multiplied with fixed weights $w_1 ... w_n$ (if not used, all weights are set to one). The different signals may interfere additively, producing a resulting interference function $r(t)$. The result function is

$$(11) \quad r(t) = w_1 e(t-T_1) + w_2 e(t-T_2) ... w_n e(t-T_n)$$

and the transmission function should be $r(t)/e(t)$.

Using a Fourier transformation we can transform $r(t)$ and $e(t)$ into the frequency domain $t \rightarrow f$: $R(f)$ and $E(f)$ (if possible) to create the frequency response $A(f)$ of the system.

$$(12) \quad A(f) = \frac{R(f)}{E(f)}$$

Let us modify the network in different ways to demonstrate further spatial and temporal abilities.

Field Equation seen as a Digital Filter Equation

Supposed the delays $T_1, T_2, ... T_n$ have a fixed relation and they are subsequent integers:

$$(13) \quad T_n = nT$$

we can modify equation 11 to a form

$$r(t) = w_1 e(t-T) + w_2 e(t-2T) \dots w_n e(t-nT)$$

$$(14) \quad r(t) = \sum_{i=1}^n w_i e(t-T_i)$$

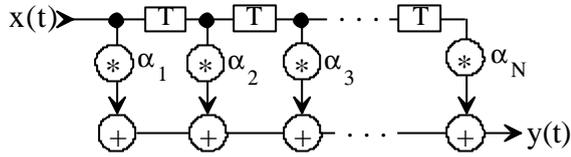


Fig. 3: Digital FIR-filter as modified IN from Fig.2

Coefficients comparison and reordering of indices we find, this is the so called *difference equation of a Finite Impulse Response Filter (FIR)*. Our weights now calls coefficients, the input function appears as a sequence of samples.

We remember to see this result as a time function of a space-time network, *as a time equation of a single point within an IN*. In consequence, we also can plot the time functions of all inner nodes of the net and get a 1-dim. wave field of the net.

The digital filter may be the simplest case of a time structure correspondence produced by an IN. We use one input time function and get a different output time function using a simplest interference net.

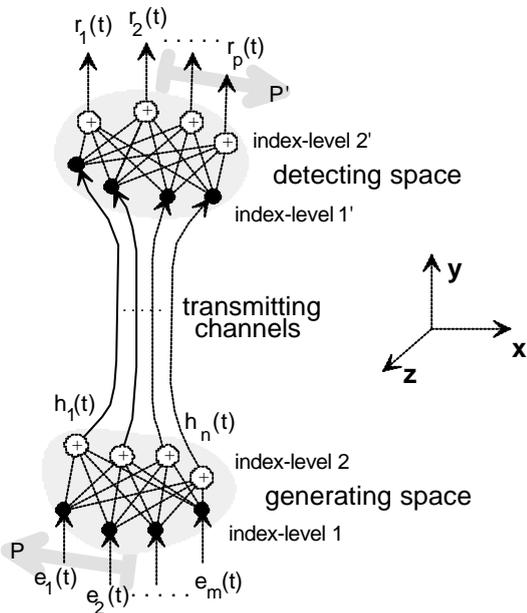


Fig. 4: Projection system built of elementary INs. Using time-functions, it maps mirroring (P => P')

Projection Systems

Let us use the net of Fig.2 and repeat and redraw it in a second way, see Fig.4. Now p elementary outputs r_p will get informations over j so called channels from m exciting

sources e_m . We call this network *projection system*, source [4].

Field equations seen as a Projection System

We can generate time functions at each node of Fig.4 index-level 2 using a superimposition of all $e_j = e_1 \dots e_m$, for example

$$(15) \quad h_j(t) = e_j(t-T_{1j}) + e_j(t-T_{2j}) + \dots + e_j(t-T_{mj}).$$

Next we construct the time functions at index-level 1' using the functions of level 2. In our case they are the same. Last we construct level 2' from level 1':

$$(16) \quad r_j(t) = h_j(t-T_{1j}) + h_j(t-T_{2j}) + \dots + h_j(t-T_{nj}).$$

If we combine this set of equations with all partial delay elements we get a large equation system that was introduced as *H-Interference Transformation (HIT)*, for example in the form [5], [6].

The set describes, how responsible any output r_i depends on excitements e_j . In words, the set of equations produces *interference projections* from the excitement layer (generator field) to the result layer (detector field). The set was implemented in an interference simulator called 'PSI-Tools' to study interference projections under varying parameters (time function type, delays, excitement maps etc.) [5].

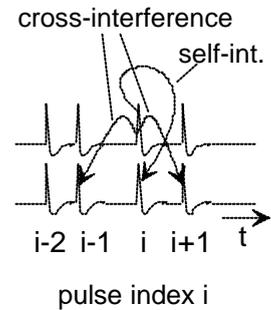
Abroad: Self- and Cross-Interference

For the next chapter, we have to introduce or remember the terms cross- and self-interference.

If any part of a time function (for example pulse i) of high interference value, that moves over different ways to a receiver, correlates with the same pulse (i), we call this self-interference.

If correlation with another pulse occurs (for example with pulse $i+1$, $i+2$, $i-1$), it is called cross-interference [4].

In rough speaking: *Self interference* characterises the ability of *location-transformations*, while *cross interference* characterises the *spectral, code-, or frequency content* of a signal set, see Fig.5.



Spatial Properties

Because it is not simple to observe IN- equations for p output functions, we use an example to interpret a net with discrete wave field functions. We have unique weights (all considered to be one, $w_i = 1$).

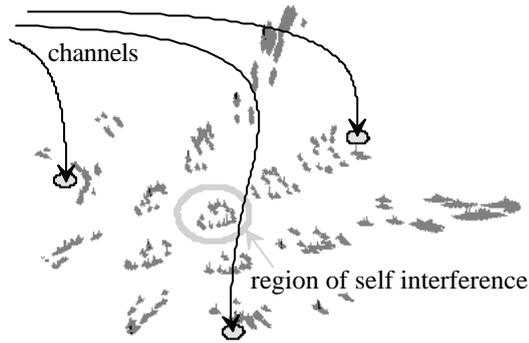
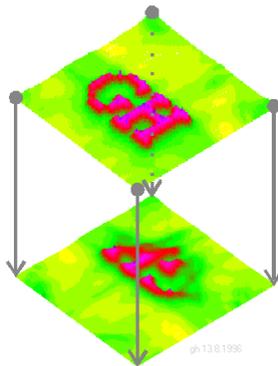


Fig. 5: Self- and cross- interference of time functions. Using an IN-model, relative to the maxima in time functions we get cross interferences in space 'Lashleys holographic memory of rats' [8]

To get observability, in- and outputs are set on a map instead of a sphere. Laying for example the inputs and outputs on a 2-dim. grid, we can observe the wave field as a bitmap. So we find for example a *mirroring property* of the spatial transfer function, Fig.6.

Fig. 6: Correspondence of interference locations between a generating and a detecting field. The image shows a reconstruction and a projection of the same set of time-functions. Differences between them occurs by the sign of time axis. Source [5]



Temporal Properties

The set of equations of a projection system can also be seen as a frequency response of one output dependent on all inputs of the net in the time domain. By analogy to digital filters we can transform the equation set into the frequency sphere. The transfer function for all net points in frequency domain can be observed from $r_f(t)/e_f(t)$.

Without derivation we can realise (for example) the frequency response of each output depending on the sum of the delays of all possible signal paths.

Frequency/Code Mapping

Behind the location-to-location projection and the time functions transformation it is a third species of properties characterising INs: The generation or detection of code or frequency in dependence of a location. We all know Huygens experiment, where the interference of two partially light waves occurs as a typical interference

pattern. We can transform this experiment in several ways into IN-space, one way is shown in Fig.7.

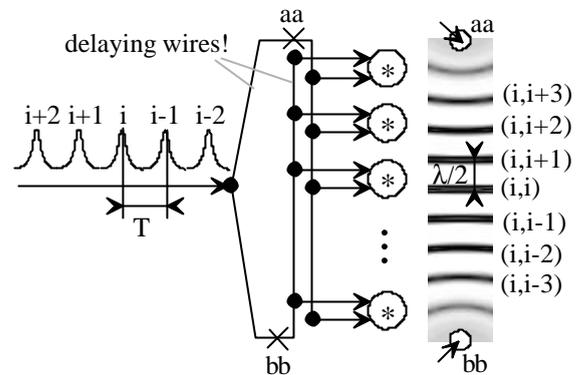


Fig. 7: Simulated neural diffraction of an IN. The energetic maxima correspond to the delay $l = vT$ of the input function. Sources ³¹ and [5].

Projection versus Reconstruction

Thinking about time direction in virtual wave space we find an interesting property: Using an identical detection space and identical arrangements, we get a non-mirroring projection for inverted time flow of channels, but mirroring and over-conditioned projections in case of forward flowing time. The case of inverted time flow we call reconstruction (of the generator map), see Fig.6, source [5].

Over-Conditioning and Inhomogeneity

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 axis⁴¹, for more see [5].

Fig.6 shows a 2-dim. projection over 4 channels. This is one channel to much. Without proof [4] we find, that any point in d -dimensional space is fixed from n different points over 'delay distances':

$$(17) \quad n = d + 1$$

where n is the used channel number. If the channel number is higher, we get an over-conditioned projection with all negative properties we know from lens systems: far away of the systems central axis, the projections disappear.

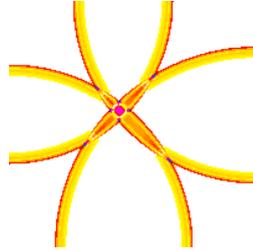
Why is that important to note? We have to consider, that in any network (for example a multi-layer NN) using any form of time functions and a channel amount greater eqn.17 it is *nearly not* able to find global maximum or minimum solutions! The problem relates performance

³¹ http://www.gfai.de/www_open/perspg/g_heinz/pressinf/pattern.gif

⁴¹ http://www.gfai.de/www_open/perspg/g_heinz/pressinf/bilder_d.htm

possibilities and restrictions of multi-layer NNs. To overcome the problem, we have to handle delays, channel numbers, space arrangements and distances very carefully.

Fig. 8: Planar wave field as part of a four channel wave projection. Four waves interfere in one point. So it gets a higher energy value. With high time resolution we see the reasoning waves.



It is also one of the stimuli to define the new network class interference networks (IN), see Fig.8. Before we can start to design an IN, we have to ask, if possible places for interferences meet our network construction. If we find out a possible result is out of our plane, or within out of the location grid, we can stop further works.

Interferential Feature Maps with Nerves

Suggesting input vectors $F_1...F_n$ as channel data sets any IN can act as a feature mapping net. Interference locations can be seen as places of solutions, because there highest effective value now can visualise the locations of maximum 'energy' or any maximum norm in statistical meaning. Related to over-conditioning the problem in (natural, free) 3D-space is, that *it restricts the possible channel number to four channels* if we suppose free (optical) wave space. To solve the problem, we have only one solution: to use inhomogenous (wiring) wave spaces.

Fig.6 illustrates for nerve system the problems of over-conditioning: more than 3 channels become problems to project on a plane surface (2D).

To realise projections with hundreds of channels demand, we need an *inhomogeneous interference space*. We need spaces, that are *not defined by square root distance norms*. (see [4] for more). One solution is, *to create an inhomogenous wave space with non-straight wires with varying velocities*.

The inhomogeneity of nerve system offers a fantastic proof for this hypothesis.

Hyperclass Interference Nets

In the work [4] wave expansion and moving on bundles of wires was observed. Because each pulse flows on a single wire, the pulses have no correspondence, each flows alone. If the wiring direction is changed, the wave

direction does change too, but it becomes more and more independent. So we do well, to *handle wiring (flow) direction and wave front direction independent*. Doing that, *we get an additional angle* into reflection and refraction equations. It is the *angle between the wave flow direction and the wave front direction*. Setting the angle to zero, we find optical reflection and refraction equations, for derivations see [4]. What does that mean? In my opinion it means, that *spherical, free wave space* (optical wave space) can only be seen as a *subspace of interference wave space*.

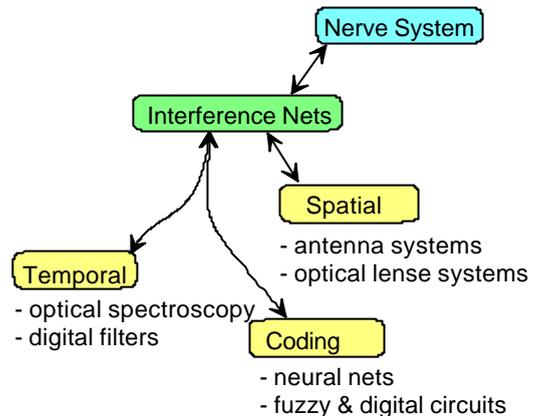
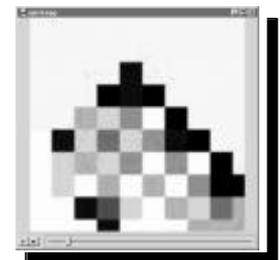


Fig. 9: Interference network subspaces

Spatial and Temporal Granularity of NN

Nerve networks have a spatial and a temporal structure. Dependent on the physical distance between any two neurons the delay distance for each signal increases (by contrast to pool of neurons circuits [1]). Using a multi-layer neural network, we are going a first step in this direction, see Fig.10.

Fig. 10: NN wave field with friendly permission of Alain Destexhe, CNRS France⁵¹ (part of spiral.mpg)



We define a signal delay (of one unit - however) between for example two layers.

Doing that we neglect, that any real spatial and temporal structure⁶¹ defines the function. Trying to realise an interference projection on a multi-layer neural net, we find

⁵¹ <http://cns.iaf.cnrs-gif.fr/Main.html>, Destexhe@iaf.cnrs-gif.fr

⁶¹ In comparison with the many researches done in neurocomputing over the last forty years this is the mutually main reason, we found the first interference projection so late, November 14, 1994; see http://www.gfai.de/www_open/perspg/heinz.htm

consequences: beside the over-conditioning problem time-delaying NNs do almost not have the necessary spatial and temporal granularity to realise interference projections. This appears also as a problem offering the IN approach.

But there is another too. Spikes supposed, different NNs changes the function quality if we implement them as INs. For example, Amaris [1] well known concept formation network will not work very well, if we introduce wave spaces (and additional delays) between neurons, that means with larger delays for larger signal distances and with spaces between neurons. So one can prove a lot of classical NN-structures [2]. An IN implementation in form of Fig.4 seems to work better, if Amari's structure is 'opened' and signals alternate between the two sites. By analogy to Fig.4, within nerve system we know a lot of projective fields, coupled via long axons.

Signal Type Dependence

A special part of spatial interference research concerns the quality of mapping [4], [5]. In opposite to other, any interference projection or transformation *depends on the type of input signals*. We know this phenomenon very well from different scientific fields, sometime the effect is called 'aliasing', in my book [4] it was called 'Fremdinterferenz' (cross interference). To illustrate the problem we will use two channels and two time functions: a Dirac-like and a sinoidal.

Within the same arrangement we find very different results (without proof): *while sinoidal functions produce the maximum cross interferences, d-like functions produce the minimum*. All other time function classes lay between them.

With some fantasy we can imagine, what function type we find in nerve system and why. For more see [4].

Relativity of Space and Time, Colours

To address a certain district in nerve system, from a theoretical viewpoint we can go different ways: First we can project with short impulses over fast wires or second we can realise the same quality using slow wires and slow impulses (we remember the sympathetic or the parasympathic structures). For example ($s = vT$):

pulse duration T	velocity v	pulse width s
1 hour	1 mm/hour	1 mm
10 microseconds	100 m/sec	1 mm

The table shows, that any 'impulse' with a duration of one hour can meet and locate any destination as exact, as an impulse with a 1 millisecond duration can do!

We know mechanisms for both types: So we know

leucin macromolecules [9] to be floating very slow and with constant velocity of 4 $\mu\text{m}/\text{sec}$ through nerves. At the other side we know ionic transport on myelinised nerves with 120 m/s. Because the velocities have different carrier types (ions resp. macro-molecules), but can theoretically occur in the same nerve fibre, we call the different carrier mechanisms *velocity colours* of a nerve fibre [4].

Geometric Wavelength Variation

A Purkinje cell carries up to 80.000 synapses [3]. So it seems not of great interest to study cases, that a single synapse is exciting. From a global point of view it seems, that the fire of some thousands exciting synapses will be suppressed before a threshold is reached. If a number of neurons greater the threshold number fires, the neuron will fire.

An investigation in [4] asked for conditions of wave shape reproduction for n firing synapses and a simplest model neuron, superimposing the synaptic values and for normalisation - dividing the result through any constant number k . One can prove linear (additive) and non-linear superimposition types. The result is as simple as useful:

- a) **Linear superimposition:** Adding the values of synapses and dividing the result by k reproduces the wave shape. Independent of the number of firing synapses the waves do not change there height- to width-ratio between input and output.
- b) **Exponential case and thresholds:** Using any non-linear superimposition in direction to multiplication or exponentiation, the resulting wave becomes smaller and smaller as higher the number of firing synapses is.
- c) **Logarithmic superimposition:** The case of logarithmic superimposition is also thinkable. It enlarges the geometrical wave length. This can be useful to control the background velocity of large areas for zooming and moving effects [4...7].

For example:

- a) Addition: supposed four exciting synapses giving each the half maximum of 0,5 units we can add $4 * 0,5 = 2$ and divide by the number to normalise the function to 1: $2/4 = 0,5$. So, the input value of any curvature is identical the output value, memorisation effects neglected, the shape of the wave is reproduced between input and output.
- b) Multiplication: taking four exciting synapses giving each the half maximum of 0,5 units we can multiply $0,5^4 = 0.0625$. The maximum is unchanged, because $F=1$. Normalisation is not necessary. That means, the input value of any curvature is many times sharper the output curvature, memorisation neglected, the shape of a wave is not reproduced, the wave is many times sharper the original wave.

A further interpretation of Fig.11 is: For symmetrical, bipolar time functions the multiplication iterates the sign dependent on k , so this is not a useful case. The multiplication is only possible using *monopolar time-functions*, that means with a positive value-range, best between 0 and 1. Again we found nerve properties.

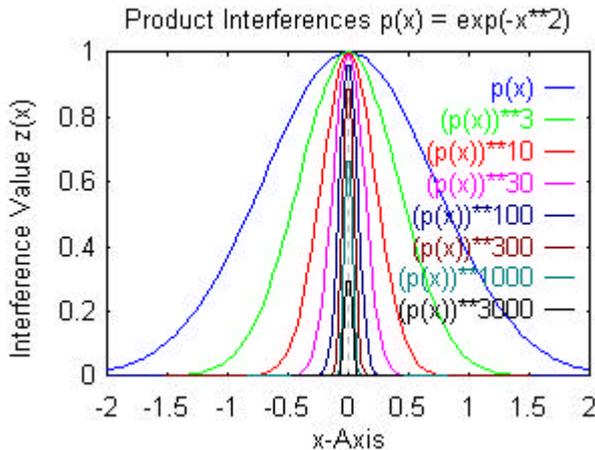
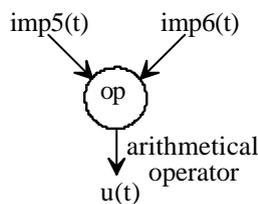


Fig. 11: Exponential case: Interference power series of a Gauss-function 1...3000. The resulting wave is sharper, the more inputs we use (source [4]), if all inputs use the same shaped time function.

Thresholds define Functions

Analysing interference systems has offered us to use classical, physical wave models basing on superimposition of time functions. Now we have to ask for the role played by thresholds in wave interference systems. We consider two time functions consisting of a pulse series with 5 delay units between the pulses and a second with 6 units delay between pulses [4].

Both functions combines using linear superimposition (addition) or non-linear superimposition (multiplication), see Fig.12. Normalisation supposed, for different thresholds a), b) and c) we ask for the function of the net.



A rectangle threshold function is used (not drawn); all values up the thresholds realise a one as output, lower values produce a zero as output. Although the method is simple we find interesting relations:

- a) Threshold level a) appears for addition and multiplication nearly identical.
- b) Threshold level b) shows only small differences in the

ON-time.

- c) But threshold level c) shows significant different output functions comparable to the difference between logical AND and OR.

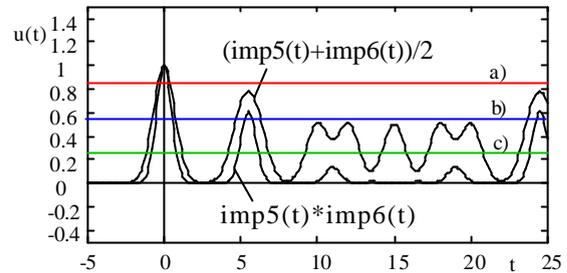


Fig. 12: Linear and exponential superimposition in relation to different threshold levels a), b), c)

Thus we have to summarise, that not only interference delay conditions, types of superimposition or weights define the (logic) function of a IN, also threshold levels contribute in case of non-binary, floating signals.

Basic Functions of Neurons

Instead to ask which functions one neuron has, we'd like to suppose, neural elementary functions can be realised with a simplest interference circuit. So we get a new set of neural basic functions, first descriptions of this hypothesis we find in [5], Fig.13.

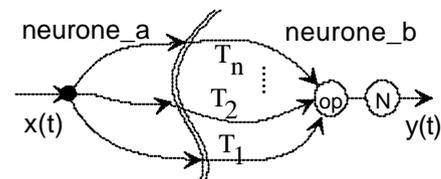


Fig. 13: The simplest IN consists of a coupling of more than one neuron(s)⁷¹

Analysing this configuration we find following signal theoretical roles (for more see [5]):

- a) code generation, suggested op is a summative operator;
- b) code detection, suggested op is multiplicative;
- c) threshold generation if we use a lot of inputs and a fine tuned normalisation function N ; [5]
- d) neighbourhood inhibition, if the delay trees of both neurons are identical (that means, neuron_a is not able to couple with b if they are neighbours in 3D-space), because the delay vectors are the same. Any self-interference is suppressed.

⁷¹ http://www.gfai.de/www_open/perspg/g_heinz/biomodel/models.htm

A Hypothetical Brain Interface (BI)

There are a lot of facts speaking for a general organisation principle of mind in form of interference networks. Although until now the learning possibility is not cleared, especially self-organising and independence of the wiring are properties of INs.

Supposed, within a certain number of channels it is possible, to address a certain neural field within the brain. We need a generator (gen), that is able to generate multiple time functions for different channels dependent on incoming signs or images. At the same time a detector (det) is listening for the traffic on the nerve axons and interfering them onto a field, reconstructing ASCII-signs or pictures of thought from the observed field.

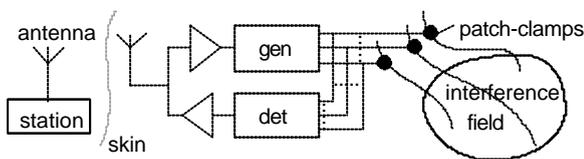


Fig. 14: Hypothetical implanted Brain Interface to exchange thought between man and machine

So it could be possible for a carrier (man), to imagine signs on the interference field, waiting for reply.

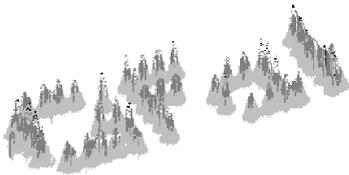


Fig. 15: Four channel reconstruction of characters in simulation - a chance to interact with brain?

Remembering the first computer screens for ASCII-text with 40 columns and 25 rows this will become a comparable development. Supposed, we get a direct data access onto large relational databases (for example via radio receiver/transmitter), this research offers an interesting new technology. In consequence it also could open the door for bridging defect nerve bundles in case of injuries. Using sufficient *small pulse densities*, in simulation it is possible to bring different ASCII-signs over 4 channels into the same interference field, see Fig.15, source GFaI/Heinz1995 (homepage⁸¹ only). By contrast to *pulse density related models* the possibility to realise high quality interference projections is *higher*, as longer are pauses between pulses (not as denser is the signal stream!).

Conclusion

The different usage of the term projectivity between wave-optics and neuro-mathematics offered a new net category - interference networks (IN). Introducing waves in net-like structured algorithms we demonstrated discrete wave fields in delaying networks. To analyse relations between speech and seeing we observed spatial and temporal properties of INs. We find, each IN has spatial and temporal properties at the same time, closely related to self- and cross-interferences of corresponding time functions. Relations to neural net research are discussed. Properties of superimposition of time-functions show possibilities for geometrical pulse length variations depending on the operator-class and the threshold levels used. Lashleys holographic brain of rats appears as a property of interference nets. To realise IN-feature maps with high channel numbers, we need net inhomogeneity to realise projections within natural 3D-space. Pulse-like time-function shapes produce minimum cross interference and highest projection quality. A first suggestion for a hypothetical brain interface is offered. The interferential approach demands different signal properties by contrast to pulse-density modulated networks.

References

- [1] Amari, S.-I.: Neural theory of association and concept formation. Biol. Cybernetics vol. 26, 1977, pp. 175-185
- [2] Anderson, J.A., Rosenfeld, E.: Neurocomputing - Foundations of Research. MIT Press, Cambridge, MA, 5th printing 1990
- [3] Eccles, J.C.: Das Gehirn des Menschen. Seehamer Verlag 2000, ISBN 3-934058-37-X
- [4] Heinz, G.: Neuronale Interferenzen oder Impulsinterferenzen in elektrischen Netzwerken. GFaI-Report 15. Juni 1993, 300 S.
- [5] Heinz, G., Höfs, S., Busch, C., Zöllner, M.: Time Pattern, Data Addressing, Coding, Projections and Topographic Maps between Multiple Connected Neural Fields - a Physical Approach to Neural Superimposition and Interference. BioNet '96, Proc. 3rd Workshop on Bio- Informatics and Pulsprop. Networks, Nov. 14-15, 1996, Berlin, pp. 45-57, ISBN 3-00-001107-2
- [6] Heinz, G.: Space-Time Relations in Wave Interference Systems with Attention to Nerve Networks. Regular paper #1402-028; 2. ICSC Symposium on Neural Computation NC'2000, May 23-26, 2000, TU Berlin, publ. in Proc. of the Second ICSC Symp. on Neural Computation, Editors H. Bothe & R. Rojas, ISBN 3-906454-22-3, ICSC Acad. Press, pp. 433-441
- [7] Heinz, G.: Abstraction Levels in Neuro-computation - from Pattern Processing to Wave Interference. Invited plenary lecture, paper #1504-436 ICSC Symp. on Biol. Inspired Systems (BIS'2000) within the ICSC Congress on Intelligent Systems and Applications (ISA'2000) Dec. 11-15, 2000 Univ. of Wollongong, Australia
- [8] Lashley, K.S.: In search of the engram. Society of Exp. Biology Symp., No. 4 (1950), Cambridge University Press, pp. 454-480
- [9] Ochs, S., Worth, R.M.: Exoplasmic transport in normal and pathologic systems. Phys. and Pathobiol. of axons. S.G. Waxmann, ed. New York, Raven Press 1978
- [10] Pribram, K.H., Nuwer, M., Baron, J.: The holographic hypothesis of memory structure in brain function and perception. Cont. Dev. in Math. Psychology, vol.II, W.H. Freeman, San Francisco, 1974, pp. 416-457

⁸¹ http://www.gfai.de/www_open/perspg/g_heinz/sim/simdemo.htm